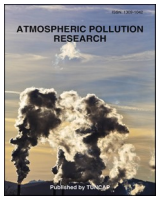
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Indoor and outdoor particulate matter source apportionment in a household in Tetovo, North Macedonia: A pilot study using low-cost sensors

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ABSTRACT

Poor air quality is of global concern due to its impacts on human and environmental health. Effective air quality management requires air pollution monitoring and source apportionment. This study uses low-cost sensors and non-negative matrix factorization, in an exploratory application pairing indoor-outdoor measurements, to identify the contributions of different pollution sources affecting indoor and outdoor environments in a household in Tetovo, North Macedonia. Tetovo was selected because it is one of Europe's most polluted cities, in a region with limited air quality monitoring. During the measurement period, outdoor PM concentrations were higher than indoor concentrations, with daily averages sometimes exceeding 50 μg m^{-3} for PM_{10} and $PM_{2.5}$ peaking at 46 μg m^{-3}. WHO 24-h guideline values were exceeded on 23% and 69% of days for PM_{10} and $PM_{2.5}$, respectively. Indoor daily averages, while still elevated, were lower than outdoors, with $PM_{2.5}$ and PM_{10} reaching maximums of 16 μg m^{-3} and 48 μg m^{-3}, respectively. NMF analysis suggested significant indoor–outdoor interactions, with two of the four indoor pollution sources linked to outdoors. Outdoor sources contributed 77% and 53% of indoor PM_1 and $PM_{2.5}$, respectively, while their contribution decreased to 15% for PM_{10}. Although limited to a single household and a short monitoring period, this study provides initial insights into indoor-outdoor particulate matter dynamics in Tetovo and represents a first step toward a more holistic understanding of its urban air quality. The results highlight the potential of low-cost monitoring approaches for supporting air quality investigations in regions with limited monitoring infrastructure.

1. Introduction

Globally, air pollution is recognised as the greatest environmental threat to public health (WHO, 2014) contributing to approximately 7 million premature deaths annually (Fuller et al., 2022). Particulate matter (PM) pollution is the major cause of premature deaths and hospital admissions globally (Liu et al., 2019), responsible for approximately 61% of the total health burden associated with air pollution (Pillarisetti et al., 2022). As a result, the World Health Organisation (WHO), recognises PM_{10} and $PM_{2.5}$ (particles with a diameter of 10 μm or less and 2.5 μm or less, respectively), as standard measures of air quality and provides recommended daily and yearly values. The WHO last updated the guideline limits in 2021, which state that the annual average concentrations for $PM_{2.5}$ and PM_{10} must not exceed a maximum of 5 μg/m^3 and 15 μg/m^3, respectively. Additionally, the 24-h average concentrations must remain below 15 μg/m^3 $PM_{2.5}$ and below 45 μg/m^3 for PM_{10}, a limit which should not be surpassed more than 3-4 times within a year (WHO, 2021).

The greatest mortality rates attributable to air pollution are observed in developing countries (Pillarisetti et al., 2022). North Macedonia (NM), a developing country, has some of the highest particulate matter concentrations in Europe, resulting in approximately 1600 annual premature deaths attributed to high $PM_{2.5}$ levels (World Bank, 2019) in a country with a population of 2.08 million people. The higher pollution levels are evident particularly in urban areas, mainly due to emissions from residential heating, traffic, industry and energy production (World Bank, 2019). Regional modelling assessments have also highlighted the importance of the energy and residential sectors in shaping $PM_{2.5}$ levels

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across the Western Balkans, with energy production, agriculture, residential combustion and road transport identified as major contributing sources (Belis et al., 2019).

Monitoring and analysing indoor air quality is important, because out of the 7 million annual premature deaths attributable to air pollution, 2.4 are estimated to arise directly from indoor air pollution exposure (Pillarisetti et al., 2022). As a result, over the past decade, research on air pollution control has started to focus more on measuring and assessing air quality inside homes and work areas rather than the outdoor environment alone, as it reflects the predominance of life spent indoors (~80-90%) rather than outdoors (~10-20%). Several studies show that a variety of household pollutants are known to pose a threat to human health, with PM, volatile organic compounds, radon, toxic metals, and microorganisms being the most important ones (Tran et al., 2020; Cincinelli, A. and Martellini, T., 2017).

While measurements of pollutants provide information about the air quality of a given area or environment, the identification of their sources is essential for developing effective mitigation strategies. By identifying the specific contributors to air pollution, policy makers can implement more precise interventions. Previous studies across South-East Europe have investigated particulate matter pollution and its sources primarily at the urban or regional scale. For example, studies conducted in Belgrade (Serbia) have used chemical composition analysis and receptor modelling techniques to identify key sources of PM, including traffic emissions, residential heating and industrial activities (Cvetković et al., 2015; Todorović et al., 2020). Similar receptor-modelling studies conducted in Athens (Greece), have identified biomass burning, traffic emissions and regional secondary aerosols as major contributors to PM pollution (Grivas et al., 2018). In addition, multi-city receptor modelling studies across European and Central Asian urban areas have highlighted biomass burning, traffic emissions, and secondary aerosols as major contributors to $PM_{2.5}$ concentrations in polluted urban environments (Almeida et al., 2020; Belis et al., 2019). In North Macedonia, source apportionment work has mainly focused on ambient PM pollution in the capital city Skopje, where studies have highlighted the importance of residential heating and regional transport in shaping winter pollution episodes (World Bank, 2019). However, most existing studies rely on fixed monitoring stations and outdoor measurements, while household level investigations of indoor and outdoor PM interactions remain comparatively limited in the Western Balkan region.NM has a limited air pollution monitoring network, with only 17 fixed stations across the country, and several cities lacking continuous monitoring coverage (MoEPP, 2017) . Due to this, the pollution in many outdoor areas remain untracked. While some studies have investigated indoor air quality in residential buildings in North Macedonia (Vilčeková et al., 2017), comprehensive investigations of paired indoor-outdoor PM dynamics at the household level remain limited, a trend also observed in other regions of the world (Tran et al., 2020). Recent studies have suggested that indoor and outdoor environments should be considered as an interconnected system, where outdoor emissions can infiltrate indoor spaces, while indoor sources may also influence local outdoor pollution (Nwokorie et al., 2026). This supports the use of paired indoor–outdoor measurements in assessing particulate matter dynamics.

To overcome the limitations associated with the lack of monitoring stations, which are often very costly and have limited spatial as well as temporal coverage, researchers have initiated the use of low-cost sensors (LCS), to collect data on air pollution concentrations, for both indoor and outdoor environments. LCSs offer a cost-effective alternative to obtain real time air pollution data, and this is particularly important for low- and middle-income countries with limited air quality monitoring capabilities, like North Macedonia. Besides being useful for obtaining information about pollution sources, they can also be used to capture a variety of episodic activities (Kumar et al., 2024).

Ferro et al. (2022), used LCS in New York to examine the spatial and temporal air pollution exposure relationships by measuring PM concentrations indoors and outdoors at 50 residences during two heating seasons. Similarly, Krebs et al. (2021) conducted a study to investigate the temporal and spatial fluctuations of PM by deploying 1000 LCS, both indoors and outdoors across various locations in California, USA. As a result, the studies conducted in this field demonstrate that incorporating LCS extends the potential scope of research leading to an increased spatial coverage of air quality measurements. Moreover, to provide effective air quality assessment, it is essential to understand the sources of air pollution, and to do so, source apportionment techniques are used to apportion and analyse the various air pollution sources. A variety of machine learning and clustering techniques can be used for source apportionment. Mills et al. (2023); Bousiotis et al. (2022); Liang et al. (2021); Hagan et al. (2019); Kfuory et al. (2016), have effectively utilized methodologies such as Non-Negative Matrix Factorization (NMF), Positive Matrix Factorization (PMF), and other techniques for the purpose of source apportionments using Low-Cost Sensor data. While such studies using LCS have been conducted exclusively on outdoor data sets, researchers are now deploying such methodologies indoors as well (Bousiotis et al., 2023a,b; Ferro et al., 2022; Rose et al., 2024; Rathbone et al., 2025), to gain a deeper understanding of the different sources and their contributions to air pollution within indoor spaces.

In this context, the present study, provides a pilot investigation of indoor and outdoor particulate matter concentrations in a household in Tetovo, NM using low-cost air pollution sensors. To explore potential pollution sources and their contributions to indoor and outdoor air quality, the study applies non-negative matrix factorization (NMF) to the measured particle size distribution data. This approach enables an assessment of the relative influence of indoor activities and outdoor pollution sources on measured PM concentrations through the analysis of particle number size distribution (PNSD) data. Specifically, the study applies source apportionment to PNSD data, with the resulting factors interpreted in terms of their contributions to PM_1, $PM_{2.5}$ and PM_{10} concentrations. Due to the limited availability of monitoring infrastructure, previous source apportionment work in North Macedonia has mainly focused on ambient PM in the capital city Skopje, while similar investigations have not been reported for Tetovo (World Bank, 2019; MoEPP, 2017). The study therefore provides exploratory insights into indoor-outdoor particulate matter dynamics at the household level in North Macedonia using low-cost sensing and receptor modelling approaches, representing a first step toward a more holistic understanding of indoor and outdoor air quality in the city. The following sections describe the study site, sensor calibration, NMF methodology, results and their implications.

2. Methodology

2.1. Study site and data

The study was conducted in a single urban household in Tetovo, North Macedonia. The house comprised four nonsmokers: two working adults and two retirees who spend most of their time at home and engage in daily activities such as prayers and household chores. The indoor monitored space was a combined living room and kitchen area, which is naturally ventilated and uses a wood stove for heating, located within the room. Indoor measurements were taken in the living room while the outdoor measurements were collected at the house's balcony. These environments were selected to capture the main indoor and outdoor conditions influencing air pollution within the monitored household. The house is a two-storey building located in a densely built urban neighbourhood, with closely spaced houses on the sides. The monitored space is on the second floor, approximately 5m above ground level. Both the room and the balcony (which is open on the three sides), face the backyard, while the main road is situated opposite side of the house (see Fig. 1). The monitored house is approximately 500 m south of the city centre of Tetovo. Tetovo is a small city located in the northwestern part of NM (see Fig. 1a) with a population of 84,770 and a density of 323.7 people/km^2(SSO, 2022) that faces significant challenges due to

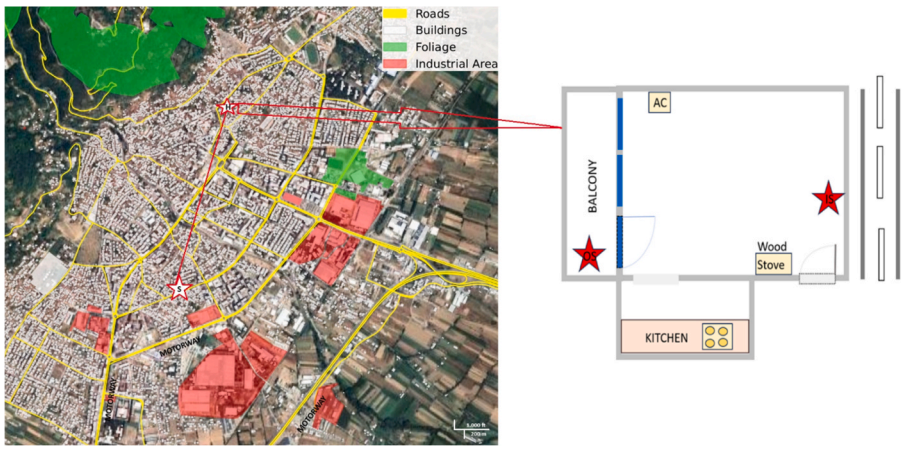


Fig. 1. Map of Tetovo (left) and the diagram of the monitored living room (right). The locations in the map are denoted with stars and marked with S for sensor (the Ministry of Environment and Physical Planning reference station) and H for house (denoting the monitored household). Major roads are highlighted in yellow, with industrial areas (red) and green spaces (green) also indicated. The schematic diagram shows the balcony and the monitored room, with the indoor (IS) and outdoor (OS) sensors indicated by stars; blue rectangles on the balcony side are the windows.

inadequate urban planning and infrastructure, with serious and ongoing air pollution issues (Memedi et al., 2018). In the year 2017, it was ranked as one of the top ten most polluted cities in Europe (World Bank, 2019). The Macedonian Air Quality Assessment Report specified that $PM_{2.5}$ and PM_{10} averages from 2005 to 2015, were the highest in the city of Tetovo, compared to the other 16 North Macedonian cities included in the report (MoEPP, 2017). There were only 15 days in the year 2015, when the air quality in the city complied with the recommended WHO threshold, as reported by the World Bank (2019).

The study uses two low cost Alphasense Optical Particle Counter (OPC-N3) sensors, measuring indoor and outdoor PM mass concentrations in the PM_1, $PM_{2.5}$ and PM_{10} size fractions simultaneously. The OPC-N3 sensors cost approximately 250 GBP, and they measure particle concentrations in the diameter range between 0.35 and 40 μm, at a 10 s sampling frequency (Alphasense, 2022). According to the manufacturer, the sensor's PM_{10} measurement accuracy is ±15%, with a detection limit of 0.01 $\mu g/m^3$ and it can measure up to 10,000 particles per second providing high sensitivity for monitoring low levels of airborne particles.

The monitoring period covered 13 winter days in January (10/1/2023 - 22/1/2023) as part of a pilot monitoring campaign designed to explore indoor-outdoor PM concentrations using LCS. The monitoring duration was limited to approximately two weeks to minimise disruption to the household occupants. The indoor sensor was positioned approximately 2 m away from the woodstove and the door, while the outdoor sensor was placed on the balcony, about 3 m above a wood storing box, facing the backyard of the house, as shown in Fig. 1. Meteorological wind direction and wind speed data were taken from the nearby monitoring station in Tetovo, which is around ≈2 km south from the main study site (Fig. 1). Additionally, an activity diary was kept, keeping track of important household activities, though missing certain details, like window opening times. The windows were primarily open in the morning for brief room airing and were kept closed for the rest of the day.

Throughout the measurement period, the air quality data was available in its entirety, however, the synoptic meteorological data exhibited some missing values. Therefore, linear interpolation was used to fill the missing meteorological data, which was applied iteratively for consecutive missing values. The indoor air pollution measurements were averaged to a 10-min resolution to allow for a high temporal resolution assessment of sources, while outdoor measurements were averaged to a 1-h resolution to better fit with the meteorological data resolution. To account for potential measurement uncertainties associated with LCS, a calibration procedure was applied, as detailed in the following section.

2.2. Sensor calibration

The calibration of LCS is crucial to ensure the accuracy of the measurements obtained by the LCS. In particular, PM mass concentrations tend to be overestimated by the OPCs in the presence of elevated relative humidity (RH) levels (>80%). This discrepancy can be attributed to the hygroscopic nature of PM (Crilley et al., 2020), which mainly affects the measurements of larger particles (>1 μm). The two OPCs were calibrated in stepwise manner. Firstly, one OPC (used for the indoor measurements) was collocated next to Tetovo's regulatory monitoring site, maintained by the Ministry of Environment and Physical Planning (MoEPP). The sensor was positioned directly on top of the regulatory site as can be seen in Figure S4. Calibration was only performed on the $PM_{2.5}$ and PM_{10} as the regulatory monitoring station does not report PM_1 concentrations. Therefore, PM_1 measurements were analysed using the raw sensor outputs. This introduces additional uncertainty in the PM_1 results, as they were not directly calibrated against a reference instrument. However, previous evaluations have shown that OPC can achieve high correlations with reference instruments for fine particle fractions such as $PM_{2.5}$ and PM_1, although performance varies depending on environmental conditions and particle composition (Sousan et al., 2021). The collocation period for $PM_{2.5}$ and PM_{10}, had a total duration of 9 days. To align with the temporal resolution of the regulatory site, the sampling time for the sensor measurements was averaged to a 1-h resolution. To calibrate the second sensor (used for the outdoor measurement), the instrument was collocated with the calibrated one for approximately 5 h at the outdoor monitoring location (balcony). While this period is not enough to fully capture the variability within a day, this was done to reduce disruption of the residents. During this period, both sensors operated simultaneously under identical environmental conditions in order to minimise systematic sensor to sensor bias. Linear regression was then applied to the paired measurements to derive calibration relationships for $PM_{2.5}$ and PM_{10}, resulting in high correlations of $r = 0.98$ and $r = 0.95$, respectively. While the collocation period was relatively short, the high correlations obtained between the sensors indicate a strong agreement.

Relative humidity (RH) data from the LCS was used for the calibration of the PM measurements. The RH measured within the LCS is lower than the ambient measurements due to passive warming within the sensor caused by internal electronics (Nurowska et al., 2023). Analysis of the OPC reported internal temperature, showed mean values of ~36.9 °C indoors and 19.4 °C outdoors (likely reflecting internal sensor conditions and the enclosed indoor environment). This passive warming reduces RH within the sensor but may also lead to partial evaporation of

semi-volatile aerosol components such as ammonium nitrate. The magnitude of this effect could not be quantified here and therefore represents a potential source of measurement uncertainty. The LCS RH measurements were calibrated against the regulatory instruments using linear regression (Figure S1), with a high correlation being observed ($r = 0.94$). During the collocation with the regulatory instrument, the LCS exhibited a minor hygroscopic effect as shown in Figure S2. The indoor sensor was calibrated using an exponential regression approach to account for potential non-linear effects at high RH. As shown in Figure S2, the ratio between LCS and the reference measurements remained relatively stable across most of the RH range (~40% - 90%), indicating that the relationship can be approximated by a constant scaling factor under typical conditions. However, deviations were observed under high RH conditions (approaching 100%), consistent with hygroscopic particle growth affecting the optical response of the sensor. The exponential correction was therefore applied primarily to account for these high RH deviations, rather than implying a strong dependence across the full RH range. LCSs are expected to perform better as size decreases, but this was not the case for the indoor measurements, with the correlations being $r = 0.59$, $r = 0.69$ for $PM_{2.5}$ and PM_{10}, respectively. This could be due to the very low $PM_{2.5}$ concentrations, the lack of bias from atmospheric conditions and the minimal variation for almost half of the collocation period, which was presumably close to the detection and sensitivity limits of the sensor.

The outdoor RH measurements were calibrated against indoor ones using linear regression, achieving a strong correlation (r = 0.99). To account for the RH effect, the same exponential regression (mentioned earlier) was used for the outdoor sensor. Subsequently, linear regression relationships derived from the collocation instrument were applied to adjust the outdoor sensor measurements. These calibration procedures ensure reasonable agreement between instruments while acknowledging residual uncertainties that should be considered when interpreting the results.

2.3. Data analysis and non-negative matrix factorization (NMF)

NMF was used for the source apportionment analysis and exploratory identification of potential air pollution sources affecting both the indoor and the outdoor measurements. Multiple air quality studies have successfully applied NMF (Rathbone et al., 2025; Rose et al., 2024; Kumar et al., 2024; Westervelt et al., 2023; Yang et al., 2022; Hagan et al., 2019) or PMF (Bousiotis et al., 2023a,b; Bousiotis et al., 2022) for source apportionment of air pollution data obtained by LCSs. The use of low cost sensors for source apportionment (LoCoSA) has recently been reviewed by Bousiotis et al. (2025). Historically, the PMF algorithm is the most commonly used method for such source apportionment studies. However, NMF is gaining popularity due to its open-source nature and simpler treatment of the measurement uncertainties, allowing for a wider range of applications while producing comparable results to PMF. The key difference between NMF and PMF lies in their approach to component weighting. NMF assigns equal weight to all components, ignoring individual errors (Ho, 2008), whereas PMF considers scaling and errors for each component. The NMF approach is a descriptive model that analyses observed data and produces a matrix of factors (F) (Ho, 2008), which in this case, represents average particle concentrations, accounting for the different sources of pollution. Simultaneously, it generates a matrix of contributions (G) normalised to 1, that reflects the relative contributions of each factor during a given timestep (Gaujoux and Seoighe, 2010). Like PMF, the NMF lacks an objective criterion for determining the number of factors (Ho, 2008). Thus, the following criteria were considered in selecting the optimal solution.

- understanding the meaning of each factor, being able to link them to specific sources or activities
- there is a low correlation between the variations of the factors, making each one unique
- the studied variables should be significantly affected by the factors, therefore those factors with minimal contributions were not considered
- minimizing the unexplained variance to the greatest extent possible

The indoor and outdoor datasets were analysed at different temporal resolutions: 10-min averages for indoors, to preserve the transient signatures of short-duration household activities, and 1-h averages for outdoors, to match the resolution of the available meteorological data used in polar plot analysis. The input matrix for the indoor NMF analysis consisted of n = 1872 rows (10 min average time points over a 13-day campaign) by m = 28 columns (particle number size bins from the OPC-N3 together with the 3 p.m. mass fractions: PM_1, $PM_{2.5}$ and PM_{10}). Similarly, the outdoor matrix had n = 312 rows (hourly averages) by m = 28 columns. PM mass concentrations were included as input variables, rather than used only for post-hoc validation of profiles, to provide additional physical constraints and improve the stability of the factor solution. While this results in a larger input matrix for the indoor analysis compared to the outdoor one, both datasets retain sufficient temporal variability for the NMF algorithm to identify stable factor solutions. This approach is consistent with several recent low-cost sensor studies (Rose et al., 2024; Rathbone et al., 2025), that incorporate mass fractions directly into the NMF/PMF input matrix to better capture contributions. The input values in this study are the particle number size distribution and the PM mass concentrations for the three size ranges (PM_1, $PM_{2.5}$ and PM_{10}). Once inputted, the estimated PM concentrations are then calculated by multiplying F and G values provided by the model, with F representing the average contribution of PM mass concentrations for each factor and G being the factors contribution at any given timestep. The outdoor and indoor datasets were analysed individually, enabling a better comparison for the different environments. Furthermore, the Openair package, developed by Carslaw and Ropkins (2012) for R was used to carry out additional analysis of the results, which included interpreting the impact of meteorological variables such as air temperature, wind speed, wind direction and relative humidity upon the PM mass concentrations. Given the limited monitoring duration and the exploratory nature of the dataset, the NMF analysis should be interpreted as an indicative tool for identifying potential pollution sources rather than as a definitive source apportionment solution. Nevertheless, these analytical steps provide a basis for exploring general PM trends and potential source contributions, which are examined in the following results section.

3. Results

3.1. General conditions and air quality assessment

Table 1 presents the mean mass concentrations of PM in the PM_1, $PM_{2.5}$ and PM_{10} size ranges, throughout the measurement period. The indoor PM values present a lower spread of values as indicated by lower standard deviations, compared to the outdoor measurements. Overall, the PM_1 and $PM_{2.5}$ concentrations within the household were generally lower than the corresponding outdoor levels. This difference reflects the combined influence of several processes: limited infiltration of outdoor particles through the building envelope (due to closed windows in winter), deposition of particles on indoor surfaces, low natural ventilation rates, and the absence of strong indoor emission sources during many periods. During the monitoring period, no air purifiers were used in the household and indoor activities consisted primarily of LPG cooking (typically 2-3 times per day, as recorded in the activity diary), wood stove heating and routine occupant movement and prayers. However, this pattern did not consistently apply to coarser PM_{10} particles, which occasionally showed higher indoor than outdoor concentrations. Previous studies have documented that indoor environments can sometimes exhibit elevated PM_{10} concentrations due to indoor processes such as dust resuspension, occupant movement and household

Table 1
Mean PM_1, $PM_{2.5}$, and PM_{10} concentrations for both indoor and outdoor environments and PM_1/PM_{10}. *Note that PM_1 mass concentrations were not calibrated due to the absence of reference data from the regulatory monitoring station.

Pollutants	PM_1*(μg/m^3)	$PM_{2.5}$ (μg/m^3)	PM_{10} (μg/m^3)	PM_1/PM_{10} Ratio	$PM_{2.5}/PM_{10}$ Ratio
Indoor Concentrations	3.41 ± 1.92	10.49 ± 5.67	36.07 ± 35.76	0.09	0.29
Outdoor Concentrations	11.21 ± 8.76	23.56 ± 18.41	57.43 ± 160.13	0.2	0.41

activities (Braniš et al., 2005; Bo et al., 2017; Bennett et al., 2019; Vardoulakis et al., 2020). These observations suggest that indoor processes likely played a more prominent role in determining coarse particle levels during this pilot monitoring campaign.

To formally compare indoor and outdoor concentrations, Spearman rank correlation and the Wilcoxon signed-rank test were applied to the hourly-averaged data. Spearman correlation revealed a strong positive association between indoor and outdoor concentrations for PM_1 ($\rho = 0.74$, $p < 0.001$) and a moderate association for $PM_{2.5}$ ($\rho = 0.57$, $p < 0.001$), suggesting that fine particle concentrations indoors are associated with, and may be partially driven by, outdoor particle levels, consistent with the expected infiltration of fine particles during the monitoring period. In contrast, PM_{10} showed no statistically significant correlation ($\rho = 0.03$, $p = 0.579$), suggesting that indoor coarse particles are largely governed by indoor processes. These findings are supported by the Wilcoxon signed-rank test, which confirmed statistically significant differences between indoor and outdoor concentrations for PM_1 and $PM_{2.5}$ ($p < 0.001$), but not for PM_{10} ($p = 0.072$). The significant Wilcoxon test result indicates that indoor fine PM concentrations were systematically lower than outdoor levels, consistent with the measured I/O ratios (<1) and the expected attenuation of particles through the building envelope. In contrast, the strong to moderate positive Spearman correlations reflect temporal co-variation between indoor and outdoor fine PM, suggesting that outdoor concentrations are associated with and likely contribute to indoor levels through infiltration. These two statistical tests are therefore complementary: fine particles infiltrate from outdoors but are attenuated indoors, resulting in lower absolute concentrations while maintaining correlated temporal patterns.The indoor/outdoor ratios were 0.3, 0.45 and 0.63 for PM_1, $PM_{2.5}$ and PM_{10}, respectively. These ratios show the expected variation, with larger particles having higher ratios compared to smaller ones. The diurnal variations of PM and their ratios, for both indoor and outdoor concentrations, are presented in Figure S5, where the notably elevated outdoor PM concentrations in comparison to indoor levels are highlighted. Table 1 also presents the PM_1/PM_{10} ratio for indoor and outdoor environments. The lower PM_1/PM_{10} ratio indoors, when compared to outdoors, suggests that the indoor air quality is less affected by PM_1 particles, which in most cases originate from outdoors (Bousiotis et al., 2023a,b; Rose et al., 2024; Rathbone et al., 2025). This trend becomes more pronounced after the extreme values of PM_{10} on the 22nd of January are removed. The outdoor PM_1/PM_{10} and $PM_{2.5}/PM_{10}$ ratios increase from 0.2 to 0.34 and 0.41 to 0.66, which aligns with previous studies, indicating that indoor sources are PM_{10} heavy (84.6% of total PM_{10} mass attributed to internal factors, see Table 3).

The polar plots of the outdoor $PM_{2.5}$ and PM_{10} concentrations are presented in Fig. 2. The $PM_{2.5}$ plot shows that the highest concentrations occur with winds from the southern and western sectors, when the wind speed is relatively low, suggesting a nearby source of pollution, with a very heavily trafficked road located in that direction, therefore making road traffic sources the most likely cause of the outdoor $PM_{2.5}$ pollution. PM_{10} concentrations, on the other hand, tend to be more influenced by moderate southerly winds, which correspond to an area where various industries are located that do not have modern emission reduction systems (MoEPP, 2017). The localised high concentration features observed under southerly and southeasterly winds likely reflect airflow disturbances, such as local recirculation or flow modification caused by nearby buildings and the dense urban layout (Vardoulakis et al., 2003).

Throughout the measurement period, the outdoor concentrations of both pollutants exceeded the recommended 24-h guideline values set by WHO, specifically on three (23.1%) and nine days (69.2%), reaching a

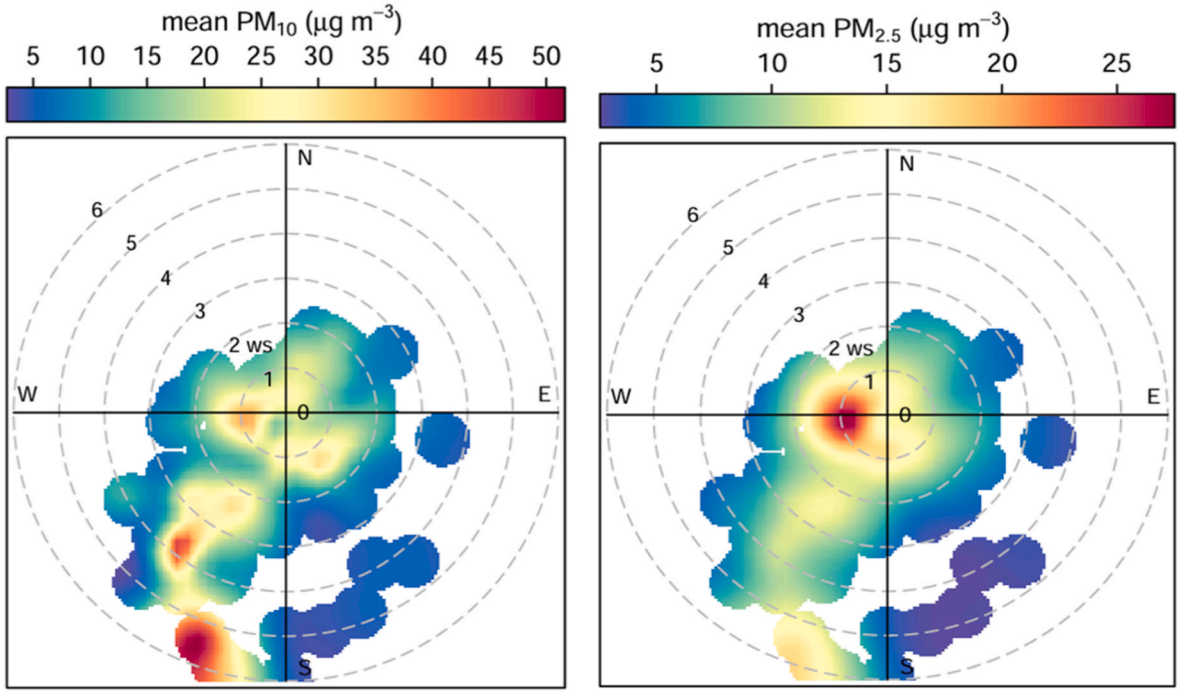


Fig. 2. Polar plots of the outdoor PM_{10} and $PM_{2.5}$ concentrations.

maximum of 56 μg/m^3 and 46 μg/m^3, for PM_{10} and $PM_{2.5}$, respectively. While WHO does not provide hourly guideline values, the 24-h threshold was used as a proxy for short-term pollution peaks, with 62% and 29% of hours having $PM_{2.5}$ and PM_{10} values above 15 μg/m^3 and 45 μg/m^3, respectively.

Even though the WHO guidelines for PM pollution were set for ambient conditions, they can also be used as a reference to analyse indoor air quality (Huang et al., 2018), as their role is to ensure public health. There were occasions when the indoor concentrations exceeded the WHO 24-h threshold, specifically on two days (15.4%) and one day (7.7%) for $PM_{2.5}$ and PM_{10}, respectively, with the highest recorded daily averages of 16 μg/m^3 and 48 μg/m^3. According to the activity diary, these exceedances usually happened on the same days when wood burning usage for heating the living room led to a noticeable bad odour, suggesting that these exceedances are likely linked to these activities. The WHO daily threshold was used for hourly exceedances, and the PM_{10} and $PM_{2.5}$ concentrations exceeded the limit in 28% and 16% of the hours, mostly associated with wood burning activities indoors.

3.2. Indoor and outdoor NMF analysis

To explore and apportion the sources of PM influencing the indoor and outdoor measurements, NMF was applied to the particle number size distribution data. For the indoor data set, a four-factor solution was chosen, as it yielded distinct factors with low correlations between them (see Figure S8a). Given the short monitoring period and the lack of chemical speciation data, factor attributions in this study are based solely on indirect evidence (temporal alignment with the activity diary, polar plots, and inter-factor correlations). Accordingly, the interpretations presented below should be regarded as indicative of dominant processes and indoor-outdoor linkages rather than definitive source apportionment. Several solutions with different numbers of factors were considered; however, as additional factors were introduced, it was observed that the correlations between two or more factors became stronger ($r > 0.70$), mostly occurring at the same time periods. As higher correlations between factors could suggest that they may be associated with the same underlying source, activity, or origin, and to ensure distinctiveness of the factors, solutions with a higher number of factors were not considered.

The particle number size distribution (PNSD) profiles for each indoor factor are presented in Figure S6a, all exhibiting a dominant mode <500 nm. This is typical for particle number size distributions, as particle number is generally dominated by fine and ultrafine particles, while coarse particles contribute relatively little to total number counts even when they dominate mass (Hussein et al., 2006; Bousiotis et al., 2025). Factor distinctions are therefore primarily reflected in their relative contributions to different PM size fractions, their diurnal patterns, and alignment with the activity diary.

Table 2
Average PM concentrations indoor (μg/m^3) and percentage contributions (%) of each individual factor to total PM_1, $PM_{2.5}$ and PM_{10} in each environment. Indoor and outdoor factors were labelled with the IN and OUT prefixes, respectively. Aggregated indoor vs outdoor contributions are provided in Table 3.

Factors	PM_1 (μg/m^3)	$PM_{2.5}$(μg/m^3)	PM_{10} (μg/m^3)	PM_1 (%)	$PM_{2.5}$ (%)	PM_{10} (%)
IN_F1	1.05	0.95	1.8	30.7	19.8	8.6
IN_F2	0.61	1.32	0.04	17.8	27.6	0.2
IN_F3	0.17	0.94	17.7	5.0	19.6	84.4
IN_F4	1.59	1.58	1.44	45.5	33.0	6.9
OUT_F1	5.87	6.68	9.91	52.4	42.5	24.9
OUT_F2	4.37	5.3	4.98	39.0	33.7	12.5
OUT_F3	0.36	0.96	21.73	3.2	6.1	54.6
OUT_F4	0.61	2.79	3.18	5.4	17.7	8.0

Figure ***SEQ Figure * ARABIC 6*** *The indoor factors' contribution to a) PM_1, b) $PM_{2.5}$ and c) PM_{10} deriving from the G contribution values.*

Table 2 provides the average PM concentrations (μg/m^3) for the indoor and outdoor factors in the PM_1, $PM_{2.5}$ and PM_{10} size fractions, along with the percentage contribution (%) of each individual factor to the total PM in each size range. This highlights distinct differences between fine and coarse particle sources. Indoor PM_{10} was strongly dominated by Factor 3 (84.4%), indicating a major contribution from coarse particle sources, likely associated with resuspension and occupant activity. In contrast, indoor PM_1 and $PM_{2.5}$ were more evenly distributed across factors, with factor 4 contributing the largest share (46.5% and 33.0%, respectively). For the outdoor environment, PM_1 and $PM_{2.5}$ were primarily influenced by Factors 1 and 2, while PM_{10} was dominated by Factor 3 (54.6%), suggesting a stronger influence of coarse-mode sources such as resuspended dust and local emissions.

Table 3 presents the percentage (%) contribution of the combined indoor factors and the combined outdoor factors to the three size ranges, further highlighting that indoor sources play a more prominent role in coarse particles, while fine particles are more strongly influenced by outdoor contributions.

In some cases, the estimated concentration contribution of $PM_{2.5}$ may appear to be higher than the PM_{10}, even when both are linked to the same factor. Such discrepancies arise because the model treats each variable independently, without considering their inherent relationships, which can lead to errors, such as estimating that a particular variable (PM_{10} in this case) has less than anticipated contribution to a factor. For the present study however, the concentrations are presented exactly as generated by the NMF model, and when such a case occurs (i.e. $PM_{10} < PM_{2.5}$, or $PM_{2.5} < PM_1$) it should be considered that the contribution of the specific factor on the greater particle size range is negligible.

It was not possible to associate the 1st factor with a single source. It was occasionally linked to specific household activities such as cooking and the activation of room air conditioning, a practice that could potentially introduce outdoor particles indoors (Bari et al., 2015) or enhance their resuspension. It exhibits a noticeable, though smaller, impact on PM_1 concentrations, compared to Factor 4, with high PM_1/PM_{10} and $PM_{2.5}/PM_{10}$ ratios (>0.50). Its temporal patterns closely resemble those of the 4th factor (discussed later), an indoor factor likely influenced by outdoor sources, with a correlation of 0.59 between them (see Figure S11). This factor also correlates well with the second outdoor factor, ($r = 0.60$,see Figure S11), supporting the likelihood of an outdoor source. These patterns, together with polar plots, support an interpretation of an outdoor origin. However, given the reliance on indirect evidence and the absence of chemical speciation or additional tracers, this attribution remains indicative rather than definitive.

The 2nd factor predominantly contributed to cooking and wood stove heating inside the room. It had very little to negligible effect on PM_{10} suggesting that the pollution sources contributing to this factor are very likely made up from smaller particles. When the variation of the G contribution (the relative contribution of this factor) was examined for each day separately, noticeable spikes in this factor's values coincided consistently with cooking activities and wood stove usage, as reported in the family's activity diary. The hourly variations of the G contribution on 12th of January are shown in Fig. 4, where the cooking activities and wood stove usage for heating are clearly outlined and coincide with the exact hours mentioned in the diary.

The 3rd factor largely contributed to PM_{10}, as visually illustrated in Fig. 3 and is characterised by low PM_1/PM_{10} and $PM_{2.5}/PM_{10}$ ratios of 0.01 and 0.05, respectively. When the variations were examined

Table 3
Estimated contribution of the effect of indoor and outdoor factors on PM_1, $PM_{2.5}$ and PM_{10} (Indoor factors were F2 and F3, while outdoor factors were F1 and F4).

Pollutants	PM_1	$PM_{2.5}$	PM_{10}
Internal Contribution	22.8%	47.1%	84.6%
External Contribution	77.1%	52.8%	15.4%

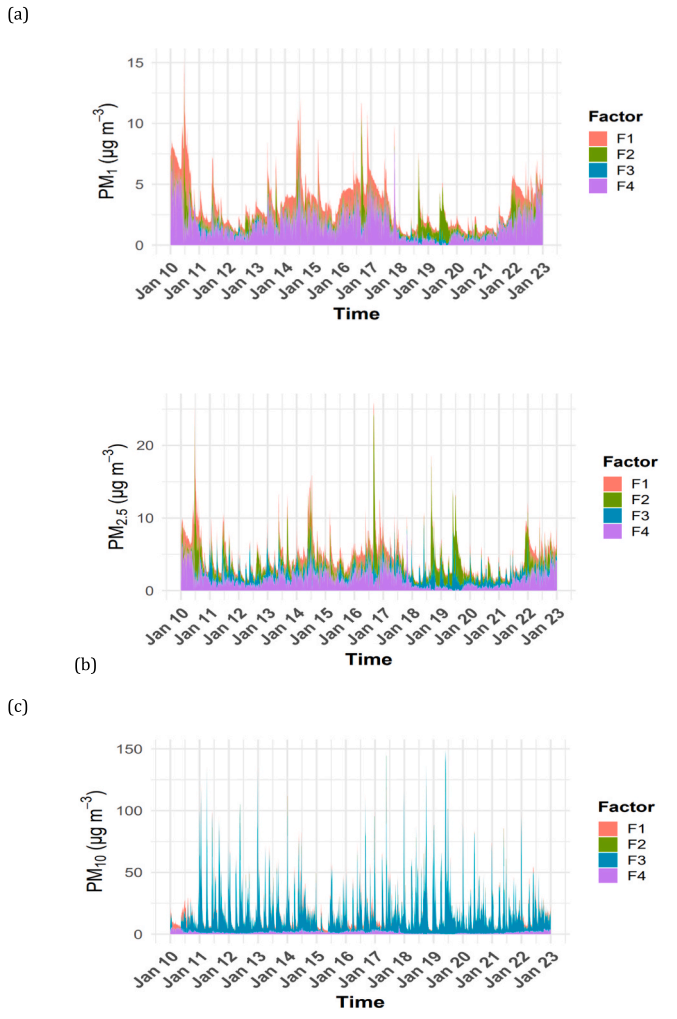


Fig. 3. The indoor factors' variation of a) PM_1, b) $PM_{2.5}$, and c) PM_{10} for the whole monitored period, deriving from the normalised G contribution values.

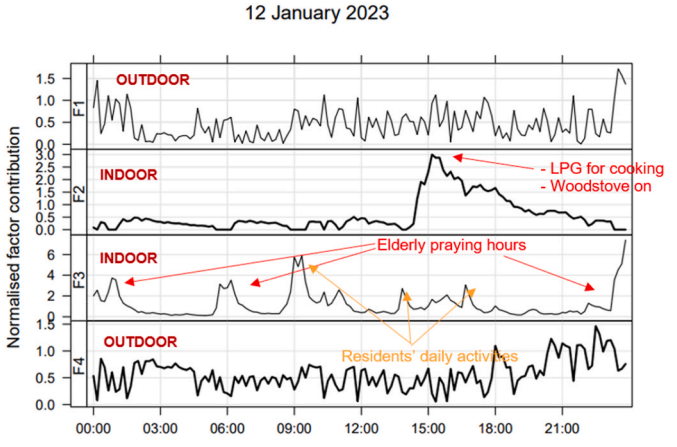


Fig. 4. Hourly variation of the G contribution for each factor of the indoor NMF analysis on the 12 of January 2023. All times shown are in local time (CET, UTC+1).

separately for each day, the high spikes were consistently evident in this factor on nearly a daily basis, the exception occurring during a day when the occupants were absent from the monitored room. Additionally, alongside the observed spikes throughout the days, the diurnal pattern of this factor (illustrated in Figure S6b), demonstrated recurring spikes around 1 a.m. and 5am. The spikes in factors 3's influence, some of which are visually represented in Fig. 5 for January 12th, closely align with the scheduled prayer times observed by Tetovo's Muslim elderly population. Moreover, the other spikes dispersed throughout the day correspond with routine activities such as waking up, performing daily chores (Braniš et al., 2005; Bo et al., 2017; Bennett et al., 2019), and engaging in regular prayers. This is consistent with the findings from Luoma and Batterman (2001), who found that occupant activities contribute to coarser particles and are a main source of indoor PM pollution. As such, these observations suggest that factor 3 is highly associated with household dynamics and the day-to-day activities of the residents.

The impact of the 4th factor predominantly influences PM_1 levels as visually illustrated in Fig. 3a. Notably, its diurnal pattern appears relatively constant, without any notable peaks (Figure S6b), and a reduced contribution in the afternoon. This factor exhibited no correlation with indoor activities, signifying that its origin likely comes from an outdoor or ambient source. Therefore, this factor's inclination towards affecting PM_1 levels and the absence of distinct diurnal fluctuations, suggests that its source may remain relatively consistent throughout the day and that there is a potential association with PM_1 that may be prevalent outdoors (e.g., urban background or traffic related emissions) (Titos et al., 2014). This aligns with the notion that certain fine particulate matter constituents, influenced by external factors such as vehicular emissions, can contribute to indoor air quality dynamics (MacNeill et al., 2012), as larger particles are less likely to infiltrate indoor environments, especially near high traffic density households (Vardoulakis et al., 2020). Furthermore, the polar plot of this factor (see Figure S12) shows that the highest concentrations occur when the wind is blowing from the south, associating it with traffic emissions, as south of the study site is a very frequently travelled road. The high correlations of $r = 0.64$ and $r = 0.66$ with the 1st and 2nd outdoor factors (mentioned later), which showed higher concentrations when the wind was blowing from the south (Fig. 5), further support this.

Similarly, after considering various alternatives with a higher number of factors, it was concluded that a four-factor solution presented the most suitable configuration for the outdoor data as well (Figure S8b), as selected based on the rules mentioned earlier.

The PNSD profiles shown in Figure S7a, present all the size bins available for the outdoor data. Factor 1 shows an increasing trend when particle diameter is below 800 nm, with no significant peaks in all the measured ranges of the OPC. Factors 2 and 3 have relatively similar patterns both spiking at 600 nm, with factor 3 having a slight increase at 1.5 μm. Factor 4's PNSD profile shows an increase with a particle diameter of 800 nm with a smaller increase again at 1.5 μm.

The first outdoor factor mainly consists of ultrafine particles, though a smaller contribution on coarser particles is also observed (Table 2). The diurnal variation of the factor's contribution remains relatively consistent throughout the day, indicating its nature as a background source (Bousiotis et al., 2022), occurring constantly without significant peaks within the day (Figure S7b). The factor has increased contributions from all wind directions (Fig. 5), making it difficult to distinguish the origin of the pollutants and probably associated with regional sources. Previous research pointed out the weakness of source apportionment using LCS data to distinguish background sources originating from greater distances (Bousiotis et al., 2023a,b).

The second outdoor factor reveals a hotspot directly to the west (Fig. 5) and its diurnal pattern tends to have a more pronounced contribution during peak traffic hours as well as in the afternoon when homeowners return from work and heat their homes (Figure S7b). Its composition primarily consists of finer PM_1 particles and a small amount of $PM_{2.5}$, as visually illustrated in Fig. 6. Traffic emissions are primarily associated with smaller particles (Pérez et al., 2010), while brake and tyre wear contribute to larger particles, like $PM_{2.5}$ and PM_{10} (Kam et al., 2012; Thorpe et al., 2007; Garg et al., 2000). Moreover, wood burning for residential heating significantly contributes to ambient $PM_{2.5}$

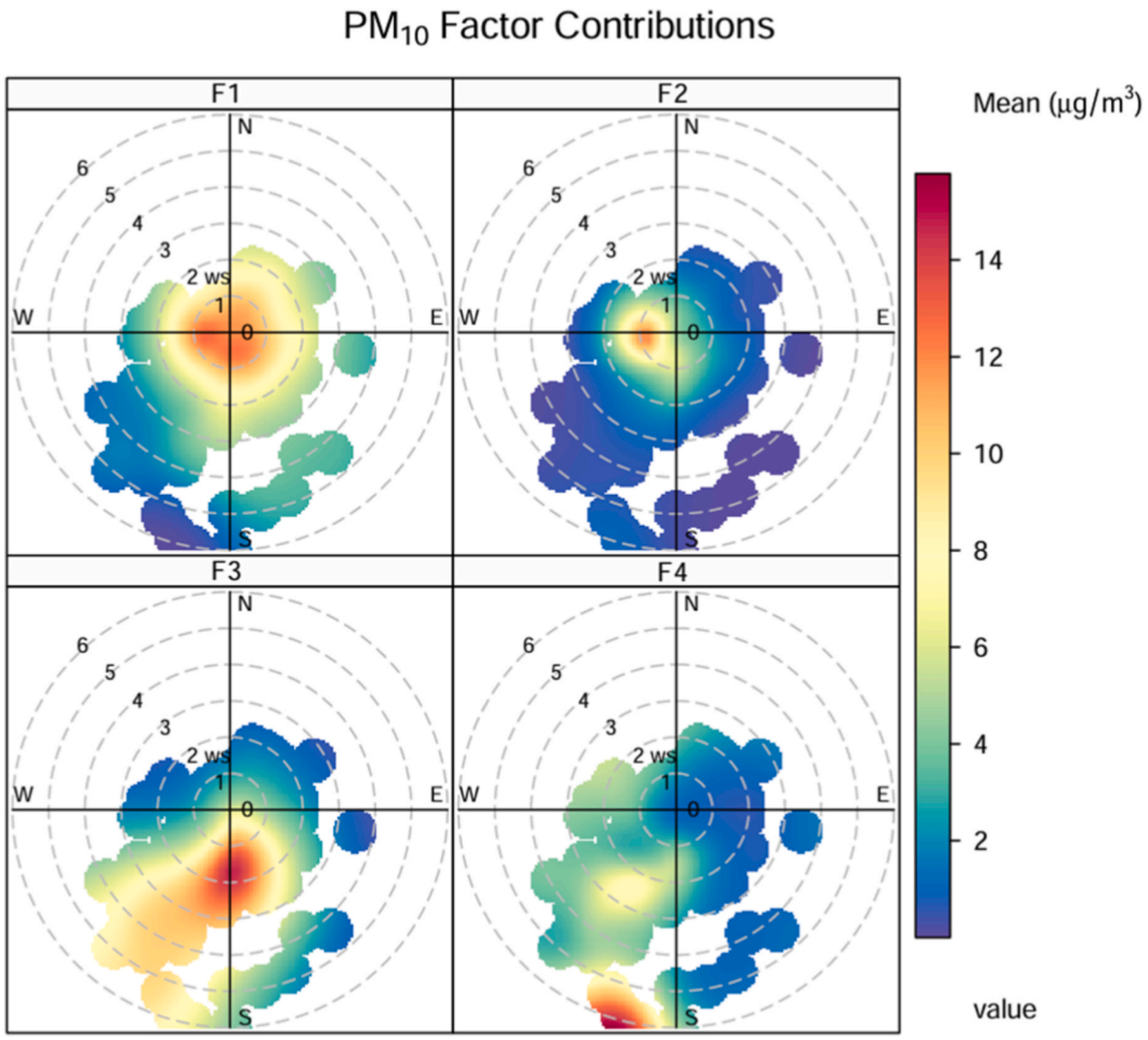


Fig. 5. Polar plot of outdoor PM_{10} for the outdoor F1, F2, F3 and F4 of the source apportionment analysis.

concentrations (Villalobos et al., 2017). This factor's association with slow western winds suggests that the source is likely relatively close. Specifically, west of the study site, is a frequently travelled road that experiences considerable traffic congestion. Moreover, the road is surrounded with a densely built residential area where wood is commonly used for home heating. Its synchronization with peak hours and its inclination towards finer particles suggests that this factor is likely associated with traffic emissions and biomass burning.

The temporal variation of the third factor is dominated by a rather high spike on the 22nd of January (Figure S9). This notable peak, which transpired on the other factors as well, was observed during the early morning hours and exhibited the most significant impact on PM_{10} levels (Fig. 6c), suggesting a potential nearby emission source. Movement and presence of people are linked to higher PM_{10} measurements detected by LCS in the surrounding area (Bousiotis et al., 2023a,b), and a plausible scenario for the spike is residents picking up firewood (an activity recorded in the diary as well), typically stored right below where the sensor is located in the balcony. This indicates that this pattern occurred in a burst making it an incident and not a constant source. Therefore, when this incident was removed from this factor, the average concentration contribution for PM_{10} dropped significantly, from F3 = 21.73 (see Table 2), to F3 = 5.21, while it remained very similar for the other smaller size ranges. According to the polar plot of this factor, the highest pollution concentrations occurred when low southerly winds were present. A major highway (E−65), connecting the city to the adjacent cities and villages, is located to the south of the regulatory monitoring station. This area, which has some unpaved roads, is also home to various manufacturing industries, ranging from steel and glass production to furniture making, likely affecting and contributing to the PM pollution in the city. Although the factor does not have a clear diurnal variation, in contrast to factor 2, its tendency towards coarse and fine particles, along with higher pollution levels coming from the south, suggest that it is likely associated with industrial related emissions, potentially influenced by the episodic event observed on January 22nd. This is consistent with previous studies (Zhu et al., 2018; Thurston et al., 2011, gon Ryou et al., 2018) which have identified industrial emissions as a common contributor to PM pollution in urban environments.

Similar to the third factor, higher contributions associated with the fourth factor were observed during periods with southerly winds (Fig. 5). The diurnal profile (Figure S7b) shows a peak around midday followed by lower contributions during nighttime hours. To the south of the study site, is the city centre of Tetovo, including the central town square, which is intersected by two busy roads. The factor's composition exclusively consists of $PM_{2.5}$ particles (Table 2). Based on its diurnal variation, its composition, and the influence of winds from the south, F4 is likely associated with urban activities in the city centre including mixed urban emissions occurring in the central area during daytime periods. The third and fourth factors may be associated with similar sources and activities which, depending on the temporal and atmospheric conditions, may have different particle size compositions.

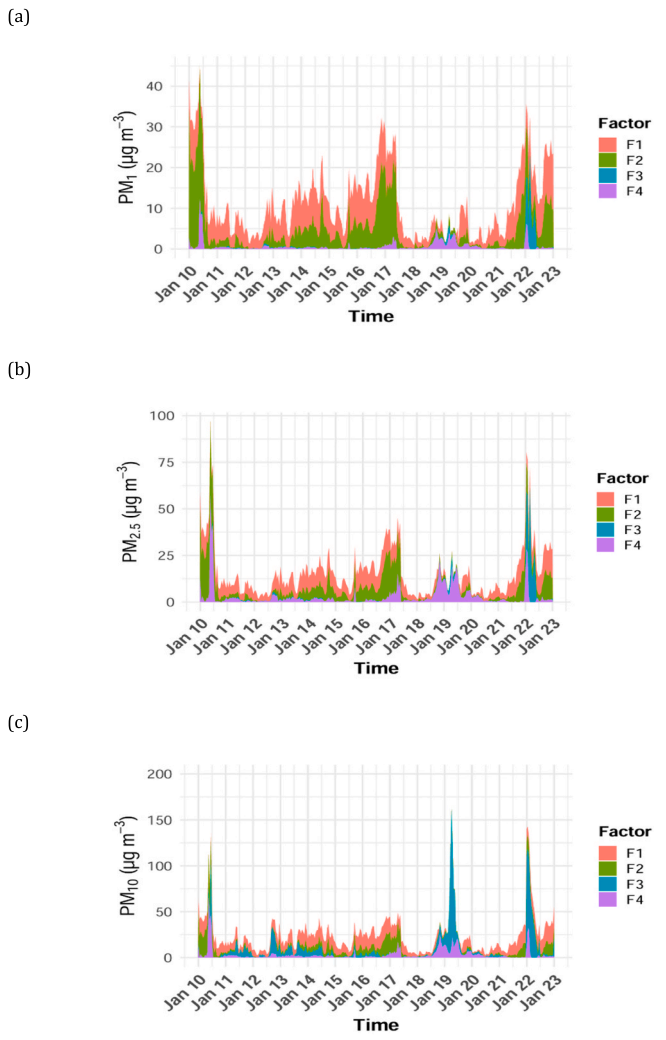


Fig. 6. The outdoor factors' variation of a) PM_1, b) $PM_{2.5}$ and c) PM_{10} deriving from the G contribution values. The factors are tentatively associated with a background source (F1), local traffic (F2), industrial sources (F3) and urban emissions from the city centre (F4).

3.3. Indoor/outdoor interactions

On average, the outdoor average PM concentrations for all size ranges were higher than the indoor ones, except on certain days when PM_{10} concentrations were higher indoors than outdoors. Specifically, indoor daily PM_{10} averages exceeded outdoor values on 3 of the 13 days; these episodes coincided with periods of elevated occupant activity (e.g., prayers and movement) as identified in the diary and were associated with high contributions from indoor factor 3 in the NMF analysis (see Table 3 and Fig. 3c). Given that the studied house was comprised of two elderly people who remained indoors most of the time (except for one day), these elevated PM_{10} levels are likely to result primarily from the activities undertaken by the occupants, consistent with previous studies (Bari et al., 2015; Bousiotis et al., 2026) that showed that the movement and activities of people are an important source of indoor PM_{10} particles. This interpretation is further supported by the diurnal variation of $PM_{2.5}/PM_{10}$ (Figure S5e), which shows consistently higher values at night, suggesting that smaller particles are more dominant when human activity is reduced. In addition, it reflects the role of fine particle emissions from wood stove heating, which may continue during night time hours, while coarse particle resuspension from occupant movement decreases. Wood stove heating was frequent during the monitoring period; however, it predominantly contributed to fine particle spikes (See Factor 2). Unfortunately, no detailed cleaning times were recorded in the activity diary. The monitored room had hard wood flooring with a large carpet, suggesting that resuspension of coarse particles could occur due to foot traffic and routine indoor movement (Bo et al., 2017; Bousiotis et al., 2026). The average indoor/outdoor (I/O) ratios were found to be 0.3, 0.45 and 0.63, for PM_1, $PM_{2.5}$ and PM_{10}, respectively. These ratios were calculated as the ratio of mean indoor to mean outdoor concentrations. The increasing I/O ratio with particle size reflects the stronger influence of indoor sources and occupant-related activities on coarse particles. The effect of the indoor and outdoor factors on PM concentrations is presented in Table 3. The estimated effect was calculated by summing the contribution of internal (F2 and F3) factors and external factors (F1 and F4) separately and then calculating the percentage by dividing their sum by the total sum for each PM fraction. PM_{10} appeared to be dominated by indoor contributions, with factors 2 and 3 being responsible for 85% of the coarse particle mass, and the outdoor sources having very little impact with only 15% of the total contribution. It is observed that $PM_{2.5}$ was almost equally influenced by both indoor and outdoor sources, with the respective sources contributing 47% and 53%. Consistent with previous studies (Viana et al., 2011, Bousiotis et al., 2023a,b; Rose et al., 2024; Rathbone et al., 2025), the analysis suggests that the dominant contribution to PM_1 concentrations was associated with outdoor sources with factors 1 and 4 accounting for 77% of the observed PM_1 mass. Consistently, a good correlation ($r = 0.73$ and $r = 0.48$ for PM_1 and $PM_{2.5}$, respectively), between indoor and outdoor finer PM mass concentrations was observed, further indicating the decisive effect of the outdoor sources on the indoor PM_1 particles. The correlation between indoor and outdoor PM concentrations decreased with increasing particle size and became negligible for PM_{10} ($r = -0.07$). This very weak (essentially zero) correlation reflects limited infiltration of outdoor coarser particles during winter conditions with minimal natural ventilation. The small negative value is likely the result of random variability in the dataset rather than a meaningful inverse relationship and does not imply that outdoor increases cause indoor decreases. Instead, indoor PM_{10} levels appear to be driven predominantly by independent indoor processes, consistent with previous studies (Thatcher and Layton, 1995; Bo et al., 2017). NMF analysis applied indoors provided valuable insights into the dynamics of indoor air quality. Observations of two out of the four indoor factors influenced by outdoor sources underscore the substantial role of the external environment in shaping indoor pollution levels. This is further supported by the correlation analysis between indoor and outdoor factors. The correlation matrix (Figure S11), shows that the first and the fourth indoor factors are positively correlated with the first and second outdoor factor, with coefficients of $r = 0.48$, 0.60, and $r = 0.64$, 0.66, respectively. These relationships highlight the interconnectedness of indoor and outdoor air pollution and the importance of outdoor contributions to indoor PM levels.

To further investigate the influence of indoor activities on PM concentrations, boxplot analysis and non-parametric statistical testing were performed using the activity diary. Median concentrations during cooking periods were higher compared to non-cooking periods for all particle sizes, with PM_1 increasing from 3.01 to 3.86 μg/m^3, $PM_{2.5}$ from 9.41 to 13.41 μg/m^3, and PM_{10} from 26.85 to 58.66 μg/m^3. The elevated PM_{10} observed during cooking periods is unlikely to arise primarily from direct cooking emissions. Instead, it most likely reflects concurrent occupant activity in the shared kitchen–living room space, which can resuspend settled coarse particles from floor and carpet surfaces, rather than direct cooking emissions, which are primarily associated with fine and ultrafine particles. The Wilcoxon signed-rank test showed that these differences were statistically significant for $PM_{2.5}$ ($p < 0.001$) and PM_{10} ($p < 0.001$), while PM_1 showed a marginally non-significant increase ($p = 0.077$). In contrast, wood stove operation did not show statistically significant differences in PM concentrations for any size fraction ($p > 0.2$), suggesting a more constant or less distinguishable contribution within the short monitoring period. This is further illustrated in

Figure S13, where boxplots show a clear shift toward higher $PM_{2.5}$ and PM_{10} concentrations during cooking periods, with increased variability and more frequent high-value events. These findings support the NMF results, indicating that indoor activities such as cooking and occupant movement play an important role in shaping indoor concentrations.

4. Discussion

4.1. Variability and factors affecting PM concentration

The air quality data collected during this pilot monitoring campaign provides insight into PM variability within the monitored household. Specifically, outdoor $PM_{2.5}$ and PM_{10} concentrations exceeded the WHO 24-h recommended limit on 9 and 3 out of the total 13 monitored days, respectively. Although WHO guideline values are typically evaluated using long term datasets, they are used here only as a reference to contextualise the pollution levels observed during the study period. The number of exceedances observed over this short monitoring period highlights the potential severity of air pollution in Tetovo and suggests the need for improved air quality management. Similarly high levels of particulate matter have been reported in other studies conducted in urban environments (Pant and Harrison, 2013; Kassomenos et al., 2014), where traffic emissions and industrial activities were the main cause of elevated pollution levels. In contrast, indoor averages were notably lower than outdoor levels (Polidori et al., 2007; Holguín et al., 2003) as indoor environments usually provide some filtration of outdoor particles (Hussein et al., 2006). However, they still revealed poor air quality, with occasionally higher indoor PM_{10} values primarily attributed to daily activities of the elderly residents that spent >90% of their time indoors. These day-to-day activities (prayers performed five times daily, routine chores and movement) likely caused resuspension of settled particles, which can significantly impact indoor air quality (Madureira et al., 2012; Wang et al., 2021). Occasional increases in indoor PM_{10} concentrations are therefore likely associated with resuspension of settled particles caused by occupant movement across the carpeted surface in the monitored room, which may act as a reservoir for coarse particles (Bo et al., 2017). The I/O ratios (<1) for all size fractions suggest relatively limited infiltration during the cold winter monitoring period, while the increase in I/O ratio with particle size (0.3-0.63) together with the NMF results (85% of PM_{10} from indoor sources) suggest that coarse particles were predominantly influenced by indoor processes. Additionally, there were two days when the indoor $PM_{2.5}$ exceeded the 24-h limit set out by WHO. The analysis indicated that a large proportion of these particles infiltrated from outdoor sources during the monitoring period. However, the measurements were conducted during winter conditions, when ventilation rates are typically lower. Seasonal differences in ventilation behaviour (e.g. open windows during warmer months) may influence indoor-outdoor particle exchange, but this was not evaluated in this short-term monitoring campaign. This effect is likely counterbalanced by typically lower outdoor pollution levels during that time, potentially reducing the overall indoor exposure risk. The concentrations could be higher, as OPC-N3 efficiency decreases for ultra - fine particles, because of its lower size limit of 350 nm. Apart from particle infiltration, the exceedances were closely linked to a bad smell, particularly smoke, coming from the wood stove used for heating. This observation suggests that certain household activities, such as the use of solid fuels for heating, contribute to indoor particles. This aligns with Xu et al. (2018), in which personal $PM_{2.5}$ exposure resulting from the use of solid fuels in rural settings was analysed. The study found that wood burning for cooking and heating led to personal exposure levels around 40% higher than indoor concentrations, highlighting the significant contributions of household combustion to personal exposure. Despite the elevated concentrations, they remained within the ranges reported in the global review conducted by Vardoulakis et al. (2020).

The NMF analysis provided valuable insight into the contribution of PM concentrations in both indoor and outdoor environments of the monitored household, based on the identified factors (four identified for indoor and four for outdoor). The analysis suggests that the usage of wood stove for heating and LPG for cooking as the main contributors to indoor finer particulate matter. This is consistent with previous literature (Abdullahi et al., 2013; Ferro et al., 2022) that observed that such activities are generally associated with ultra fine particles which are below the detection limit of LCS. Nevertheless, the observed correlations between these sources and PM_1 and $PM_{2.5}$, together with their temporal alignment with cooking and heating periods, suggest a likely association with these activities, although this cannot be considered definitive. Additionally, PM_{10} particles appeared to be influenced by occupants' activity, consistent with Bousiotis et al. (2023).

Conversely, the outdoor environment was heavily dominated by residential heating, industrial activities and traffic emissions. Tetovo's geographical location within a valley surrounded by mountains influences high concentration levels of PM pollution and often leads to stagnant conditions and temperature inversions, especially during the winter months (MoEPP, 2017). During the measurement period of the study, residential heating demand was at its peak, as many households rely on wood burning stoves as their primary source of heat. Thus, residential combustion was identified as a primary source of PM pollution in NM, alongside vehicle emissions and industrial activities (World Bank, 2019). Recent work in NM has further shown that air pollution levels are strongly influenced by regional energy production patterns, including emissions from coal-fired plants and shifts in energy demand during periods of instability (Nuredini et al., 2026). These sources are particularly significant in urban areas, such as the site's location, where elevated PM levels are more pronounced due to the combined effect of the topographical and meteorological conditions. The World Bank also indicated that residential heating was the largest source of $PM_{2.5}$ at national level in NM (World Bank, 2019). Additionally, previous studies have also shown that wood burning has the highest impact on $PM_{2.5}$ (Villalobos et al., 2017), and as a PM pollution source is mainly associated with lack of efficient household heating sources as well as the limited financial capacity to afford cleaner options (Villalobos et al., 2017), which is also the case in Tetovo. Despite the different variations of PM concentrations, for two out of four identified outdoor sources they were the highest when the wind was blowing from the south. South of the study site are located a major highway, various industries that do not have modern emission reduction systems (MoEPP, 2017), as well as the city centre. Industrial emissions primarily affected PM_{10} concentrations in the city, with traffic also being a contributor. This is in accordance with (gon Ryou et al., 2018), who reviewed 21 source apportionment studies in South Korea and reported that motor vehicle and industrial emissions were among the most commonly identified contributors to $PM_{2.5}$ and PM_{10}. Although these findings are based on studies conducted in South Korea, they are referenced here to support general source patterns rather than as a direct regional comparison. The moderate correlations observed between certain indoor factors, suggest potential overlap in source contributions or incomplete resolution within the NMF solution, likely due to the short duration of the campaign and the absence of chemical speciation data. Factor interpretations should therefore be viewed as exploratory insights into dominant processes and indoor–outdoor connectivity rather than quantitative source apportionment.

The I/O ratios were <1 for the 3 p.m. size ranges, which indicates the limited infiltration of the particles due to the reduced natural ventilation during the colder period. The indoor source contributions increased with particle size, from PM_1 to $PM_{10,}$ aligning with previous studies (Bousiotis et al., 2023a,b). An expected shift in these ratios was observed when occupants were absent for a couple of hours one day, further suggesting that human activities within homes have a significant impact, especially on coarse particles. I/O ratios were generally lower than those reported by Jones et al. (2000), who investigated indoor and outdoor particulate matter in residential homes in Birmingham, a major

metropolitan area with a population of approximately one million, more than ten times larger than Tetovo (~85,000). In that study, mass-based PM_{10} I/O ratios were typically around or above unity across most homes, reflecting the influence of indoor sources such as cooking, smoking, and particle resuspension, with some cases showing substantially elevated values. Using sulphate as a tracer of outdoor-origin particles, I/O ratios were generally below unity (~0.8 for fine particles and ~0.6 for PM_{10}), indicating a stronger outdoor contribution to finer particles. The lower I/O ratios observed in the present study (0.3, 0.45 and 0.63 for PM_1, $PM_{2.5}$ and PM_{10}, respectively) likely reflect the combined influence of limited natural ventilation during winter conditions (closed windows), the absence of smoking, and the single-household, short-duration design of this pilot investigation. In a study by Rathbone et al. (2025), conducted across multiple student residences in Birmingham, UK, indoor source apportionment using LCS showed that average I/O source contribution ratios varied with particle size and location. It reported values ranging from below 1 to above 1 depending on the monitored house. The lowest and most comparable ratios to those observed in the present monitored household, were recorded on the residence located closest to a road influenced by traffic emissions, similar to the current study's urban setting which is greatly impacted by vehicular pollution.

4.2. Study limitations

The low-cost sensors used in the study provided valuable data on air quality dynamics in an urban household in Tetovo, and they offer a cost-effective way to monitor air pollution, especially in regions with limited financial resources and monitoring stations. However, it is important to note that these LCS still have certain limitations that need to be addressed. Their data require calibration against a standard monitoring system to ensure reliability. As calibration considers measurements and atmospheric conditions for specific periods, the possibility of overestimation or underestimation of concentrations under extremely high or low PM conditions remains. Because of this, in their present form they may not provide the same level of accuracy as more sophisticated monitoring systems. A further limitation specific to LCS-based PNSD measurements is the lower size cut-off of the OPC-N3 (approximately 350 nm). This means that particles in the nucleation and Aitken modes (typically <100 nm) and the lower accumulation mode (100–350 nm) are not captured. Sources that predominantly emit in these sub-350 nm size ranges, including traffic exhaust, wood combustion, and cooking, may therefore be underrepresented in the PNSD data, particularly in terms of particle number, and their contributions to indoor and outdoor PM may be partially underestimated by the NMF analysis. An additional source of uncertainty relates to the calibration procedure of the outdoor sensor. While the primary sensor was calibrated against the regulatory monitoring station, the outdoor sensor was calibrated through short-term collocation with the already calibrated sensor. Although strong correlations were observed between the sensors during the collocation experiment, the relatively short calibration period may not fully capture sensor performance under a broader range of environmental conditions, and some uncertainty associated with sensor to sensor variability may remain. Furthermore, PM_1 could not be directly calibrated as the regulatory monitoring station did not report this size fraction. As a result, PM_1 analyses were based on the raw sensor outputs and should therefore be interpreted with greater caution than the calibrated $PM_{2.5}$ and PM_{10} measurements. Since PM_1 plays an important role in the indoor-outdoor contribution analysis, this uncertainty should be considered when interpreting the reported results. However, by providing a broader spatial coverage than standard fixed monitoring stations, LCS are capable of filling critical gaps in air quality monitoring, particularly in places like Tetovo where only one fixed monitoring station measures air quality data. Another key limitation of this pilot study is the relatively short monitoring period (13 days) and the inclusion of a single household, which restricts the representativeness of the results and limits the ability to generalise the findings to other households or to the wider urban environment of Tetovo. Indoor air quality can vary significantly depending on building characteristics, ventilation behaviour, heating systems and household activities. In addition, the short monitoring period may not fully capture temporal variability in indoor air quality, including the potential differences between weekdays and weekends driven by changes in occupant behaviour and activity patterns. Therefore, the results presented here should be interpreted as an exploratory case study rather than as representative of typical conditions across the city. Nevertheless, the dataset still allows useful insights into the main factors influencing PM concentrations in a Tetovo household during winter. Furthermore, the monitoring campaign was conducted during the winter heating season, and air pollution dynamics may differ substantially during other seasons when heating demand and ventilation patterns change. Extending this monitoring period and including multiple households with different building characteristics and heating systems would allow future studies to better capture seasonal variability and spatial heterogeneity in indoor-outdoor PM dynamics. Another limitation of the study is the reliance on particle size distribution and PM mass data alone, without collocated chemical tracers. Such tracers would have improved the ability to distinguish and more confidently name sources, particularly for overlapping indoor processes. This reflects the exploratory, low cost design of this pilot campaign, which aimed to test feasibility in a resource-limited setting. Lastly, the main focus of the study was PM pollution, and considering other significant contributors to air quality, like nitrogen oxides (NO_x), volatile organic compounds (VOCs), and sulfur dioxide (SO_2), would further enhance the results. Specifically, while SO_2 is considered as a controlled pollutant in countries of the Global North, it is still a nuisance in many developing countries, including North Macedonia, where coal remains a major fuel for electricity production and household heating (World Bank, 2019). Another recommendations for future research would be an improved record of daily activities, which could enhance the depth and precision of the analysis, as there was a lack of information regarding household activities in the provided diary which made the assignment of sources to certain activities a challenge. Despite these limitations, the results provide useful preliminary insights into indoor-outdoor PM dynamics in a residential setting in Tetovo and demonstrate the potential of low-cost monitoring approaches for exploratory air-quality assessments in regions with limited monitoring infrastructure.

5. Conclusions

The study monitored indoor and outdoor PM_1, $PM_{2.5}$ and PM_{10} levels for 13 consecutive days in an urban household in Tetovo, NM, using LCS. The analysis showed that the PM levels were notably high in both environments, with outdoor $PM_{2.5}$ and PM_{10} concentrations exceeding the WHO 24-hr limit on nine and three separate days. The source apportionment analysis of indoor and outdoor pollution data was done using NMF and showed that pollution was the highest when the wind had a southerly component, and that the key sources affecting outdoor air pollution were traffic, industrial emissions and residential heating. A similar pattern was observed for indoor PM_1 and $PM_{2.5}$, while coarser particles were primarily generated indoors, with a contribution of approximately 85% attributed to indoor sources. The source apportionment analysis showed that outdoor air pollution strongly influenced indoor air quality. It was estimated that outdoor sources contributed 77%, 53% and 15% to indoor PM_1, $PM_{2.5}$ and PM_{10} levels, respectively, indicating that finer particles tend to infiltrate indoors and that the indoor activities heavily influence coarser particles. The contribution of indoor sources to PM_1, $PM_{2.5}$ and PM_{10} levels was 23%, 47% and 85%, respectively. The PM_1/PM_{10} and $PM_{2.5}/PM_{10}$ ratios of 0.09, 0.20, and 0.29, 0.41 for indoor and outdoor, respectively, further highlighted the differences in particle size distribution between indoor and outdoor environments. The I/O ratios of 0.3, 0.45 and 0.63, for the three size ranges from (PM_1, $PM_{2.5}$ and PM_{10}) further support the assumption that

indoor PM_{10} is more influenced by indoor activities compared to the other PM sizes.

The study provides initial evidence on the sources of PM pollution affecting both indoor and outdoor environments, helping to identify key factors contributing to poor air quality in the city of Tetovo. With the effective use of LCSs, the study suggests a feasible and affordable alternative to traditional, high cost monitoring methods, making air quality assessment more accessible in regions with limited financial resources such as North Macedonia. Given Tetovo's serious air quality issues, extending such studies across various locations in NM could allow ongoing and detailed monitoring of pollutant dynamics and evaluate and compare the different seasonal variations. The present study offers a low-cost alternative for continuous air quality monitoring using LCS. Such research is particularly important in regions suffering from severe air pollution. This comprehensive understanding not only enhances the knowledge of pollution sources but also informs strategies for effective mitigation and management of indoor and outdoor air quality in Tetovo.

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CRediT authorship contribution statement

Lejla Ademi Shaqiri: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Dimitrios Bousiotis:** Conceptualization, Data curation, Formal analysis, Methodology, Supervision, Writing – review & editing. **Mennan Selimi:** Conceptualization, Data curation, Methodology, Writing – review & editing. **Francis D. Pope:** Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Supervision, Writing – review & editing.

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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Appendix ASupplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apr.2026.103065.

Data availability

The data that support the findings of this study are openly available in Birmingham Institutional Research Archive (UBIRA) at https://doi.org/10.25500/edata.bham.00001342, reference number 00001342.

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