Kaunas University of Technology

Faculty of Chemical Technology

Sensor-Based Analysis of Airbone Particulate Dispersion in High-Traffic Urban Area

Master's Final Degree Project

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Environmental Engineering (6211EX003)

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Summary

Air pollution, particularly fine particulate matter 2.5, has a serious impact on human health and urban environmental quality. In response to growing concerns and the need for more spatially detailed air monitoring, this thesis investigates the use of low-cost particulate matter 2.5 sensors to quantify air pollution trends in urban areas of Kaunas city. The study's goal was to assess the effectiveness of these sensors, compare particulate matter concentrations in various Taikos avenue areas, and discover the link between outdoor and inside pollution levels.

Measurements were takes from February to July 2024, with low-cost sensors displayed in six urban areas of Kaunas city. To examine spatial variation and infiltration potential, one sensor was installed outside and one inside at each site. Furthermore, one sensor was co-located with the official Environmental Protection Agency monitoring station to ensure data quality.

Descriptive statistical analysis and Pearson correlation test were performed using IBM SPSS Statistics software. The low-cost sensor's dependability in measuring $PM_{2.5}$ concentrations has been demonstrated by a good correlation ($r = 0,832$, $p<0,000$) when compared to the Environmental Protection Agency's monitoring station. $PM_{2.5}$ levels differed significantly among outdoor locations ($p<0,001$), with the greatest median values reported at monitoring sites near high-traffic routes like Kaunas College and Vytautas Magnus University residential hostel. In terms of indoor and outdoor dynamics, the Kaunas College, first building ($r=0,895$) and Vytautas Magnus University residential hostel showed the largest correlations, whereas the library ($r=0,752$) and Kaunas College, second building ($r=0,656$) had moderate correlations. The medical station ($r=0,488$) and residential building (0,357) had the weakest indoor and outdoor correlations, which could be attributed to more restricted ventilation and distance from direct traffic pollution.

The findings demonstrate that, low-cost sensors are a good tool for dense urban air monitoring and can help to measure spatial differences in air pollution within urban environments. The study demonstrated that proximity to traffic, building orientation, and ventilation characteristics significantly influence $PM_{2.5}$ infiltration indoors. The approach applied here presents a viable foundation for assessing fine-scale air quality. These results are particularly relevant for cities seeking cost-effective methods to monitor localized exposure and support data-driven air quality management.

Ema Šilerytė. Jutiklių matavimais grįsta kietųjų dalelių sklaidos ore analizė intensyvaus eismo miesto teritorijoje. Magistro baigiamasis projektas / vadovė dr. Violeta Kaunelienė; Kauno technologijos universitetas, Cheminės technologijos fakultetas.

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Santrauka

Oro tarša, ypač smulkiomis kietosiomis dalelėmis 2.5, daro didelį poveikį žmonių sveikatai ir miestų oro kokybei. Reaguojant į didėjantį susirūpinimą ir poreikį vykdyti išsamesnę erdvinę oro stebėseną, šiame darbe nagrinėjamas nebrangių kietųjų dalelių 2.5 jutiklių naudojimas kiekybiniam oro užterštumo tendencijų nustatymui Kauno miesto urbanizuotose teritorijose. Tyrimo tikslas – įvertinti šių jutiklių efektyvumą, palyginti kietųjų dalelių koncentraciją įvairiose Taikos prospekto vietose ir atrasti ryšį tarp lauko ir vidaus užterštumo lygio.

Matavimai buvo atliekami nuo 2024 m. Vasario iki liepos mėnesio, naudojant nebrangius jutiklius, kurie buvo sudėti šešiose Kauno miesto vietose. Siekiant ištirti erdvinius pokyčius ir infiltracijos potencialą, kiekvienoje vietoje buvo įrengta po vieną jutiklį lauke ir viduje. Be to, siekiant užtikrinti duomenų kokybę, vienas jutiklis buvo įrengtas oficialioje Aplinkos apsaugos agentūros monitoringo stotyje.

Aprašomoji statistinė analizė ir Pearson koreliacijos testas buvo atlikti naudojant IBM SPSS Statistics programinę įrangą. Nebrangių jutiklių patiklumą matuojant $KD_{2.5}$ koncentraciją įrodė stipri koreliacija ($r=0,832$, $p<0,000$), lyginant su Aplinkos apsaugos agentūros stebėsenos stotimi. Kietųjų dalelių 2.5 koncentracija lauko vietose labai skyrėsi ($p<0,001$), o didžiausios vidutinės vertės buvo užfiksuotos stebėsenos vietose, esančiose šalia intensyvaus miesto maršrutų, pavyzdžiui, Kauno kolegijos ir Vytauto Didžiojo universiteto bendrabučio. Vertinant patalpų ir lauko dinamiką, stipriausi koreliacijos rodikliai buvo Kauno kolegijos pirmame korpuse ($r=0,895$) ir Vytauto Didžiojo universiteto bendrabutyje ($r=836$), o bibliotekos ($r=0,752$) ir Kauno kolegijos antrame korpuse ($r=0,656$) – vidutiniai. Medicinos punktas ($r=0,488$) ir gyvenamasis pastatas ($r=0,357$) pasižymėjo silpniausiomis patalpų ir lauko koreliacijomis, o tai galima paaiškinti labiau apribota ventiliacija ir atstumu nuo tiesioginės transporto taršos.

Rezultatai rodo, kad nebrangūs jutikliai yra gera priemonė tankiai miestų oro stebėsenai ir gali padėti įvertinti erdvinius oro taršos skirtumus miesto aplinkoje. Tyrimas parodė, kad eismas, pastato orientacija ir vėdinimo ypatybės turi didelę įtaką kietųjų dalelių 2.5 infiltracijai patalpose. Čia taikytas metodas yra perspektyvus pagrindas sumlaus masto oro kokybei vertinti. Šie rezultatai ypač svarbūs miestams, ieškantiems ekonomiškai efektyvių metodų, kaip stebėti vietinį poveikį ir paremti duomenimis pagrįstą oro kokybės valdymą.

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Abbreviations:

MOS - Metal Oxide Semiconductor;

PM – Particulate matter.

Terms:

Low-cost sensor – a cost-effective sensor for air pollution measurements with simple design, real-time data logging.

Microenvironment – a specific, limited environment whithin an urban structure, e.g. a building facade, where pollutant concentration can differe significantly from the surrounding background.

Spatial Dispersion of Pollutants – the distribution of pollutants /9e.g. particulate matter 2.5) in different geographical or urban areas, depending on source location, meteorological conditions, terrain and environmental structure. This phenomenon allows an assessment of how air pollutats disperse and affect different urban micro-environments differently.

Introduction

Traffic represents a pressing concern as it amplifies vehicular emissions, compromises ambient air quality, and elevates associated hazards. Air pollution is one of our most serious social and environmental issues. According to the World Health Organization, approximately 25% of energy-related greenhouse gas emissions that are linked to air pollution and climate change‘s adverse health effects are caused by transportation [5]. In the European Region, where non-communicable illnesses like diabetes, cardiovascular disease, cancer, chronic respiratory diseases, and mental disorders account for about 86% of deaths and 77% of the disease burden, transportation can have a significant impact on people‘s health [5]. Despite the fact that most air quality regulations and atmospheric chemistry studies have traditionally concentrated on outdoor air, increased awareness has been stimulated by concerns about the negative impacts of indoor air quality on the health of people [21]. Since the quality of the air we inhale is significantly affected in urban areas by a variety of factors, including as manufacturing processes, households, transportation, etc., it is important that we monitor and control it [22, 37].

Low-cost air quality sensor networks present a promising approach to monitoring air quality with enhanced temporal and spatial accuracy. The accuracy level is usually evaluated by comparing data from the low-cost sensors to data collection from an official air quality monitoring system.

Research hypothesis:

1. outdoor airborne particles ($PM_{2.5}$) are more prevalent in buildings near high - traffic than indoor airborne particles ($PM_{2.5}$), especially during peak hours;
2. the morning and evening hours have the highest amounts of both indoor and outdoor pollutants because of increased traffic and human activity;
3. buildings with insufficient ventilation will have higher concentrations of pollutants than those with adequate ventilation because efficient ventilation lowers the quantity of dangerous particles.

The research object is the dispersion of high – traffic generated air pollution.

The goal of this research is to comprehensively investigate the spatial and temporal dynamics of air quality in a high-traffic environment based on measurements using a low-cost sensor network.

Research objectives:

1. to assess the reliability of low-cost $PM_{2.5}$ sensor data by comparing it’s measurement data to an Environmental Protection Agency monitoring station;
2. to analyse the spatial distribution of fine $PM_{2.5}$ concentrations in selected street environment;
3. to assess the penetration of outdoor particles to indoor environments;
4. to evaluate temporal variation of $PM_{2.5}$ concentration in street environment.

1. Literature Analysis

1.1. Principles of Sensor Operation and the Pollutants They Monitor

Advances sensor technologies are progressively employed to precisely measure air quality, pollutant concentrations, and other critical environmental parameters in the evaluation of vehicular pollution. Traditionally, expert air quality stations that adhere to stringent accuracy requirements have been used to measure air pollutant concentrations. Although the stations are quite accurate, they are also very costly, a single usually costing thousands or millions of dollars. Such stations are expensive to operate and need regular maintenance from engineers with specialised training. Professional stations are few in number and typically only have one measuring station in a metropolitan area due to their high development and operating expenses. Recently, low-cost air quality sensors under $10,000 have been available to increase deployment densities and achieve higher spatial resolutions in air quality monitoring [3]. There is a wide range of pollution sensors on the market, most of which are gas and particle matter sensors [1]. The principles of operation and associated sensing technologies are the basis for the titles of the categories. The most common types of gas sensors include photo-ionized, solid state, electrochemical (EC), catalytic, non-dispersive infrared radiation absorption, Amperometric, and solid state [1, 31, 2].

Amperometric gas sensors are extensively utilized in carbon monoxide detectors in both indoor and outdoor settings, owing to their exceptional sensitivity and selectivity for toxic gas, hence facilitating early detection and enhancing environmental safety [2]. Usually, gases can be found in the 1-1000 ppm range [2]. Nevertheless, the concentration in the air quality monitoring applications is typically two or three orders of magnitude lower than in safety applications, and it is initially difficult to measure such low concentrations with Amperometric gas sensors [2]. “Amperometric gas sensors have been identified as one of the most promising sensor technology platform for measuring inorganic gases in air quality monitoring“ [20]. It implies that Amperometric sensors have a lot of potential to develop into a crucial technological platform for environmental inorganic gas measurement.

Conventional Amperometric sensors, which are widely used in the industrial gas safety sector, are 2 or 3 electrode fuel cell-based sensor [2]. A further benefit of these sensors is that their signal output current is directly proportional to the gas concentration they have measured [2]. O_2, CO, NO_2, NO, O_3, H_2S, SO_2, NH_3, HCN, HCl, HBr, CS_2, Cl_2, H_2, HCl, HBr, and HF are the most often used target gases [2]. Along with that, these sensors can also detect some VOCs, expanding is use in environmental monitoring applications where precise management of organic contaminants is necessary [2]. Vapours like H_20_2 can also be found [2].

Three parts are needed for an Amperometric gas sensor. Only targeted pollutants can be correctly detected according to the gas chamber‘s flexibility to adjust the sensor‘s sensitivity and gas availability. To increase selectivity and decrease sensitivity, unsuitable gases can be filtered out utilizing a chemical filter [2]. The electrochemical cell itself, with its electrodes impregnated with an electrolyte solution, is located in the central part [2]. The liquid electrolyte may occasionally be a component of a polymer matrix [2]. Precious metals or carbon in the form of nanoparticles are very thin PVD or CVD formed layer are typically used to make the electrodes [2]. Generally, a gas permeable membrane supports the working electrode [2].

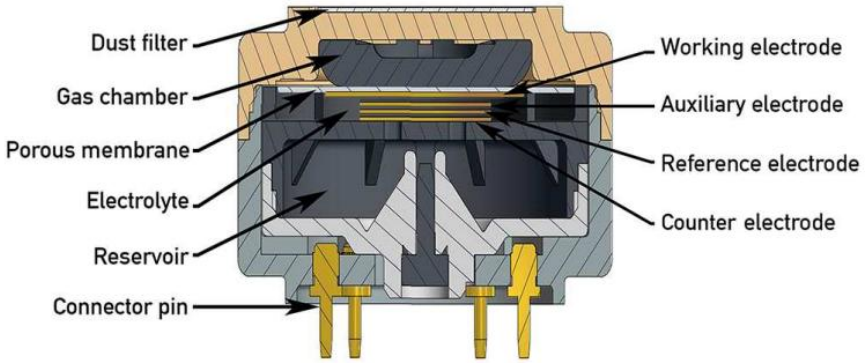


Fig. 1. Standard Amperometric gas sensor design

The gas chamber is where chemical filters improve selectivity after the gases first permeate through the dust filter [2]. The target gas then enters a three-phase contact with the liquid electrolyte and catalyst after passing through a porous membrane that supports the working electrode, at this interface, which is seen in the Figure 2, the working electrode reaction takes place [2].

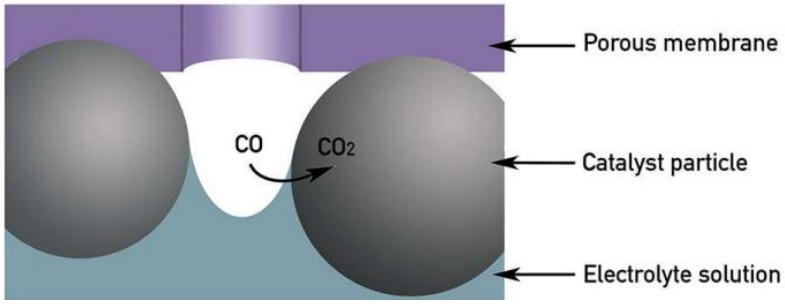


Fig. 2. Illustration of the three-phase interface‘s CO oxidation

In the thin electrolyte layer that forms around the electrode, the gas dissolves [2]. Selectivity is increased, and full gas reaction is ensured by maintaining a stable voltage between the working and reference electrodes [2]. The production or consumption of electrons is balanced by a counter electrode, as a result, the sensor output-a current- is produced [2]. Diffusion of the gas analyte to the electrode controls the reaction when reaction kinetics are fast [2]. The various components that comprise the gas channel can be broken down to determine the diffusion to the sensor (figure 3) [2].

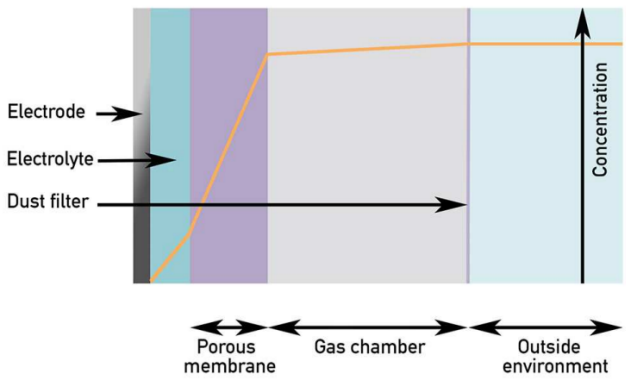


Fig. 3. The profile of target gas concentration using an Amperometric gas sensor

MOS is widely utilized sensing material for intelligent sensory assessment, owing to its sensitivity to various pollutants, straightforward production technique, and compatibility with intelligent analytical systems [7]. The majority of these sensors are metal oxides, or semi-conducting materials, like titanium dioxide, iron oxide, zinc oxide, tin oxide [7]. Because MOS sensors are suitable for a wide range of gases, they are frequently utilised in e-nose for the detection and classification of food scents [7]. There are two types of gas sensors, depending on whether the sensing materials are reduction or oxidation-based: the first one is n-type sensors, which are primarily responsive to reducing substances like H2S and are constructed from oxides of zinc, tin, or iron; and the second one is p-type sensors, which are composed of cobalt or nickel oxides, are primarily reactive to oxidising substances like O_2 [7]. The most commonly utilised sensors in e-nose are p-type sensors because of their excellent selectivity and sensitivity [7].

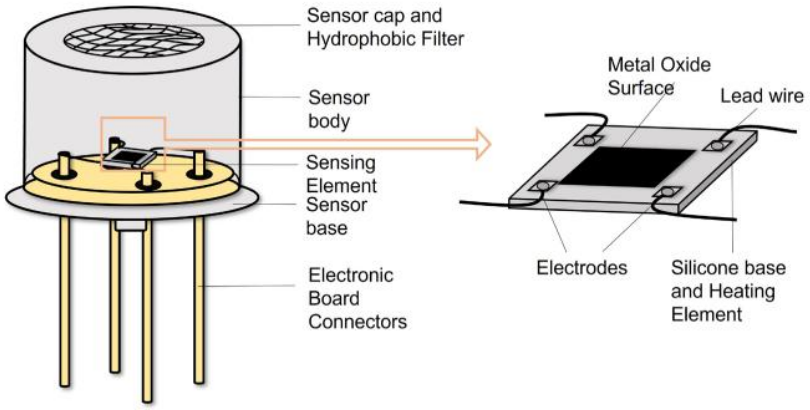


Fig. 4. The mechanism by which metal oxide semiconductor (MOS) sensors operate (https://www.scielo.br/j/cta/a/VzVNTQ6F5wYkJLLhFCgcyyv/?lang=en)

After the sensor "element's surface" is heated to between 300°C and 500°C by the heater, a chemical reaction takes place on it that allows it to detect gasses [3]. The sensing element's electrical conductivity changes as a result of this reaction, and the detected gas level can be measured by monitoring this change using an external circuit [3].

Since many gases exhibit characteristic vibration or rotation absorption spectra with narrow, non-overlapping bands in the infrared spectrum between 2 μm and 20 μm, infrared (IR) techniques are widely used in gas detection technologies [8]. Infrared sources, detectors, gas cells, wavelenght selectors, and optical components (lenses or, more often, mirrors) are the standard components of commercial IR sensors [8]. The radiation is coupled from the source through the gas cell and into the detector and the detector detects radiation at the target gas's absorption band wavelenght after the sample gas has passed through the gas cell [8]. The signal that reaches the detector is at its highest when there is no target gas present since there is no absorption, the recorded signal decreases as the concentration of the target gas rises while it is in the route [8].

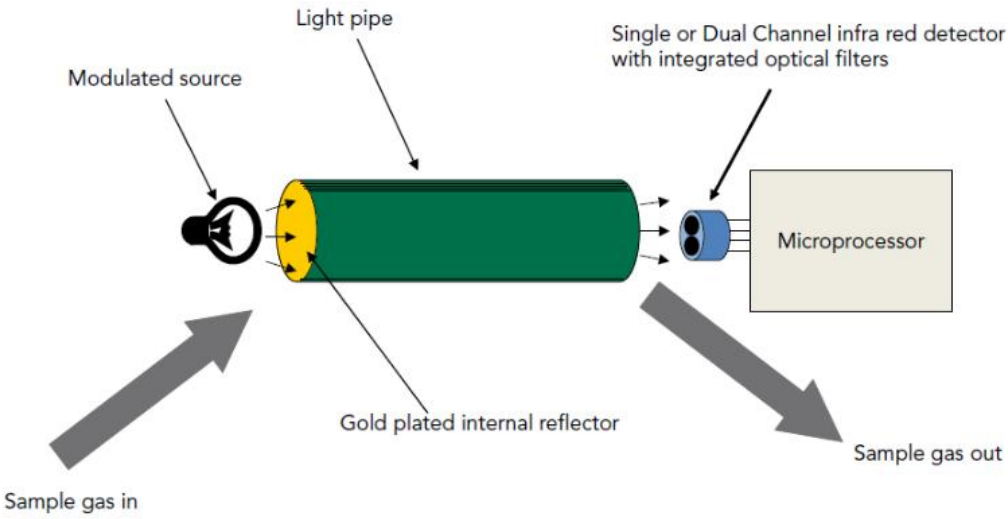


Fig. 5. Model of infrared sensor (https://edinburghsensors.com/non-dispersive-infrared-sensing-technology/)

1.2. Benefits and Drawbacks of Sensor Technology

Metal oxide semiconductor (MOS), electrochemical (EC), non-dispersive infrared (NDIR), and photo-ionization detector (PID) sensors are the four primary types of sensing technologies found in low-cost gaseous pollution monitoring systems. Many advancements have been made in the field of gas sensors in the modern era, and each technique has advantages and disadvantages of its own [2, 3].

Amperometric sensors have shown to be reliable and reasonably priced, and they are utilized in both fixed-site and portable gas detectors [2]. In addition to being affordable and dependable, they often have a linear output, consume very little power, and may be made to be selective toward particular gases [2]. Because they are lightweight and need little power, air quality monitors with amperometric sensor technology can be deployed in a variety of urban settings with limited space and demanding access to mains electricity [2]. They can be put up on lampposts at busy intersections, on walls of office and school buildings, in open areas, and close to transportation hubs [2].

Solid-state metal oxide sensors (MOS) are widely used sensor technology for observing the concentrations of several gases, including CO, O_3, NO_x, NO_2, and non-methane hydrocarbons (NMHC) [3].

Advantages: MOS sensors exhibit cost-effectiveness compactness [3]. Additionally, they demonstrate elevated sensitivity, achieving detection levels in the sub-parts per billion (ppb) range for specific gases [3]. MOS sensors possess a rapid response time, facilitating data acquisition at a high sampling frequency [3]. Further merits of MOS sensors encompass their extended operational lifespan and robustness against severe environmental conditions [3]. Notably, these sensors are capable of functioning in elevated temperature and humidity settings, rendering them apt for prolonged deployments [3].

Disadvantages: MOS present several challenges that can impact the overall processing pipeline, while they exhibit resilience, their sensitivity can be influenced by atmospheric conditions and other gases [3]. This necessitates the inclusion of inputs from temperature and relative humidity sensors during MOS calibration [3]. Another limitation is their tendency for reduced accuracy and susceptibility to

drift, demanding frequent recalibration to maintain data quality. Drift is characterized by diminished measurement precision, stemming from a decline in the conductance of the sensing element over time [3]. Additionally, MOS response is influenced by humidity, with increased humidity leading to heightened sensor error [3]. Lastly, they necessitate access to a sufficiently robust power source due to the requirement to energize an electric heater [3, 39].

Because metal oxide sensors re inexpensive and very resilient to environmental changes, they are a good choice for low-cost sensing system. Their high-power needs and environmental sensitivity, however, are cause for concern, but they have high power requirements, which makes them more appropriate for deployments with fixed power supplies than for those using battery power [3, 39].

Electrochemical sensors are another well-known and affordable way to measure gas concentrations. These sensors are used for monitoring CO, NO, NO_x, SO_2, O_3 concentrations [3]. They use electrodes separated by an electrolyte material, such as mineral acid, to detect gasses through oxidation-reduction reactions and a porous membrane is used to monitor the contact between the working electrode and the electrolyte as well as the surrounding air [3]. The sensor‘s outer pins can be used to measure the electrical current that is produced by the reaction between the electrodes [3].

One of these sensors benefits is that it uses electrodes that are separated by an electrolyte material, like mineral acid, to detect gases through oxidation-reduction reactions. The electrolyte and ambient air are in contact with the working electrode, which is observed using a permeable covering and the outer pins can be used to measure the electrical current [3].

The primary disadvantage of EC sensors is that the chemical reaction‘s pace is contingent upon the operating environment [3]. The operational range of them is typically smaller than that of MOS sensors and is also based on the properties of the chemicals utilized in the sensor [3]. They also have a shorter lifespan than MOS sensors, and the total longevity is influenced by the level of pollution to which they are exposed [3]. Low humidity and high temperatures can be especially harmful to EC sensors as they can dry out the electrolyte and cause the sensor to break [3]. Another disadvantage is that other gases may tamper with the data [3].

An infrared light source, an atmospheric sample chamber, an optical filter, and a detector make up a non-dispersive infrared sensor [3]. The light from an infrared source flow into the chamber as a gas pass through it; depending on the gas, other frequencies are absorbed [3]. The detector and optical filter receive the remaining light, and the detector outputs the frequencies using an electrical current [3]. The majority of NDIR sensor applications have used CO_2 concentration detection; however, by adjusting the light‘s wavelength, they can also be used to detect other gases [3].

The benefits are that they are easy to use, have low power consumption, and come in small quantities [3]. They do not deteriorate when exposed to gasses, so they last a long time and need little care [3].

However, they are subject to spectrum interference from several gases as well as water, and they have high detection limits, meaning they cannot monitor minuscule pollutant concentrations [3]. In addition to having a cost that can grow by up to ten times that of MOS or EC sensors, NDIR sensors are also susceptible to drift [3].

Even with admitted limitations, NDIR sensor's longer lifespan makes them a desirable choice for long-term use in arid areas. Their higher cost and threshold for detection indicate that they are better

suited for use in sparsely populated deployments, which is in contrast to the goals that low-cost sensing initiatives often aim to achieve.

Ionization through photosynthesis UV photons with high energy illuminate chemicals in detectors [3]. As a result, compounds absorb UV photons and become ionized, producing an electrical current that may be detected by a detector within the sensor [3]. More ions are created, and a higher current is produced in the compound with higher concentrations of the measured component [3].

Photoacoustic spectroscopy (PAS) has been used recently to create miniature CO_2 sensors. PAS measures the concentration of materials through the acoustic waves that are created when they are exposed to light. PAS is a method of indirect absorption spectroscopy that depends on the detection of sound waves. When light is absorbed by a particular targeted gaseous pollutant, waves are produced. When it came to CO_2 detection, PAS outperformed all other evaluated NDIR-based sensors [29].

Photo-ionization detectors (PIDs) are advantageous due to their low energy consumption, small size, lightweight design, quick response time, and high sensitivity [3]. Since PIDs detect all molecules with ionization potentials lower than the UV light that affects them, they are not very selective [3]. Additionally, they might be affected by water vapour or excessive humidity levels [3, 32].

Furthermore, even while their moderate price, which ranges from 5,00 $ to 500,00 $ is still reasonable when compared to expensive monitoring stations, it could still be a barrier [3]. In addition, PID drift problems necessitate regular recalibration, usually once a month [3].

PID sensors are very adaptable to a variety of situations because they perform exceptionally well under ambient conditions when evaluating low-concentration samples. Their success in small-scale investigations shows their usefulness, particularly when examining tiny particles and gasses [3]. However, their vulnerability to interference from water and relatively high cost make them less viable for long-term, densely populated deployments.

Among the many benefits of MOS are their affordability, small size, high sensitivity, quick response time, long operation life, and resistance to harsh environmental factors. However, they have throwbacks, including decreased precision, drift susceptibility, atmospheric sensitivity variations, and the need for firm power supplies. Conversely, EC sensors – which are employed in monitoring – offer selective detection and a compact design, but they also have a shorter lifespan than MOS sensors depending on the operating environment and are susceptible to changes in temperature and humidity. Although NDIR sensors are long-lasting, easy to use, and consume little power, they have high detection limits, are prone to drift, and are subject to interference from other gases and water vapor in the spectrum. PIDs have high sensitivity, fast response times, and low energy usage, but they are not selective and can be impacted by humidity. Thus, they need to be calibrated on a regular basis regularly. Because each type of sensor has unique benefits and drawbacks, it can be used for a variety of purposes based on variables, including deployment time, cost, sensitivity, and environmental conditions.

LCS small size, portability, and capacity to adapt to changing conditions have made their use in mobile platforms more and more relevant. When LCS is integrated with bicycles, cars, public transportation, and unmanned aerial vehicles (UAVs), it makes it possible to collect high-resolution data in a variety of microenvironments, especially in places that are hard to reach or do not have

permanent monitoring infrastructure. Particularly with UAB-based surveillance, directed sampling and vertical profiling provide more geographical flexibility.

Despite these benefits, there are still difficulties in guaranteeing data reliability, especially when it comes to real-time data transmission in fluctuating environmental conditions, calibration, and quality assurance. With additional methods like site selection using reference instruments and quantitative correction models, the usage of LCS for mobile monitoring is still growing, even if the results of permanently places gadgets tend to be more stable. It is expected that further technological developments will enhance LCS‘s functionality and suitability for use in mobile networks of sensors [29].

Table 1. Comparison of sensors advantages and disadvantages

Sensor type	**Advantages**	**Disadvantages**
Metal-oxide semiconductor (MOS)	Cost effective, compact, elevated sensitivity, rapid response time, extended operational lifespan, robustness against severe environmental conditions	Sensitivity influenced by atmospheric conditions and other gases, requires calibration with temperature and humidity sensors, susceptible to drift, high power requirements
Electrochemical (EC)	Selective detection, compact design	Limited operational range, shorter lifespan compared to MOS sensors, susceptible to changes in temperature and humidity, vulnerable to pollution exposure
Non-dispersive infrared (NDIR)	Easy to use, low power consumption, long lifespan, enduring under harsh environmental conditions	High detection limits, susceptible to interference from other gases and water vapor, costlier compared to MOS and EC sensors, prone to drift
Photo-ionization detector (PID)	Low energy consumption, small size, lightweight, quick response time, high sensitivity	Non-selective, vulnerable to interference from water vapor and humidity, requires regular recalibration, moderately priced, may pose a barrier to some deployments

1.3. Sensor calibration and data quality assurance

One limitation of these sensors lies in the requirement for pre-operation calibration and periodic recalibration. Calibration involves subjecting the sensor to a known concentration of the targeted gas of detection, followed by adjustments to various sensor parameters to ensure accuracy [1]. Common gases of concern across various air pollution monitoring applications include carbon monoxide (CO), ozone (O_3), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2) [1, 33].

Sensor drift and environmental changes necessitate periodic recalibrating of low-cost sensors used in static or mobile networks for long-term air pollution monitoring, and these changes are frequently noticed within a month after deployment. Reference sensors for validation are frequently absent from post-deployment calibration techniques. Calibration serves as a method to mitigate inaccuracies in low-cost pollution sensors by establishing a model that correlates the readings of such sensors with precise reference data. Both pre-placement and post-placement calibration is essential to enhance sensor performance. Various mathematical techniques are employed for calibration, with distinct

models tailored to different sensor categories [1]. Offset and gain calibration address errors stemming from the dynamic threshold and systematic inaccuracies, while adjustments for temperature and humidity incorporate contemporaneous environmental data to extend measurement accuracy [1]. Sensor array calibration mitigates the influence of interfering environmental factors, such as other gases [1, 33].

Based on how much they rely on virtual references, these three main methods for network re-calibration are described: blind, collaborative, and transfer calibrations [4].

Originally intended for general sensor networks, the idea of blind calibration [BN07]., also known as macro calibration, has been used for temperature and relative humidity sensor networks [4]. The objective is to achieve a high degree of consistency among measurements obtained from multiple sensors within a network, and it is commonly assumed that neighbouring sensors exhibit similar readings or are correlated [4]. However, this assumption faces challenges in air pollution monitoring scenarios due to the inherent complexity of air pollution dynamics, characterized by significant spatiotemporal variations [4]. Additionally, inherent discrepancies among low-cost sensors impede uniform measurements, even within densely deployed networks [4]. Consequently, measurements obtained from air pollution sensors in large-scale deployments typically exhibit variations and may not exhibit consistent correlations [4]. A more pragmatic approach involves leveraging spatiotemporal contexts where it is reasonably assumed that all sensors within the deployment measure equivalent pollution concentrations [4].

The research conducted in 2017 employed the In-situ calibration method as developed by David M. Broday. Using multi-sensor unit (MSU) observations from 1:00 from 4:00 am, in-situ calibration of MSU installed in a residential neighbourhood required calibrating O_3 sensors against data from neighbouring air quality monitoring (AQM) stations. Because local O_3 precursor emissions were minimal, uniform neighbourhood-wise O_3 concentrations were assumed for each 30 minute interval. After calibration, the mean absolute deviation of the sensors raw O_3 values was reduced from 13,3 ppb to 1,3 ppb by using linear regression coefficients. In the absence of AQM data, the calibration used mean sensor readings every half hour to create a baseline at the neighbourhood level, bringing mean absolute deviations down to 1,5 ppb. Whether or not direct AQM data calibration was performed, the calibration process was still dependable for inner-neighbourhood spatial patterns. In-situ calibration operations can be repeated daily to counteract the effects of sensor engaging . Data from two to four nights can stabilize the “rolling forwards“ calibration. Node-to-node (N2N) calibration is an alternative method that minimizes sensor relocations and allows simultaneous measurements while sequentially calibrating sensors installed in pairs. The efficiency of N2N calibration relies on the performance of each sensor as well as ambient concentrations. Areas with heavy traffic and pollution are predicted to have better performance [5].

By establishing virtual references when two mobile sensors meet in space and time such that they should measure the same physical phenomenon, collaborative calibration goes beyond blind calibration [4]. Collaborative calibration‘s fundamental concept is to make use of sensor rendezvous – a term used to describe the meeting of two or more mobile sensors in space and time [4]. A sophisticated method for addressing the problems caused by sensor drift in both stationary and mobile sensor systems is collaborative calibration [9]. In a study by Xiang et al., the foundation of their methodology is the creation of drift models, also known as drift predictors, which are built using drift data from the past [9]. By estimating sensor drift at any given time, these predictors partially

compensate for drift inaccuracies in sensor measurements. Moreover, the drift models help estimate residual errors in drift prediction over time, providing important information about how sensor drift changes [9]. In their collaborative calibration architecture, sensor fusion is a complementary technique that combines data from co-located sensors intelligently to increase the combined results' accuracy. Because it happens when sensors change to be close to one another, this fusion process os opportunistic in nature, optimizing the advantages of cooperation. However, identifying true sensor drifts is a major difficulty since it usually needs to be compared with very accurate sensors, which are uncommon in most personal sensing applications. Because of this, drifts frequently need to be calculated using models created from earlier calibration events and sensors with different levels of accuracy [9]. The temporal correlation in sensor drift, which decreases with time, is a critical factor in their collaborative calibration paradigm. As a result, when more time passes since the last drift measurement, the drift model‘s uncertainty grows [9]. Their method also highlights the value of cooperative calibration events, in which sensors share data to improve overall calibration events wherein sensors share data to improve overall calibration effectiveness and revise error estimations in order to overcome this difficulty [9].

Transfer calibration is the third category of network calibration techniques. Its conception mostly stems from industrial applications employing metal oxide sensor electronic noses (e-noses) to detect potentially dangerous odours [4]. Transfer calibration can be used with any kind of sensor model, and neural networks are commonly used to calibrate e-noses so that they can identify several district gases or odours using a single calibration model [4]. It takes a lot of labour to train such a neural network, mostly because of the calibration of training samples and model optimization [4]. The study by Zhang et al. (2011) delves into the critical aspect of sensor calibration transfer among e-nose instruments for the real-life monitoring of VOCs in indoor air quality. Gas sensors are usually installed on specially designed printed circuit boards. Even with identical sensor arrays and electrical components, individual sensor responses may vary in mass-produced e-nose equipment for indoor air quality monitoring, resulting in inaccurate concentration measurements and false discriminations. A strong calibration transfer technique is necessary to overcome this and make standardizing results between various instruments easier. A novel approach utilizing global affine transformation (GAT) and Kennard-Stone sequential samples selection algorithm (KSS) is proposed for online mass calibration of e-nose instrument. Affine transformation coefficients are determined using a robust weighted least square (RWLS) algorithm, while sample selection is based on Euclidean distance. Additionally, a feed-forward multilayer perception neural network, trained using a back-propagation algorithm, is employed for organic gas concentration prediction, leveraging the computational efficiency of artificial neural networks. This innovative calibration methodology aims to achieve high-accuracy standardization between e-nose instruments, overcoming the inherent challenges posed by the multidimensional nonlinear characteristics of e-nose systems [6].

1.4. Comparison of Sensor Prices

When comparing the purchase and running costs of sensors to those of the term “low-cost“ is applied. According to the user‘s needs and the intended application, the term may become relative. Many published articles utilize inexpensive air quality sensor modules or monitors that range in price from a few hundred to several thousand dollars. Based on one study, a sensor module that costs less than $1000 USD is considered low-cost [10].

The cost of air quality sensors varies based on the manufacturer, the contaminants they assess, and their working principle. Although MOS sensors tend to be less expensive – between a few tens and a few hundred euros – their effectiveness is contingent upon calibration capabilities and environmental factors. Due to their high sensitivity to particular gases and their moderate cost (some versions start at 50 euros), EC sensors are widely used. Since their technology enables more precise measurement, particularly for CO_2 measurements, nondispersive infrared (NDIR) spectroscopic sensors are typically more costly with prices varying from 3000 euros to 4000 euros and more. Among the most expensive air quality sensors are photoionization detectors (PIDs), which can cost anywhere from a few thousand to over 8000 euros and are used to detect volatile organic compounds. The accessibility of the sensors to the data also affects price differences: "black box" type systems are frequently more expensive and have fewer usability options, whereas open-source devices are less expensive and provide more calibration possibilities [18, 34].

According to a study by Karagulian et al., the most reasonably priced sensors are MOS ones, which can cost anywhere from 40 euros to 500 euros, depending on the model and gas sensitivity. While EC sensors for ozone, carbon monoxide, or nitrogen dioxide detection typically range from 50 euros and 500 euros, they need to be calibrated on an ongoing basis to function. Carbon dioxide sensors that use NDIR technology can cost up to 2000 euros. At up to 4500 euros, PIDs are some of the priciest tools available for detecting volatile organic chemicals. The detectors' technological sophistication, data transparency, and applicability determine their price [19, 35].

The MICS-EK1 Metal Oxide Semiconductor (MOS) Gas Sensor Evaluation Kit is available from SGX Sensor tech for 273,47 euros. Although it includes all the hardware and software required for data logging and sensor functioning evaluation, this kit enables a rapid start-up of MOS gas sensors. One or two sensors can be connected, controlled by a USB interface, and the data collected can be analysed using free PC software. Automatic measurement of variations in sensor resistance is part of sensor control. Data logging and basic control are provided via the supplied software. Additional features like digital inputs, analog outputs, and integrated temperature measurements can also be included [11].

Carbon Monoxide Sensor ME3-CO is available from Winsen Electrochemical for 14 Eur. This gas sensor manufacturer uses fuel cell and electrochemical technology to create industrial and carbon monoxide sensors. According to the electrochemical principle, which uses the electrochemical oxidation process of the target gas on the working electrode inside the electrolytic cell, the ME3-CO electrochemical sensor measured the current to determine the concentration of the gas. The current generated in the electrochemical reaction of the target gas is directly proportional to its concentration while adhering to determine by measuring the current value. These sensors offer a wide linear range, low power consumption, high precision and sensitivity, good anti-interference ability, and excellent repeatability and stability [12].

MH-Z16 NDIR CO_2 Sensor is available from Winsen Sensor for 286 USD. A typical form of tiny sensor, the infrared gas module uses the non-dispersive infrared (NDIR) principle to detect the presence of CO_2 in the air. It is long-lasting, non-oxygen dependent, and has good selectivity. It features digital and PWM wave outputs, as well as built-in temperature correction. Precision optical circuit design and established infrared absorbing gas detection technology are tightly integrated to create this common type of infrared gas sensor. High sensitivity, high resolution, and low power consumption are this sensor's primary characteristics [13].

Zhengzhou Winsen Electronics Technology Co., Ltd. Created the 4R-PID sensor, a high-performance photoionization detector (PID) intended for the detection of certain inorganic vapours and volatile organic compounds (VOCs). It is distinguished by its high accuracy (+-2%), quick response time (≤5 s), broad detection range (1 ppb-10,000 ppm) and high sensitivity. It can be used in both stationary and portable devices for managing soil contamination, industrial hygiene, and environmental quality monitoring, among other uses. With the exception of the bulb and electrodes, the sensor has a three-year lifespan and operating temperature range from -20°C to 50°C [14].

The Clarity Black Carbon Module unit uses DualSpot correction and AethLabs 5-wavelenght absorption analysis to measure the amount of black carbon in the air. Black carbon concentrations between 0 and 1 mg/m3 can be measured by the sensor with a resolution of 1 ng/m3. The gadget may be fuelled by a solar panel or the grid and functions at temperatures ranging from -10°C to 45°C. The cost is determined by a customized order [15].

The PurpleAir Zen device is made to measure air quality in real-time, including the concentration of PM_1, $PM_{2.5}$ and PM_{10}. The gadget is effortless to install and may be used both indoors and outdoors. The starting price is $299 USD [16].

WoMaster ES101PM PM_1, $PM_{2.5}$, and PM_{10} measurements using a stationary device. It works at temperatures ranging from -40°C to 85°C and is waterproof, making it appropriate for outdoor use. It enables Ethernet or LoRaWAN data transmission and uses laser light scattering. The cost is determined by each order [17].

Although the three instruments are all made to assess ambient air pollution, their uses and purposes differ. The Clarity Black Carbon Module is perfect for analysing particular sources of air pollution, including diesel engine exhaust, because it focuses on black carbon data. The PurpleAir Zen is a straightforward, easy-to-use particulate matter monitoring gadget more reasonably priced than competing models (starting at 299 USD). Because of its durability and extreme environmental construction, the WoMaster ES101PM can be used in harsh outdoor climates or industrial settings. The particular context of use determines how to balance cost and functionality. While the WoMaster ES101PM and Clarity Black Carbon Module are appropriate for more complex and specialized applications, the PurpleAir Zen is the greatest option for home or local use.

Due to their numerous applications in outdoor as well as indoor, low-cost sensors are now a crucial part of modern air quality monitoring programs. Their implementation makes it less difficult to gather high-resolution geographical and temporal data, which makes it possible to characterize pollutant dispersion patterns, identify localized emission sources, and evaluate exposure at the population level. Beyond conventional regulatory frameworks, environmental surveillance has been improved through incorporation of LCS into residential settings, educational institutions, and urban infrastructure. On top of that, LCS‘s increased commitment to participatory monitoring programs highlights how well they can assist decentralized, data-driven methods to air quality management [29, 36].

1.5. The role of fine particulate matter in assessing environmental and human health impacts

Fossil fuel usage has increased due to the rapid growth of industrialization, leading to issues such as extreme air pollution and hazy weather. Serious issues with public health have also resulted from it. Sulfates, ammonia, nitrates, black carbon, mineral dust, sodium chloride and water are the main constituents of PM.

The health hazards of particles are directly correlated with their size. The primary threat comes from fine particles (PM10 and below), which can enter the lungs and, in rare cases, the bloodstream. In individuals with heart or lung illness, non-infarction heart attacks, arrhythmias, exacerbations of asthma, decreased lung function, irritation of the respiratory tract, coughing, and breathing difficulties, exposure is associated to an increased risk of premature death, elderly, vulnerable communities, and people with chronic illnesses are the groups most at risk. Indoor air quality is not regulated to international regulations, in contrast to ambient air quality. Given that individuals spend more than ninety percent of their time indoors – and almost one hundred percent of that time during the coronavirus disease 2019 (COVID-19) pandemic – controlling the quality of indoor air is even more crucial [27, 29].

In terms of environment, temperature, precipitation, and relative humidity are examples of climate factors that have an impact on $PM_{2.5}$ concentrations and compositions both directly and indirectly. Temperature tends to lower nitrate concentrations while rising OC, BC, and sulfate levels. Particulate matter is frequently removed by precipitation via moist deposition. While high relative humidity inhibits the development of carbonaceous aerosols, it promotes the formation of secondary inorganic aerosols including nitrate and sulfate. Particularly in fire-sensitive areas where their frequency and intensity are predicted to rise, wildfires – which are fuelled by shifting climatic conditions, are anticipated to become increasingly important in determining $PM_{2.5}$ dynamics.

By modifying surface – atmosphere interactions, land-use and land-cover changes (LULCC), such as urbanization, agricultural expansion, and vegetation alterations, also affect $PM_{2.5}$ levels. These modifications have an impact on transportation, albedo, dry deposition rates, and emissions of biogenic volatile organic compounds (BVOCs), all of which are involved in aerosol dynamics and atmospheric chemistry. Depending on the particular land transformation processes and related emissions pathways, studies show that LULCC can lead to both increased and decreased $PM_{2.5}$. Fo example, major changes in the generation of secondary organic aerosols (SOA) have been associated with the increase of agriculture in East Asia [30].

Handling air pollution while encouraging economic expansion remains and obstacle to overcome. Therefore, having accurate information about the levels of PM in municipal air is crucial. This information may be used to choose efficient ways to lower PM concentrations, regulate emissions, and maximize the health benefits of abatement measures [23, 24, 25, 26, 28].

2. Research methods

2.1. D-GEM low-cost sensor and Environmental Protection Agency's monitoring station sensor specification

To find airbone particulate matter ($PM_{2.5}$) pollution, low-cost sensors were employed. For this project, the D-GEM low-cost sensors were taken on lease from the company *Devlabs*, Denmark. Optical Particle Counter (OPC) combined into a low-cost D-GEM type air quality sensors was utilized to measure these $PM_{2.5}$ concentrations. At high concentration coverage (0-1000 μg/m³), this sensor's activity of 1 μg/m³ and precision of 5 μg/m³ provide precise detection of small particulate matter, including $PM_{2.5}$, with a quick 1 second sample collection rate. Real-time, high resolution environmental monitoring is made possible by these factors.

Environmental Protection Agency monitoring stations in Kaunas use high – precision, certified instruments to monitor ambient $PM_{2.5}$ concentrations, following European Air Quality Directive standards. It ensures high accuracy and reliability over a wide concentration range (up to ~1,000 $\mu g/m^{3)}$, with precision around ± 2-5 $\mu g/m^3$. The system operate effectively under varying environmental conditions (temperature, humidity), ensuring data quality.

Table 2. $PM_{2.5}$ sensors specification summary

Parameter	**DGEM**	**EPA**
Mass concentration range	0~1,000 $\mu g/m^3$	0-1,000 $\mu g/m^3$
Precision	± 10 $\mu g/m^3$ (for range 0 - 100 $\mu g/m^3$) ± 10 % (for range 100 - 1000 $\mu g/m^3$)	± 2-5 $\mu g/m^3$
Sampling interval	1 ± 0.04 s	1-60 min
Maximum long-term precision limit drift	± 1.25 $\mu g/m^3$ (for range 0 - 100 $\mu g/m^3$) ± 1.25 % (for range 100 - 1000 $\mu g/m^3$)	<1-2%
Temperature Range	-10 to 60 °C	-20 to 50 °C
Humidity Range	0 to 95 % RH	0 to 95% RH
Accuracy	5 $\mu g/m^3$	1-2 $\mu g/m^3$
Sensitivity	1 $\mu g/m^3$	1 $\mu g/m^3$
Sample collection	1s	1 min – 1 hour

2.2. Site Allocation for Sensor Deployment

The study area covers Dainava district, which is characterized by a dense distribution of apartment buildings that form confined blocks with limited air circulation (Figure 5). Taikos Avenue, Pramones Avenue are major transportation routes that are heavily trafficked throughout the week. The multiplicity of crossroads and roundabouts, particularly in the Urmas retail centre, creates circumstances for local pollution accumulation, especially in bad weather. The neighbourhood is also densely populated with commercial, educational, and public facilities, resulting in a large distribution of people flows at various times of day.

Fig. 6. Kaunas city and the area where the pollution was measured

The air quality sensors were deployed at seven different locations in the Kaunas city, geographically close to each other, allowing detailed analysis of the distribution of $PM_{2.5}$ at the micro-scale (see Fig. 6). The small distance between locations is an essential factor for determining whether or not local urban and environmental characteristic (such as crowded streets, open spaces, and enclosed courtyards) can significantly affect variations in pollution levels even within the same section of a city. This methodological approach allows not only the study of overall urban air pollution levels, but also of microclimatic differences in pollution, which are sometimes overlooked in large scale investigations.

Table 3. Technical and geographical parameters and data coverage of measurement points

Name of the station	**Location coordinates**	**Sensor mounting direction**
Medical station	54.91501159656382, 23.984751188927554	East side
Kaunas College, second building 22	54.922220144981836, 23.982681235087348	West side
Kaunas College, first building 20	54.92035424399472, 23.9841099256128	West side
Library	54.916510395521854, 23.981624314307975	South side
VDU University residential hostel	54.918754378097375, 23.987087778360173	North side
Residential Building	54.918779167166065, 23.980626254902404	East side
Monitoring station	54.91679483649582, 23.983277750071966	East side

In order to evaluate the effect of outdoor pollution on indoor air quality, sensors were places both inside and outside the buildings at each location. This methodology allows to analyse if the level of outdoors pollutants that enter the domestic environment and the concentrations of $PM_{2.5}$ outside and indoors are correlated. That type of data is especially useful for developing recommendations for the usage of buildings ventilation, filtration systems, or preventive measures in urban planning, as well as for assessing the effects of air quality on population health.

To guarantee the accuracy and representativeness of the data, standardized guidelines were used when installing the internal sensors. The sensor had to mounted within 2 metres of the flow to avoid attenuation or deformation of the air flows due to air stratification in the room. To prevent localized disruptions in air flow, the device needed to be installed in an open unhindered area away from windows, vents, heat sources and corners. Also, to prevent data variances brought on by positional changes, it was also made sure that the sensor was securely attached, out of direct human touch, and motionless for the duration of measurement. In addition, a periodic check of the power supply was carried out to avoid malfunctions of the instrument.

The outside sensors were places no higher than the second floor, recognizing that $PM_{2.5}$ concentrations change dramatically down the vertical axis and that lower measurements stations are more reflective of actual pollution in the human breathing zone. The sensors were positioned towards the street to record the direct effects of traffic and other urban emission sources. The installation locations were chosen to assure free air flow, with no towering structures or physical impediments that could alter air movement and pollutant distribution.

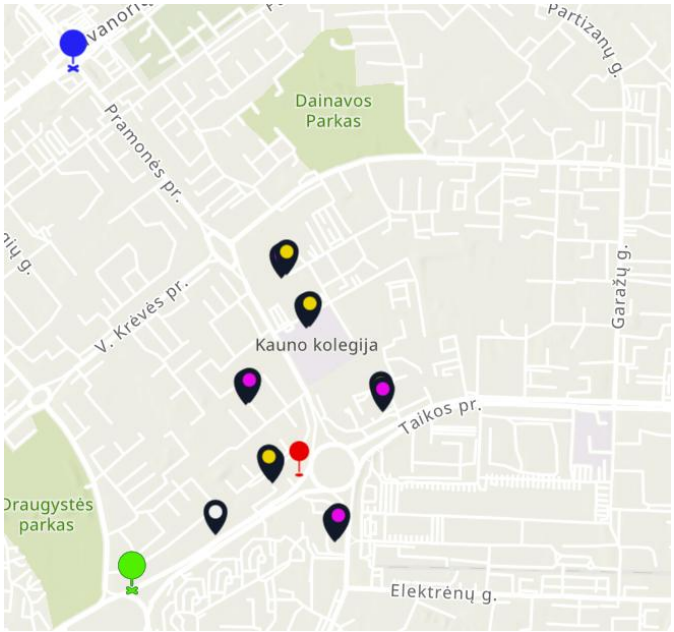


Fig. 7. Map of deployed low-cost sensors

One sensor was collocated with the air quality monitoring station operated by the Lithuanian Environmental Protection Agency in Taikos avenue. This enables the obtained data to be directly compared to reference, standardized measures. It allows the accuracy and dependability of a low-cost sensor to be evaluated in equivalent environmental setting and under realistic circumstances. Since it contributes in validating or modifying data from other sensors in a wider urban area, this comparison is also methodologically significant, assuring data validity, enter comparability, and quality.

The sensors continually gathered data for six months, from February to July 2024. They were gathered every minute. This minute-by-minute data collection identifies pollution peaks associated with traffic or diurnal rhythms and records short-term variations in $PM_{2.5}$ concentrations. Long term and consistent monitoring allows weekly trends to be analysed. The data‘s quality, dependability, and analytical utility are all enhanced by the high temporal resolution.

Fig. 8. A low-cost sensor mounted on an Environment Agency monitoring station

2.3. Methods and Techniques of Data Analysis

Statistical analysis was carried out to analyse and process the measurement data obtained. The analysis was used to assess the impact of pollution on the population of Kaunas city. Statistical analyses were conducted using IBM Statistics 30.

The box-whisker plot method was utilized in the analysis, with Excel used to visually represent data distribution along the axis. These plots use a quartile system for the data, with the lower quartile, median value, and upper quartile forming a “box“ separately. The trend of the data centre, the distribution symmetry, the data‘s fluctuation, and any outliers that could be analytically significant for evaluating variations in $PM_{2.5}$ concentrations between observed locations or time periods are all displayed in this visualization.

The initial stage of the analysis involved descriptive statistics, which aimed to assess the main indicators of the distribution of the data, such as n (the number of observations), the minimum, the maximum, the mean and the standard deviation. This analysis provided a foundation for evaluating the comparability of the data across several measurement points and for additional interpretation of statistical trends.

In a further stage of the analysis, correlation analysis was used to evaluate the connection between indoor and outdoor sensor ta at each measurement site. This analysis allowed us to determine whether there is statistically significant relationship between outdoor and indoor $PM_{2.5}$ concentrations and the strength and direction of this relationship. The correlation coefficients helped to assess the extent to which outdoor air pollution can influence indoor air quality and whether the indoors environment is

a direct reflection of the outdoor conditions. When evaluating the possibility of outdoor pollutants penetrating within and the possible necessity of pollution control measures in public or residential areas, this stage was essential.

The next stage of the research was to see if there were any statistically significant correlations between the outdoor sensor data from various measurement locations. In order to achieve this, a correlation analysis was utilized to determine not only the existence of a relationship, but also its strength and direction. This step was necessary to determine whether pollution levels vary synchronously throughout the city and whether changes in pollution at one location are associated with changes at another. Statistically strong correlations imply that places may be influenced by common or related pollution sources and atmospheric conditions, whereas weak or insignificant correlations indicate that local factors or microclimatic differences between spots are more important.

Scatter plots were then produces to visually compare the differences in $PM_{2.5}$ concentrations between the various measurement sites. These plots provided a clear picture of the distribution of data among locations, as well as any trends, patterns or outliers. Scatter plots supplemented the statistical analysis by providing a clear perspective of site relationships, as well as identifying potential data anomalies or case where pollution at one site differed dramatically from others.

To provide a more complete assessment of $PM_{2.5}$ concentration fluctuations throughout the week, hourly medians were determined for each day of the week. This data processing allowed us to lessen the impact of short-term variations and identify the normal dynamic of pollution at specific times of day on each day of the week.

In a subsequent stage, box-whisker plots were used to visually and statistically examine variations between days of the week. These plots depicted the median $PM_{2.5}$ distribution, quartiles, extreme values, and data scatter for each day of the week individually. This analysis assisted in determining which days of the week are more or less polluted, as well as whether there are regular cyclical changes in pollution associated with the rhythm of human activity intensity throughout the week.

3. Results

3.1. Comparison of data from low-cost sensor and an official Environmental Protection Agency monitoring station

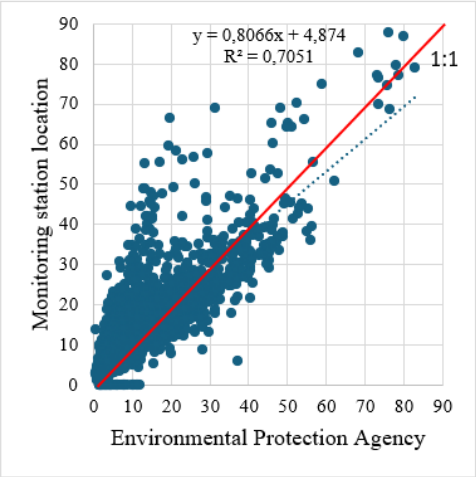


Fig. 9. $PM_{2.5}$ concentrations - the relationship between a low-cost sensor and an official monitoring station

The scatter plot of data from the Environmental Protection Agency monitoring station vs data from the low-cost sensor installed at the same location reveals a clear upward distribution of points, demonstrating a positive link between the two data sources. Statistical investigation validates the visual perception, with a robust correlation (r=0,832) and p<0,000. This means that the data from the low-cost sensor closely matches the official monitoring station‘s values and accurately depicts real-time changes in $PM_{2.5}$ concentrations. This finding indicates that this sort of sensor can be utilized efficiently for extra monitoring in urban environments, particularly in areas without public air quality monitoring stations.

The slope of the regression line (0,8066) indicates that for every unit increase detected by the EPA’s monitoring station, our low-cost sensor reports almost 80% of that number. This minor underestimation which can respond differently to particle composition, humidity, or optical characteristics. Nonetheless, the slope near shows right agreement, which validates the low-cost sensor’s appropriateness for real-time ambient monitoring and its potential applications.

A study by Heintzelman et al. (2023) investigated $PM_{2.5}$ changes utilizing a network of low-cost sensors and EPA monitoring stations, concentrating on neighbourhood-level spatial patterns. Low-cost sensors captured consistent $PM_{2.5}$ patterns, even with variances in equipment class. Calibration against humidity and meteorological conditions improved data dependability. [41]

3.2. Spatial variation of $PM_{2.5}$ concentrations in street environment

An analysis of variance (ANOVA) was performed to evaluate whether there are statistically significant differences in $PM_{2.5}$ concentrations between all of the measurement sites, this analysis showed that $PM_{2.5}$ levels at the different stations were statistically significantly different from each other (p<0,001).

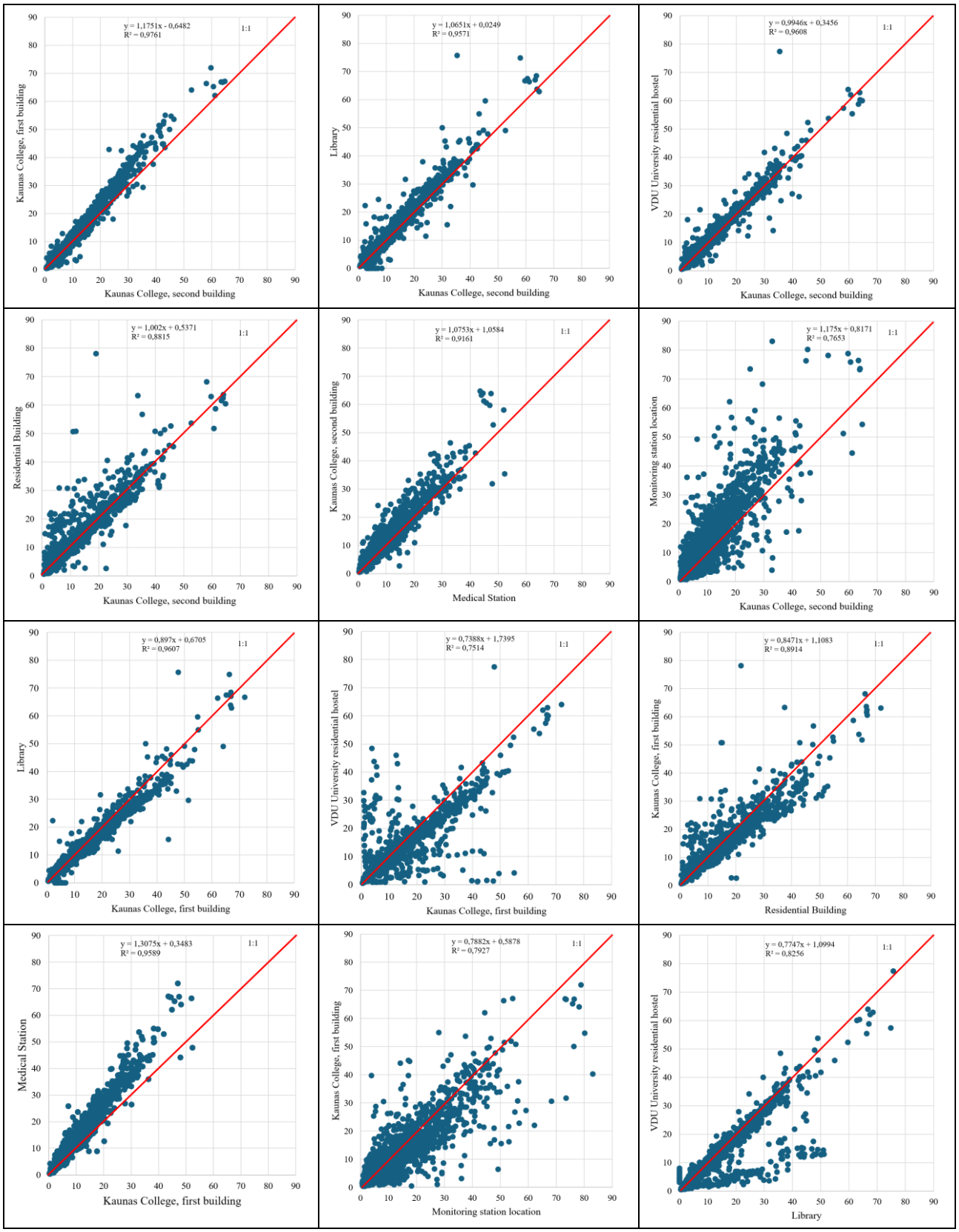
A Pearson correlation test was carried out to assess the correlations between the different sites (see Table 4). This method allowed the determination of correlation coefficients that reveal the strength and direction of the relationship between each pair of stations. The results showed that most of the stations have a strong correlation with each other: both Kaunas College buildings, Library with both Kaunas College buildings, Vytautas Magnus University residential hostel with the second Kaunas College building, medical station with almost all of the stations except the residential building. This may indicate the effect of common pollution sources from transportation.

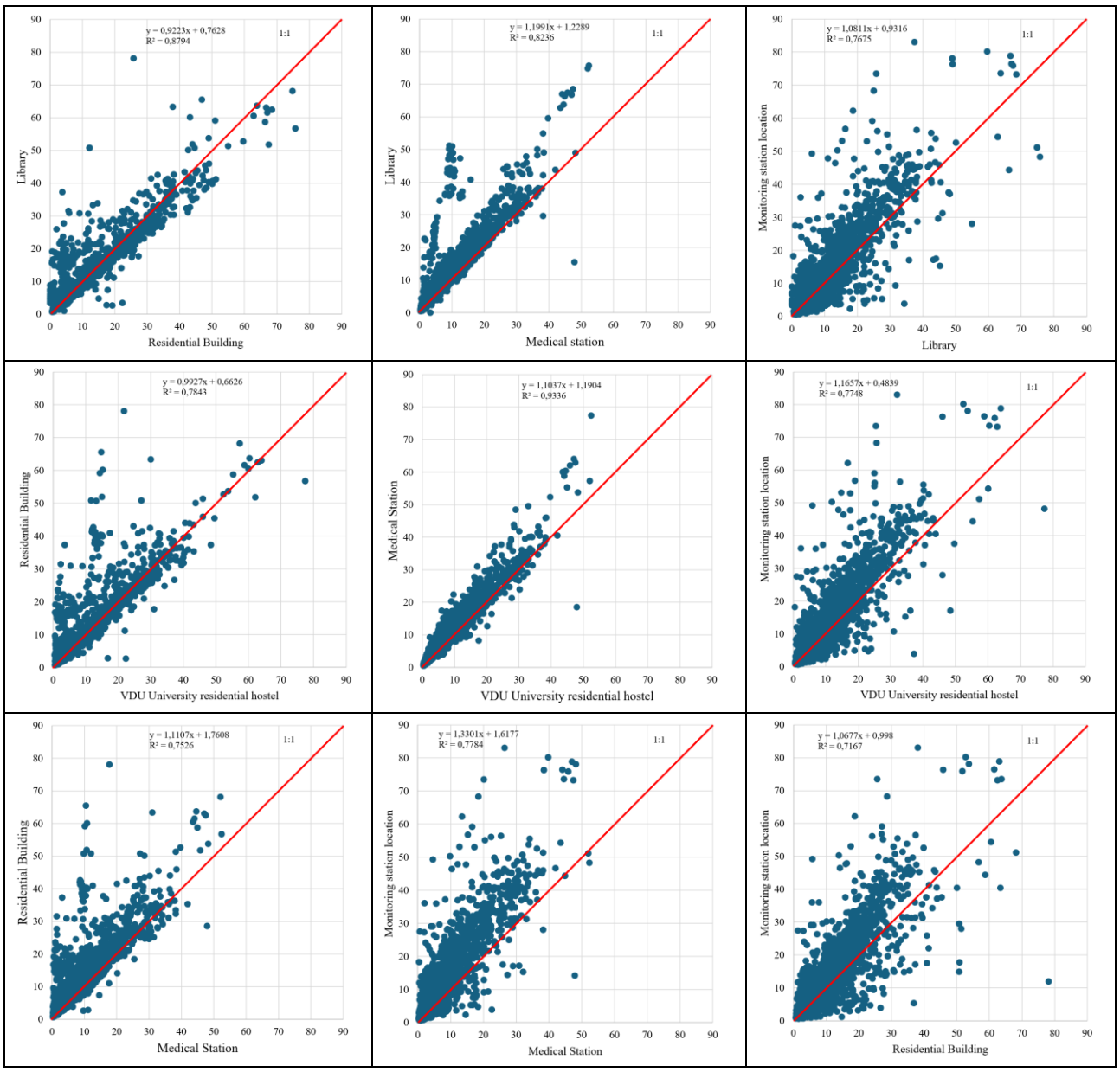
In contrast, the results also showed that the residential apartment block located deeper away from the main streets did not have a strong correlation with any of the other stations. This result suggests that $PM_{2.5}$ concentrations at this location vary independently of other points in the city, which may be due to localised micro-environment conditions, limited air circulation, the location of surrounded buildings or weak direct influence from major sources such as traffic flows.

Table 4. Relationships between particulate matter 2.5 concentrations in various measurement locations (Pearson Correlation, all values are statistically significant (p<0,001))

	Kaunas College, second building	**Kaunas College, first building**	**Library**	**VDU University residential hostel**	**Residential Building**	**Medical station**	**Monitoring station location**
Kaunas College, second building		-	-	-	-	-	-
Kaunas College, first building	0,988		-	-	-	-	-
Library	0,979	0,981		-	-	-	-
VDU University residential hostel	0,98	0,867	0,909		-	-	-
Residential Building	0,773	0,782	0,795	0,75		-	-
Medical station	0,957	0,979	0,907	0,966	0,738		-
Monitoring station location	0,875	0,890	0,879	0,880	0,702	0,882	

Table 5. Pairwise scatter plots for $PM_{2.5}$ concentration comparisons between measurement sites





The outdoor $PM_{2.5}$ concentrations at Kaunas College's first and second building shows a very strong linear relationship (R^2 =0,9761) with slope of 1,1751, indicating that, on average, $PM_{2.5}$ levels at the first building are about 17% higher than at the second one. The tights data clustering reflects highly synchronized pollution patterns, likely driven by shared exposure to traffic emissions along Pramonė Avenue, similar urban positioning, and aligned meteorological conditions. This consistency suggests that both locations experience comparable external pollution dynamics.

The outdoor $PM_{2.5}$ concentrations between Kaunas College's second building and the library demonstrate a very strong linear relationship (R^2 = 0,9571) with a slope of 1,0651, indicating that the library's outdoor levels are on average about 6,5% higher. The close data alignments suggest both locations are similarly influenced by regional traffic and urban emissions, with minor elevation in the library likely due to its slightly more open surrounding or proximity to additional local sources.

The comparison of outdoor $PM_{2.5}$ concentrations between Kaunas College's second building and the VDU University residential hostel reveals an exceptionally strong linear relationship (R^2 =0,9608)

with a slope of 0,9946, indicating nearly identical average values between these two locations. This near one-to-one values suggests that both sites experience highly synchronized pollution patterns, likely drive by shared exposure to regional traffic emissions.

The scatter plot of Kaunas College second building and the residential building reveals a strong positive relationship (R^2 = 0,8815) with a slope of 1,002, indicating nearly equal average outdoor $PM_{2.5}$ concentrations across both sites. Despite the overall alignment, the scatter reveals more variability in the residential area at higher concentration levels, likely reflecting localized factors such as microenvironmental conditions or intermittent location emission.

The scatter plot of the medical station and Kaunas College‘s second building indicates a strong positive correlation (R^2 = 0,9161) with a slope of 1,075, indicating slightly higher average $PM_{2.5}$ concentrations at the college site. These results suggests that both location are similarly influenced by shared urban traffic emissions, though the medical station likely benefits from microclimatic controls, filtration that slightly modulate these local measurements.

The scatter plot between Kaunas College, second building and the monitoring station location shows a moderately strong positive correlation (R^2 = 0,7653) with a slope of 1,175, suggesting that, on average, the monitoring station reports slightly higher $PM_{2.5}$ levels. This relationship reflects shared exposure to urban emissions but also points to potential local differences in air flow, microclimate.

The comparison between Kaunas College’s first building and the library reveals a very strong correlation (R^2 = 0,9607) with a slope of 0,897, which indicates nearly proportional $PM_{2.5}$ concentrations between these two locations. This suggests that both sites are influenced by similar pollution sources.

The scatter plot between Kaunas College first building and the student dormitory demonstrates a moderate to strong positive correlation (R^2 = 0,7514) with a slope of 0,7388, indicating that approximately 74% of the outdoor $PM_{2.5}$ variations measured at the hostel. This suggests shared external pollution sources, though the hostel records proportionally lower concentration, likely due to differences in building placement and exposure.

The scatter plot of the residential building and the Kaunas College first building demonstrates a strong positive correlation (R^2 = 0,8914), with a slope of 0,8471, meaning that approximately 85% of the outdoor $PM_{2.5}$ variations at the residential site are reflected at Kaunas College. This indicates that, despite possible local shielding, microenvironmental differences. Both sites experience similar pollution patterns.

The graph between Kaunas College‘s first building and the medical station indicates a strong correlation (R^2 = 0,9589) with a slope of 1,3075, which indicates that $PM_{2.5}$ concentrations at the medical station are about 31% of those at the college. This suggests slightly amplified readings at the medical site, potentially due to local factors.

The scatter plot comparing Kaunas College, first building and monitoring station location reveals a moderately strong correlation (R^2 = 0,37927) with a slope of 0,7882, meaning the college’s $PM_{2.5}$ readings reach about 79% of those recorded at the monitoring station. This indicates that while both locations reflect similar pollution trends, the college site registers slightly lower concentrations, likely due to minor local differences in emissions.

The comparison between VDU residential hostel and the library shows a strong correlation (R^2 = 0,8256), with a slope of 0,7747, indicating that $PM_{2.5}$ concentrations at the hostel reach approximately 77% of the levels recorded at the library. This suggests both locations experience similar pollution dynamics, though slightly lower at the hostel.

The comparison between the residential building and the library reveals a strong positive correlation (R^2 = 0,8794), with a slope of 0,9223, indicating that $PM_{2.5}$ concentrations at the library reach about 92% of the levels observed at the residential site. This suggests both locations experience similar pollution trends, though slight variations may arise from local structural or ventilation differences.

The scatter plot between the medical station and the library indicates a strong positive correlation (R^2 = 0,8236), with a slope of 1,1991, meaning $PM_{2.5}$ concentration at the library are on average 20% of those at the medical station. This suggests slightly elevated levels at the library, possibly influenced by its more open structure or proximity to additional emission sources.

The scatter plot between the library and the monitoring station shows a moderate to strong positive correlation (R^2 = 0,7675), with a slope of 1,0711, indicating that on average, the monitoring station records 8% of the $PM_{2.5}$ levels seen at the library. This reflects generally consistent outdoor pollution patterns but also highlights some variability, likely due to localized environmental and traffic influences near each site.

The comparison between the VDU residential hostel and the residential buildings shows a strong positive correlation (R^2 = 0,7843) with a slope of 0,9927, meaning the $PM_{2.5}$ levels on average are nearly identical. This suggests generally consistent outdoor pollution trends, although variations points to localized microenvironmental and structural factors at each site.

There is a strong positive link between the medical station and the student housing block (R^2 = 0,9336), with data distributed reasonably evenly along a linear relationship and no significant scatter. The slope of 1,1037 indicated that on average, the medical station records about 10% higher PM2,5 levels compared to the VDU hostel. This reflects consistent outdoor pollution patters, but the slight overestimation may arise from the medical station’s proximity to intense traffic.

The scatter plot between the residential building and the medical station shows a moderate to strong positive correlation (R^2 = 0,7526), with a slope of 1,1107, indicating that the residential building records on average about 11% higher $PM_{2.5}$ levels compared to the medical station. This suggests that while the general pollution trends align, localized emissions in the residential are may slightly elevate particulate levels.

The scatter plot between the Medical Station and the Monitoring Station shows a moderate positive correlation (R2 = 0,7784), with a slope of 1,3301, indicating that on average, the monitoring station reports about 33% higher $PM_{2.5}$ levels compared to the medical station. Although the overall trends are similar, localized factors near the monitoring station may contribute to elevated particulate matter levels.

The scatter plot between the Residential Building and the monitoring station displays a moderate positive correlation (R2 = 0,7167), with a slope of 1,0677, suggesting that the monitoring station records approximately 7% higher $PM_{2.5}$ levels on average. This indicates that while general pollution

trends align, localized conditions near the residential site, such as reduced traffic and enclosed spaces, may reduce outdoor pollution levels compared to the monitoring station.

Biancardi et al. (2024) found that low-cost sensor networks can detect small seasonal and diurnal fluctuations in $PM_{2.5}$ concentrations that daily or annual averages alone cannot. In comparison, the findings of this study demonstrate that local microenvironmental factors influence pollution levels rather than regional emissions alone, necessitating thorough multipoint monitoring. Furthermore, Biancardi et al. point out that features of the urban fabric, such as building height or pavement type, can influence pollutant dispersal [40].

3.3. Penetration of outdoor $PM_{2.5}$ to indoor environment

One of the most important analyses was to assess whether outdoor air pollution has an impact on air quality indoors (Table 6). An analysis of variance showed that the differences between indoor and outdoor measurements were statistically significant ($p<0,001$).

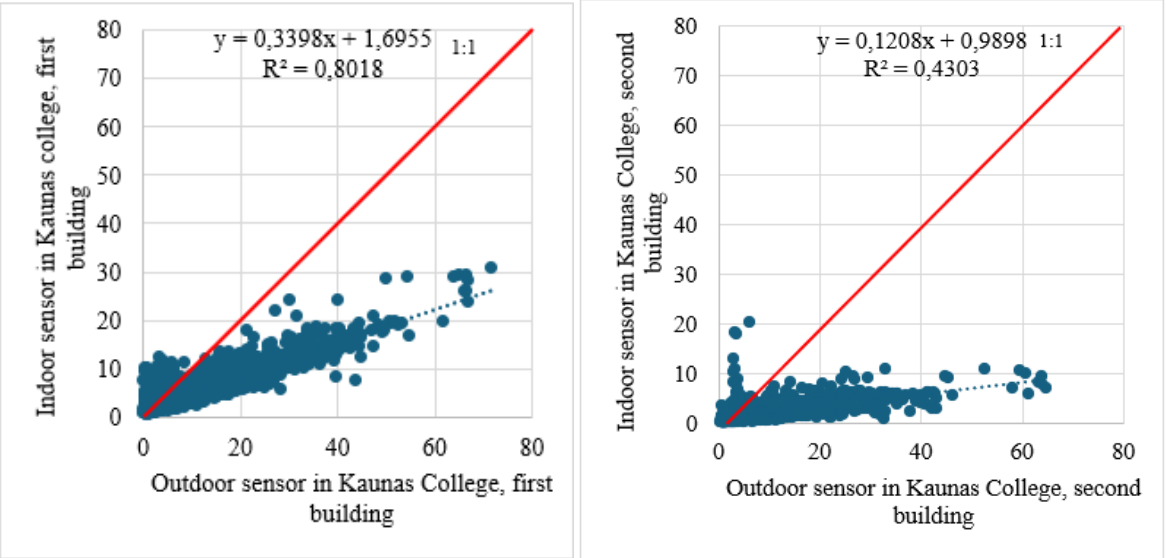


Fig. 10. Indoor and outdoor sensor scatter plots for both buildings of Kaunas College

The analysis of $PM_{2.5}$ from both buildings of Kaunas College demonstrates clear differences in the proportion of outdoor pollution reflected indoors. In the first building, the slope value of 0,3398 indicates that approximately 34% of outdoor $PM_{2.5}$ particles are transferred indoors, reflecting a moderate infiltration rate likely driven by natural ventilation with open windows, or airflow pathways.

In the second building, the slope of 0,1208 indicates that only around 12% of outdoor concentrations affect indoor levels, reflecting minimal pollutant transfer. This is further shown by the trend, which deviates significantly from the red 1:1 line, suggesting restricted air exchange, stronger building isolation, or dominant internal factors shaping indoor air quality.

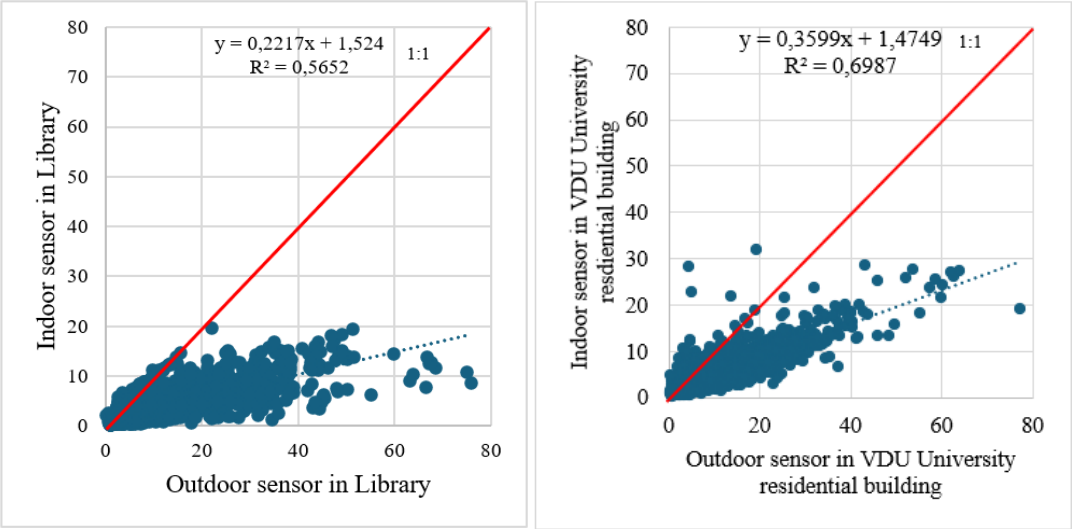


Fig. 11. Indoor and outdoor sensor scatter plots of the library and the VMU student apartment building

In the library, the correlation between indoor and outdoor concentrations is weaker, and the values are irregularly distributed, with the bulk of points concentrated at low outdoor values and high indoor concentrations. This suggests an internal source of pollution or inadequate indoor ventilation, causing particles to accumulate indoors despite low levels of ambient pollution. The slope is equal to 0,2217, meaning only about 22% of outdoor $PM_{2.5}$ concentrations are transferred indoors. This low infiltration rate suggests that the building's ventilation system or structural features limit outdoor particle penetration, despite external fluctuations.

A moderate positive correlation between indoor and outdoor $PM_{2.5}$ concentrations was found in the VDU student dormitory, and the scatter plot showed a very even distribution along the rising trend. This shows that outdoor pollution has a major but indirect impact on the indoor environment, and that pollutant penetration may be limited by the building's orientation or limited air exchange with the outside. In the VDU dormitory, the slope is slightly higher – at 0,3599, indicating that approximately 36% of outdoors $PM_{2.5}$ enters in the indoor environment.

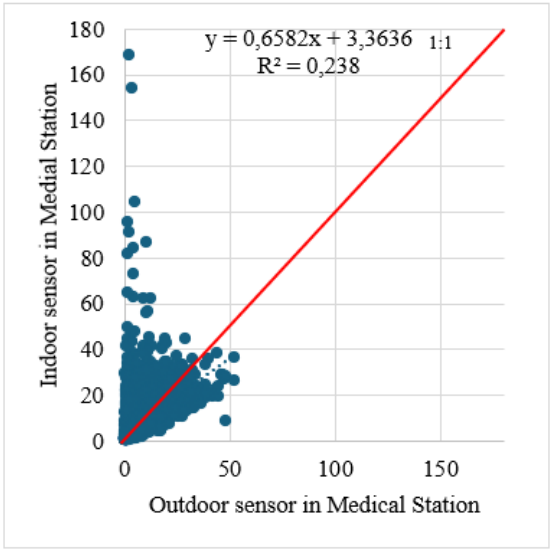


Fig. 12. Scatter plot of indoor and outdoor sensors at the Medical Station

The medical station shows a slope of 0,6582, indicating that approximately 66% of outdoor $PM_{2.5}$ concentrations are reflected indoors – the highest share among the examinated locations. Despite this, the low R^2 value (0,238) suggests substantial data scatter and weak overall fit, meaning the relationship is inconsistent. This pattern likely results from the medical facility's controlled indoor environment, where filtration systems or internal emission dynamics disrupt direct outdoor-indoor linkage, causing variability and reducing predictability despite the relatively steep slope.

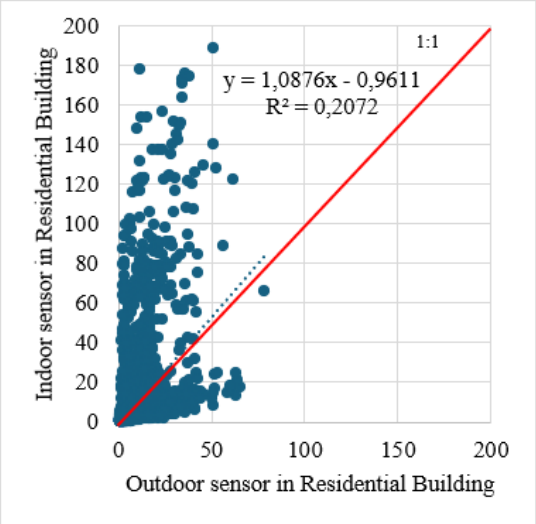


Fig. 13. Scatter plots of indoor and outdoor sensors at the Residential Building

The residential building's data shows a slope of 1,0879, indicating that indoor $PM_{2.5}$ levels can ever surpass outdoor concentrations by approximately 9%. However, the very low R^2 value (0,2072) highlights a weak relationship between outdoor and indoor values. The scatter plot confirms this by displaying a highly dispered pattern, suggesting that indoor air quality ir largely unbound from outdoor conditions. This points not only to effective isolation from external pollution sources but also strongly indicates the presence of indoor $PM_{2.5}$ sources, such as cooking, heating, or human activities, which can drive elevated indoor particulate levls independently of outdoor fluctuations.

Table 6. Correlation of $PM_{2.5}$ concentrations between indoor and outdoor sensors at different measurement sites

	Kaunas College, second building	**Kaunas College, first building**	**Library**	**VDU University residential hostel**	**Residential Building**	**Medical station**
Pearson Correlation	0,656	0,895	0,752	0,836	0,357	0,488
Sig.	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001

3.4. Weekly variation in median particulate matter 2.5 concentration

Particulate matter ($PM_{2.5}$) concentrations at the Medical Station vary between days of the week (Figure 14). Friday had the highest $PM_{2.5}$ concentrations, with a median value approximately 5 µg/m³. The values were also the most widely distributed suggesting a significant daily variations in pollution. Wednesday and Sunday provided the lowest median concentrations, with median values below 4 µg/m³.

Significant inter-daily differences are also displayed by the box-and-whisker plots, particularly when comparing weekdays and weekends. The median. Upper quartile, and maximum values for Friday‘s results are different, which might indicate that transportation or other anthropogenic activities are becoming more intense near the end of the workweek.

On the other hand, $PM_{2.5}$ concentrations tend to decline on weekend days (Saturday as well as Sunday), which is frequently connected to a decrease in industrial or traffic activities. Overall, a notable diurnal change in concentrations is evident from examination of the days of the week, which may be connected to the rhythm of human activity.

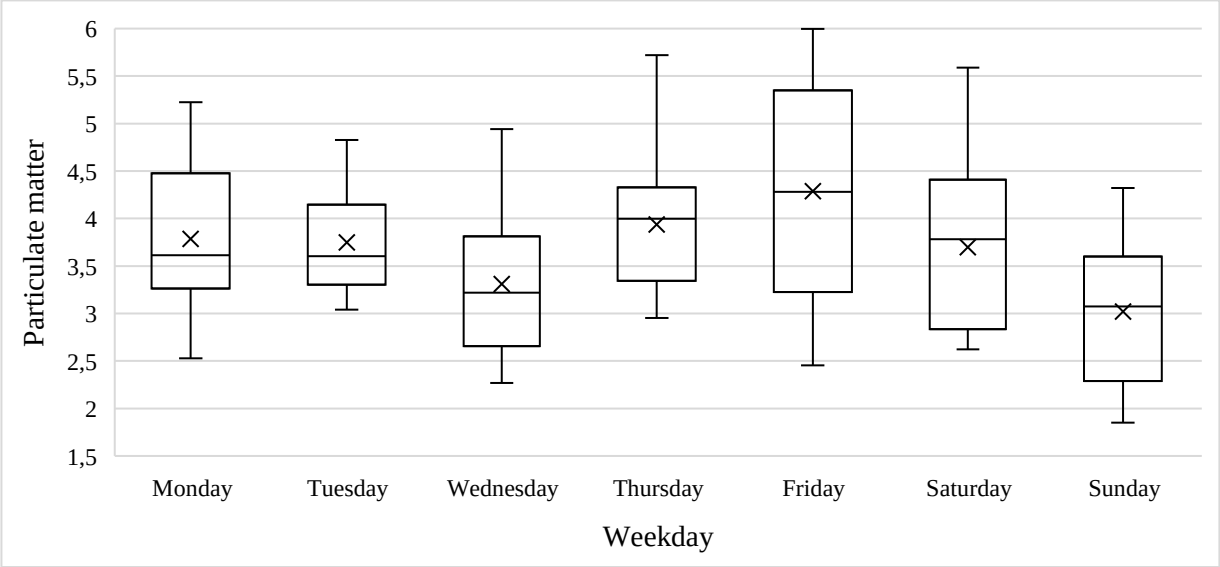


Fig. 14. Particulate matter 2.5 concentrations in Medical Station

There are noticeably higher levels on all days of the week, especially on Fridays and Saturdays, when comparing the daily distributions of $PM_{2.5}$ concentrations at Kaunas College, second building site (figure 15). The greatest value was close to 10 µg/m³, and the highest median concentration was obtained on Friday (about 7 µg/m³), suggesting a notable rise toward the conclusion of the week. This explained by the rise in traffic and the heightened level of human activity prior to the weekend.

The high and widely distributed $PM_{2.5}$ concentrations on Saturday also reflect the variety of sources and potential local influences (e.g., household heating, shopping area nearby, students returning to campus). Although the median results drop significantly on Sunday (to about 5 µg/m³), some extreme levels still point to higher background pollution.

$PM_{2.5}$ levels remain consistent throughout the week (Monday through Thursday), with median values falling between 5 and 6 µg/m³. Weekday pollution levels are more predictable since the value dispersion is lower than on weekends.

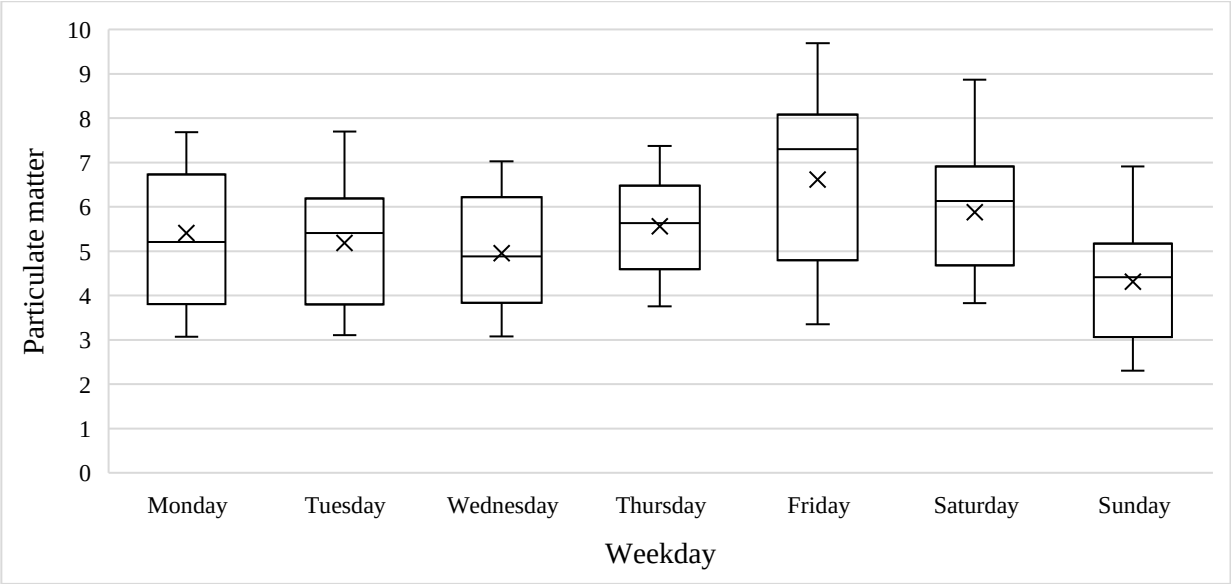


Fig. 15. Particulate matter 2.5 concentrations in Kaunas College, second building

With several exceptions, the third station, which is next to the one previously investigated, likewise exhibits comparable patterns in $PM_{2.5}$ concentrations (figure 16). With a median value above 7 μg/m³, Friday shows the biggest rise. The wide variation in data suggests that pollution varies significantly, which may be due to local sources or peak traffic volumes. Like at the second station, $PM_{2.5}$ concentrations remain somewhat high on weekends, particularly Saturdays, suggesting that the local air quality is not appreciably better on weekends than it is during the week.

It is noteworthy to observe that the data from both of these stations reveal some variations in the microenvironment, even when they are relatively close. On Tuesday and Saturday, the median concentrations at the first Kaunas College building were marginally higher than those at the second building. This could be due to variations in traffic flow distribution, or air circulation. Nonetheless, the data from both locations reflects a broad pattern: Saturdays and the end of the workweek resulted in a decline in air quality, The recurrence of pollution in multiple nearby areas indicates that these are systematic occurrences connected to human activity rather than random fluctuations.

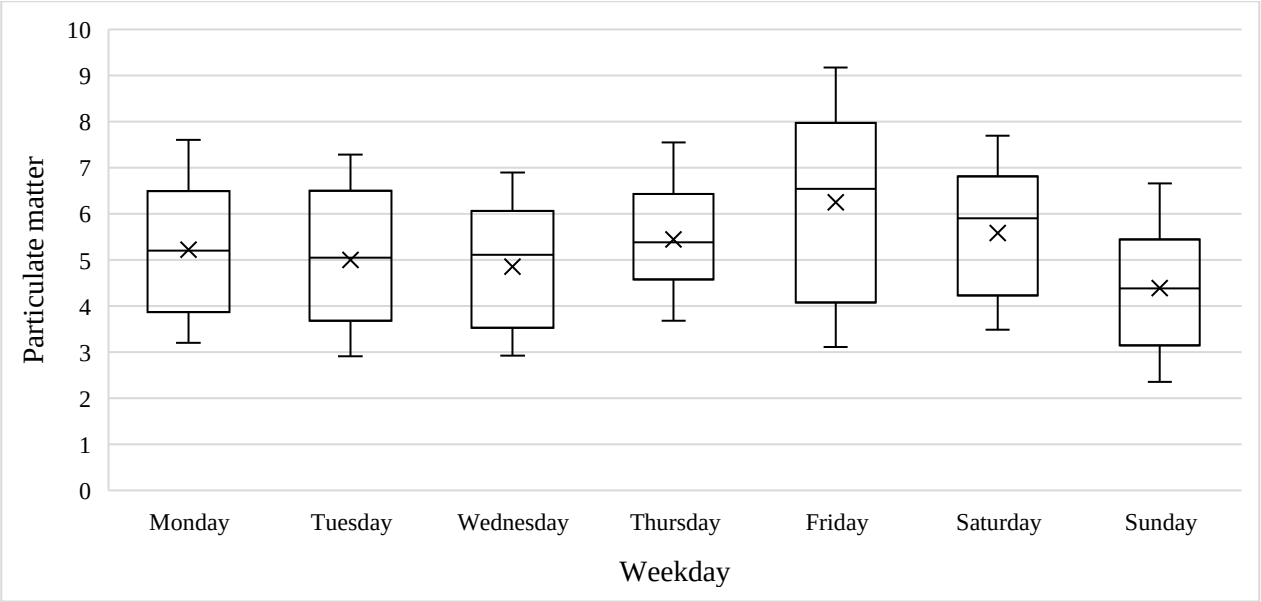


Fig. 16. Particulate matter 2.5 concentrations in Kaunas College, first building

The distribution of $PM_{2.5}$ concentrations at the fourth station, which is Library, exhibits trends that are strikingly comparable (figure 17). With the highest median value (about 7 µg/m³) and a broad interquartile range ranging from approximately 4 to more than 9 µg/m³, Fridays continue to clearly dominate the data. These results indicate that anthropogenic sources had a significant impact at the end of the week. Tuesday and Saturday likewise have rather high pollution levels, with median values exceeding 6 µg/m³. This could possibly have some factor associated with the volume of traffic on Tuesdays and the weekend‘s business or recreational activities.

Alternatively, the lowest concentrations of $PM_{2.5}$ were recorded on Wednesday and Sunday, when both the median and the distribution of values are significantly lower. This supports the idea that the activity of local sources declines on particular days of the week. But like other stations in the area, this one also exhibits a certain baseline background pollution, that could be brought on by ongoing urban activities.

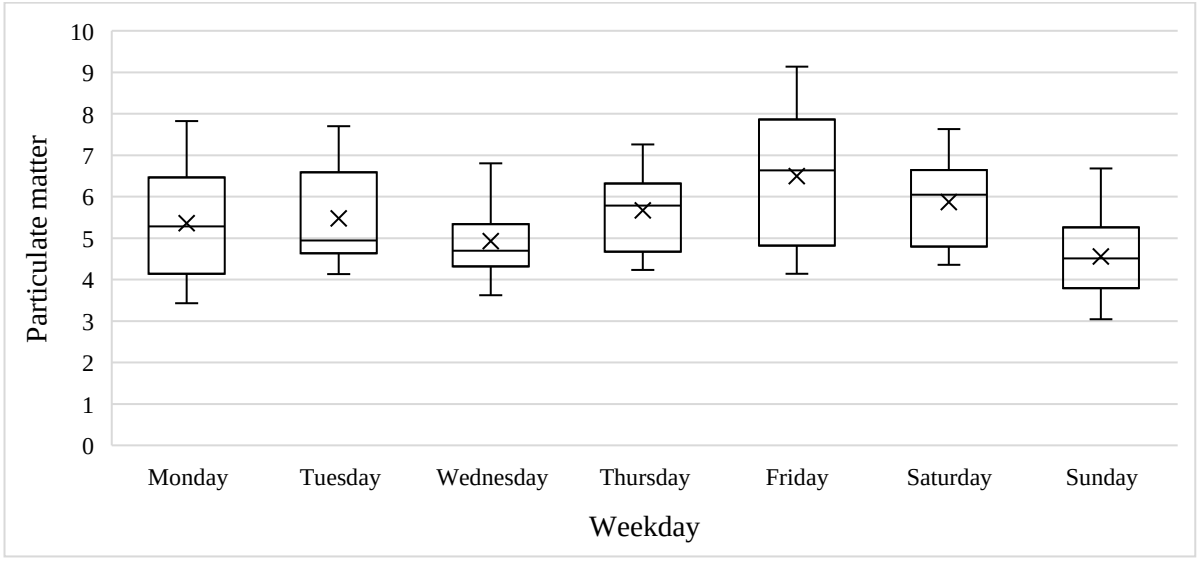


Fig. 17. Particulate matter 2.5 concentrations in Library

The weekly distribution of $PM_{2.5}$ concentrations is displayed in Figure 18. The $PM_{2.5}$ concentrations at the location on the site of the Kaunas Environmental Protection Agency monitoring station are consistently reasonably high throughout the week, according to the box-whisker plot. On Sunday, median reading is approximately 6 µg/m³, but on Friday, they are nearly 9 µg/m³. With a peak value of over 12 µg/m³ on Friday, the maximum interquartile range is also seen, suggesting a potential rise in extreme pollution occurrences as the workweek comes to an end.

Tuesday, Thursday, and Saturday‘s comparatively high values suggest a steady, gradually rising background level of $PM_{2.5}$. The median concentration stays around 6 µg/m³ even on Sunday, which is frequently characterized by less anthropogenic activity. This could be a sign of ongoing exposure to pollution sources or a lack of meteorological changes for dispersion. These finding imply that there is constant high level of pollution in the area of the Kaunas monitoring station, and that the Friday peak might be caused by an increase in traffic or the escalation of other pollution sources at the end of the workweek.

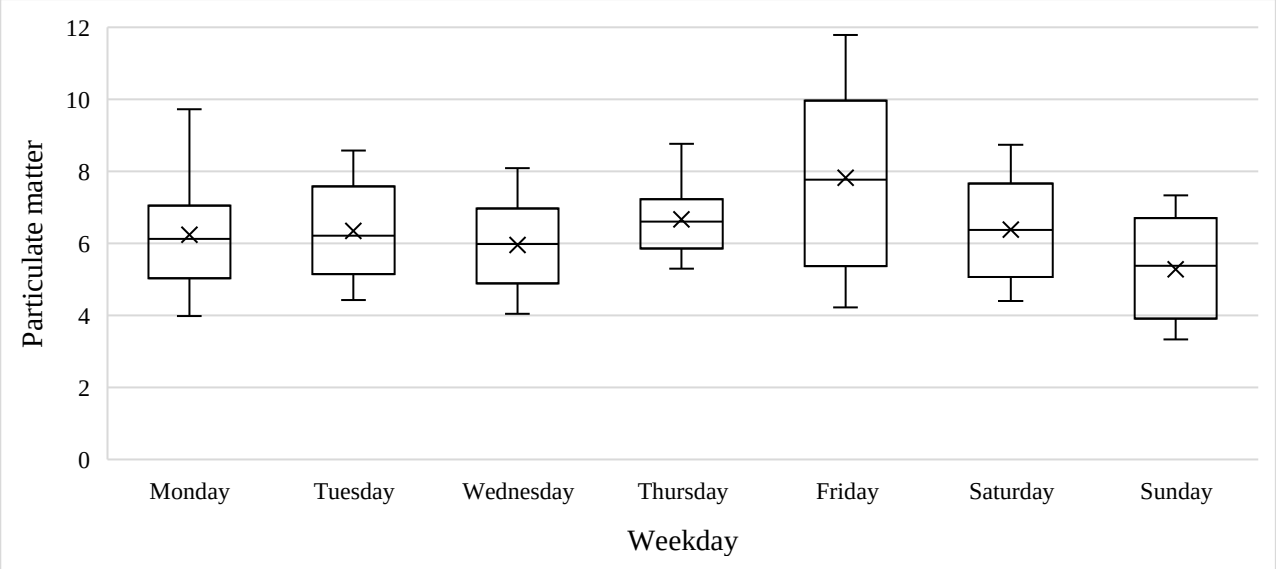


Fig. 18. Particulate matter 2.5 concentrations in Monitoring Station

The weekly distribution of $PM_{2.5}$ concentrations, as determined by data from a sensor places outside a Vytautas Magnus University residential hostel, is displayed in Figure 19. Friday had the highest median $PM_{2.5}$ concentration (about 6,5 µg/m³), with maximum values reaching up to 9 µg/m³, according to an analysis of the box-whisker-plot. The broad dispersion of the data and the wide interquartile range indicate significant variations in pollution, which may be caused by peak traffic and weather circumstances that restrict dispersion.

Concentrations remain high on Tuesday, Thursday, and Saturday, illustrating the impact of transportation on the region. The lowest concentrations are found on Wednesday and Sunday, when human activity generally slows down slightly and transportation flows are projected to decrease. The location can be particularly vulnerable to shifts in the daily and weekly cycles of traffic and the surroundings environment because of its closeness to major thoroughfare.

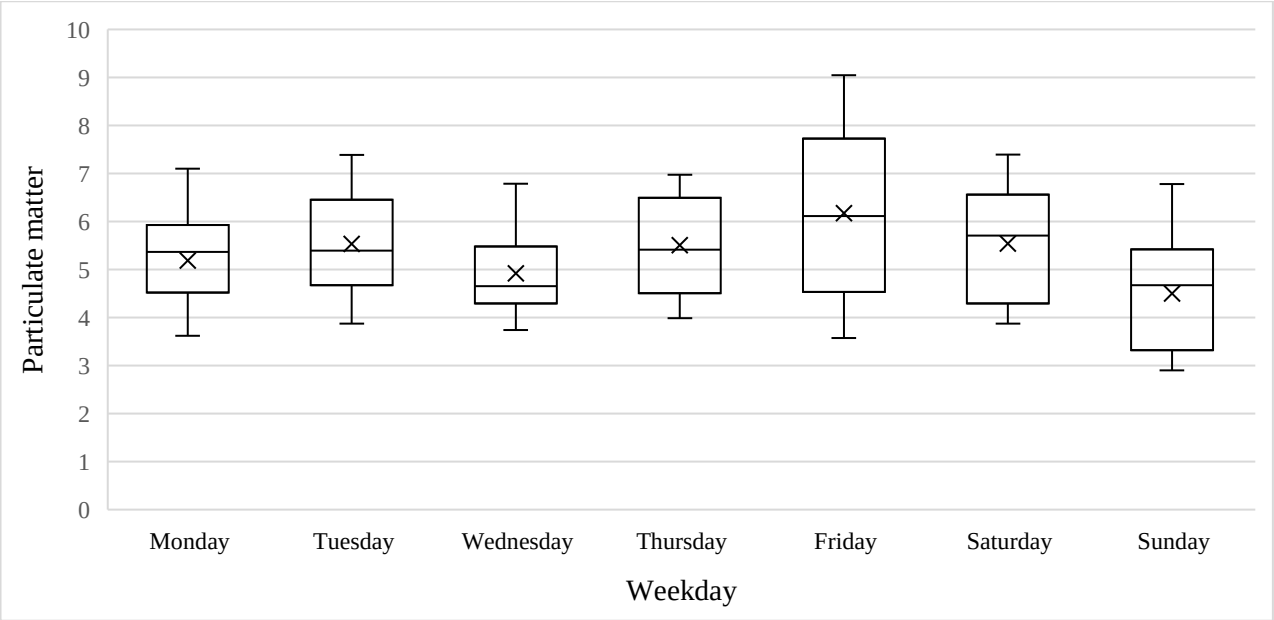


Fig. 19. Particulate matter 2.5 concentrations in VDU University residential hostel

The weekly distribution of $PM_{2.5}$ concentrations from a sensor places in a residential apartment complex encircled by other apartment complexes is displayed in Figure 20. This enclosed urban building might impede airflow and cause pollutants to accumulate up in the area. According to the graph, Friday and Saturday have the greatest median amounts, at the around 7 µg/m³. The Friday data are also characterised by a wide interquartile range and a spread of values up to over 10 µg/m³, indicating possible short-term but intense pollution episodes.

Median concentrations are relatively constant from Monday through Thursday (around 5,5-6 µg/m³), with Sunday demonstrating the lowest values in both the median and lower quartile. This drop may be attributed to a decrease in traffic volume and a slowdown population activity towards the end of the weekend. These finding highlight that even residential areas that are not directly adjacent to major streets or industrial sites may experience increased pollution due to the local urban structure and the conditions limiting air circulation.

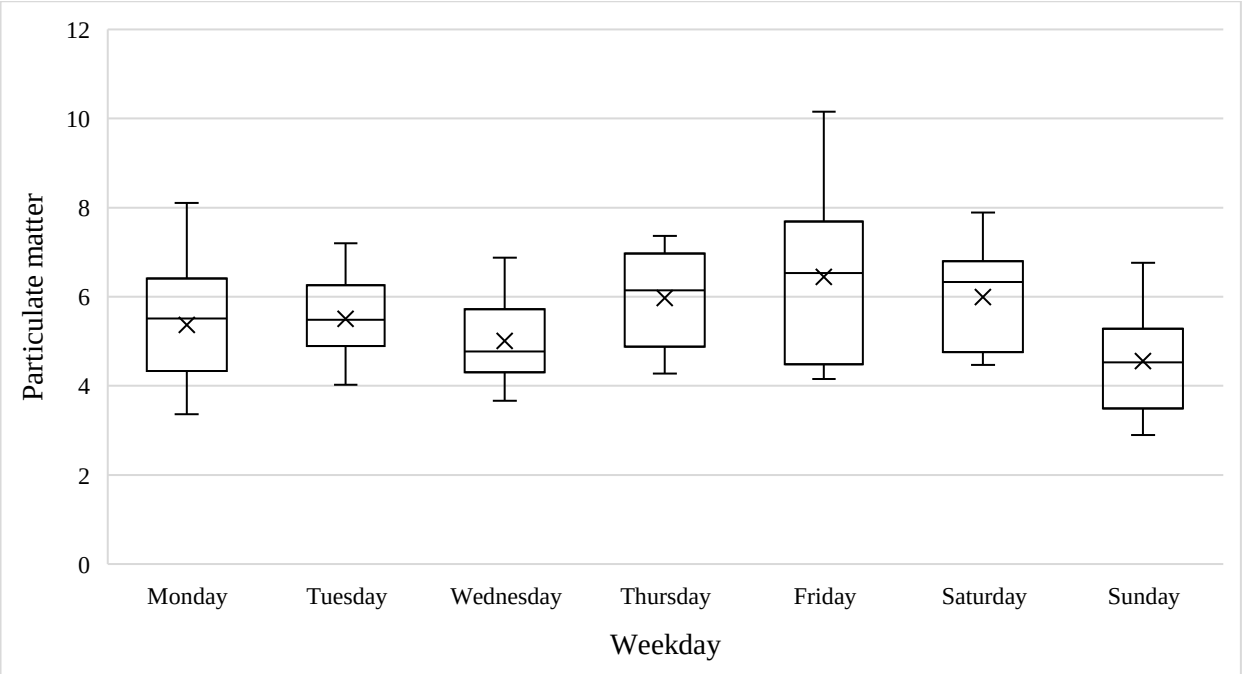


Fig. 20. Particulate matter 2.5 concentrations in Residential Building.

Conclusions

1. The results show a strong positive correlation (r=0,832, p<0,000) between the data from the low-cost sensor installed whithin the Environmental Protection Agency monitoring station and the data from the EPA's station. The slope of the regression análisis (slope = 0,8066) shows that, while the low-cost sensor tends to slightly underestimate absolute particle concentrations, it may properly depict real time pollution patterns by 80%. This demonstrates the sensors appropriateness for supplemental air quality monitoring in urban environments.
2. The análisis of outdoor $PM_{2.5}$ concentrations across all studied locations reveal cosistent strog pocitive correlations. The most strongest correlations were found between Kaunas College's first and second buildings (R^2 = 0,9761, slope 1,1751, ~17% higher at the first building), the second building and the library (R^2 = 0,9571, slope 1,0651, ~6,5% higher at the library), and the second building and the VDU residential hostel (R^2 = 0,9608, slope 0,9946, nearly identical). The second building align strongly with residential building (R^2 = 0,8815, slope 1,002) and the medical statn (R^2 = 0,9161, slope 1,075), demonstrating consistent external pollution exposure. Kaunas College's first building had weaker but still significant connections with the library (R^2 = 0,9607, slope 0,897) and the VDU hostel (R^2 = 0,7514, slope 0,7388), with indicating common but slightly modulated pollution patters. The first building had a strong correlation with the residential building (R^2 = 0,8914, slope 0,8471) and the medical station (R^2 = 0,9589, slope 1,3075, indicating ~31% higher levels at the medical site), as well as a moderate correlation with the monitoring station (R^2 = 0,7927, slope 0,7882, ~79% of monitoring station levels). The VDU hostel alligned strongly with the residential building (R2 0,7843, slope 0,9927) and the library (R^2 = 0,8256, slope 0,7747). The medical station had a moderate to strong correlation with the residential building (R^2 = 0,7526, slope 1,1107) and the monitoring station (R^2 = 0,7784, slope 1,3301). The monitoring station had moderate correlations with the residential building (R^2 = 0,7167, slope 0,7675, slope 1,0711), indicating similar pollution levels but with local variations. In summary, the findings indicate that although the investigated urban locations are predominantly influenced by common regional pollution patterns, local environmental conditions, structural characteristics, and traffic dynamics exert a significant modifying effect on $PM_{2.5}$ concentrations.
3. The analysis of indoor and outdoor $PM_{2.5}$ concentration relationships across six urban locations reveals heterogeneous patterns of pollutant inflitration influenced by buildings characteristics and functual use. Kaunas College's first building and the VDU residential hostel showed moderate infiltration (~12-22%), indicating stronger building isolation or limited ventilation. The medical station showed a relatively high slope (~66%), though with weak correlation, reflecting disrupted outdoor-indoor linkage likely due to filtration systems. Remarkably, the residential building displayed a slope slightly above one (~1,0879), suggesting that indoor $PM_{2.5}$ levels can, on average, exceed outdoor levels by ~9%, pointing to dominant internal sources such as cooking, heating, rather tan outdoor pollution infiltration. Overall, the findings highlight that the influence of outdoor air quality on indoor environments is determined by site-specific factors.
4. Across all invesigated locations, the temporal variation of $PM_{2.5}$ concentrations consistently reveals clear temporal patterns linked to human activity. The highest median and máximum $PM_{2.5}$ concentrations were consistenly observe don Fridays and Saturdays, with peaks nearly 12 $\mu g/m^3$ at the Environmental Protection Agency monitoring site, reflecting intensified traffic and urban

activity at the end of the workweek. In contrast, the lowest median levels, around 6 µg/m³, were generally recorded on Sundays, coinciding with reduced mobility and emissions. These patterns confirm the importance of temporal dynamics in shaping urban air quality and underscore the necessity for implementing targeted, temporally adaptive pollution mitigation strategies to effectively address peak exposure periods.

Recommendations: the study shows that air quality is influenced by regional and local factors, as evidenced by the distribution of $PM_{2.5}$ concentrations, correlations between indoor and outdoor environments and weekly variations. The findings revealed that the outdoor – indoor air quality relationship was strong in some buildings (e.g. Kaunas College, first building or the VDU dormitory), but weaker relationships were observed in others (e.g., medical station or residential building), most likely due to improved airtightness or filtration. It is therefore recommended that more detailed studies of the microenvironment of building would be carried out to assess the effectiveness of airflow, ventilation, and filtration systems, and that these results would be used to implement targeted interventions to protect residents from the effects of environmental pollution.

List of references

1. IDREES, Z. and L. ZHENG. Low cost air pollution monitoring systems: A review of protocols and enabling technologies. *Journal of Industrial Information Integration* [online]. 2020, vol. 17, 100123. ISSN 2452-414X [viewed 2025-05-11]. ISSN 2452-414X. Available from: doi:10.1016/J.JII.2019.100123
2. BARON, R. and J. SAFFELL. Amperometric Gas Sensors as a Low Cost Emerging Technology Platform for Air Quality Monitoring Applications: A Review. *ACS Sensors* [online]. 2017, vol. 2(11), 1553–1566. [viewed 2025-05-11]. ISSN 23793694. Available from: doi:10.1021/acssensors.7b00620
3. CONCAS, F., J. MINERAUD, E. LAGERSPETZ, S. VARJONEN, X. LIU, K. PUOLAMÄKI, P. NURMI, S. TARKOMA. Low-Cost Outdoor Air Quality Monitoring and Sensor Calibration: A Survey and Critical Analysis. *ACM Transactions on Sensor Networks* [online]. 2021, vol. 17, no. 2, article no. 20, pp. 1–44. [viewed 2025-05-12]. Available from: https://doi.org/10.1145/3446005
4. MAAG, B. Air Quality Sensor Calibration and its Peculiarities [online]. 2019, (26082). [viewed 2025-05-12]. Available from: https://doi.org/10.3929/ethz-b-000379520
5. BRODAY, D. M., A. ARPACI, A. BARTONOVA, N. CASTELL-BALAGUER, T. COLE-HUNTER, F. R. DAUGE, B. FISHBAIN, R. L. JONES, K. GALEA, M. JOVASEVIC-STOJANOVIC, D. KOCMAN, T. MARTINEZ-IÑIGUEZ, M. NIEUWENHUIJSEN, J. ROBINSON, V.SVECOVA, P. THAI. Wireless distributed environmental sensor networks for air pollution measurement - the promise and the current reality. *Sensors (Switzerland)* [online]. 2017, vol. 17(10). [viewed 2025-05-12]. ISSN 14248220. Available from: doi:10.3390/s17102263
6. ZHANG, L., F. TIAN, C. KADRI, B. XIAO, H. LI, L. PAN, H. ZHOU. On-line sensor calibration transfer among electronic nose instruments for monitoring volatile organic chemicals in indoor air quality. *Sensors and Actuators B: Chemical* [online]. 2011, vol. 160(1), 899–909. [viewed 2025-05-12]. ISSN 0925-4005. Available from: doi:10.1016/J.SNB.2011.08.079
7. WANG, A., Y. ZHU, L. ZOU, H. ZHU, R.CAO, G. ZHAO. Combination of machine learning and intelligent sensors in real-time quality control of alcoholic beverages. *Food Science and Technology (Brazil)* [online]. 2022, vol. 42. [viewed 2025-05-12]. ISSN 1678457X. Available from: doi:10.1590/fst.54622
8. EDINBURGH SENSORS. Non-Dispersive Infrared Sensing Technology [online]. [viewed 2025-05-12]. Available from: https://edinburghsensors.com/non-dispersive-infrared-sensing-technology/
9. Xiang, Y., L. BAI, R. PIEDRAHITA, R. P DICK, Q. LV, M.HANNIGAN, L. SHANG. Collaborative calibration and sensor placement for mobile sensor networks. *In Proceedings of the 11th International Conference on Information Processing in Sensor Networks* [online]. ACM, 2011, pp. 73–74. [viewed 2025-05-12]. ISBN 9781450305452. Available from: https://doi.org/10.1145/2185677.2185687
10. KANG, Y., L. AYE, T. D. NGO, J. ZHOU. Performance evaluation of low-cost air quality sensors: A review. *Science of The Total Environment* [online]. 2022, vol. 818, 151769. [viewed 2025-05-12]. ISSN 0048-9697. Available from: doi:10.1016/J.SCITOTENV.2021.151769

11. TME.EU**.** *MICS-EK1 - Gas sensor evaluation kit - Amphenol SGX Sensortech* [online]. [viewed 2025-05-12]. Available from: https://www.tme.eu/en/details/mics-ek1/gas-sensors/amphenol-sgx-sensortech/
12. ROBU.IN. *Winsen Electrochemical Carbon Monoxide Sensor – ME3-CO* [online]. [viewed 2025-05-12]. Available from: https://robu.in/product/winsen-electrochemical-carbon-monoxide-sensor-me3-co/
13. WINSEN. *MH-Z16 NDIR CO2 SENSOR* [online]. [viewed 2025-05-12]. Available from: https://cnwinsen.com/MH-Z16-NDIR-CO2-SENSOR.html
14. WINSEN. *Photoionization PID Sensor 4R-PID User's Manual* [online]. [viewed 2025-05-14]. Available from: www.winsen-sensor.com/d/files/4r-pid-manual-v2_0.pdf
15. CLARITY. *Black Carbon Module* [online]. [viewed 2025-05-14]. Available from: https://www.clarity.io/products/black-carbon-module
16. PURPLEAIR. *PurpleAir Zen* [online]. [viewed 2025-05-14]. Available from: https://www2.purpleair.com/products/purpleair-zen
17. WOMASTER. *ES101PM – IoT Environmental, Water, Parking, Waste Bin Sensor* [online]. [viewed 2025-05-14]. Available from: https://www.womaster.eu/products_detail_Smart-City-%EF%BC%86-Industrial-IoT_IoT-Environmental-%7C-Water-%7C-Parking-%7C-Waste-Bin-Sensors_ES101PM.htm
18. KARAGULIAN, F., M. GERBOLES, M. BARBIERE, A. KOTSEV, F. LAGLER, A. BOROWIAK. *Review of sensors for air quality monitoring* [online]. 2019. [viewed 2025-05-14]. ISBN 9789276092551. Available from: doi:10.2760/568261
19. MORAWSKA, L., P. K. THAI, X. LIU, A. ASUMADU-SAKYI, G. AYOKO, A. BARTONOVA, A. BEDINI, F. CHAI, B. CHRISTENSEN, M. DUNBABIN, J. GAO, G. S.W. HAGLER, R. JAYARATNE, P. KUMAR, A. K.H. LAU, P. K.K. LOUIE, M. MAZAHERI, Z. NING, N. MOTTA, B. MULLINS, M. M. RAHMAN, Z. RISTOVSKI, M. SHAFIEI, D. TJONDRONEGORO, D. WESTERDAHL ir R. WILLIAMS. Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone? *Environment International* [online]. 2018, vol. 116, 286–299. [viewed 2025-05-14] ISSN 0160-4120. Available from: doi:10.1016/J.ENVINT.2018.04.018
20. BARON, R. and J. SAFFELL. Amperometric Gas Sensors as a Low Cost Emerging Technology Platform for Air Quality Monitoring Applications: A Review. *ACS Sensors* [online]. 2017, vol. 2(11), 1553–1566. [viewed 2025-05-14]. Available from: doi:10.1021/acssensors.7b00620
21. RÓDENAS GARCÍA, M., S. ANDREA, B. PEDRO T.B.S., B. FRANCESCA, V. GUILLERMO, C. ANDREA, D. G. ALESSIA, M. VICTOR G., G. Á. ELENA, L. SÉRGIO IVAN, B. BENJAMIN, O. CEZARY, K. KOSTAS, M. GONÇALO, S. JOHN ir S. I V AND SOUSA. Review of low-cost sensors for indoor air quality: Features and applications. *Applied Spectroscopy Reviews* [online]. 2022, vol. 57(9–10), 747–779. [viewed 2025-05-14]. ISSN 0570-4928. Available from: doi:10.1080/05704928.2022.2085734
22. TÉKOUABOU, S., J.CHENAL, R. AZMI, E. B. DIOP, H. TOULNI, A. DE PADOUE NSEGBE. Towards air quality particulate-matter monitoring using low-cost sensor data and visual exploration techniques: case study of Kisumu, Kenya. *Procedia Computer Science* [online]. 2022, vol. 215, 963–972. [viewed 2025-05-14]. ISSN 1877-0509. Available from: doi:10.1016/J.PROCS.2022.12.099

23. LV, K., H. ZHENG, L. GE. Digital empowerment to reduce air pollution: The impact of urban network infrastructure construction on PM2.5. *Journal of Asian Economics* [online]. 2025, vol. 98, 101930. [viewed 2025-05-14]. ISSN 1049-0078. Available from: doi:10.1016/J.ASIECO.2025.101930
24. RAKHOLIA, R., Q. LE, K. VU, B. Q. HO, R. S. CARBAJO. Accurate PM2.5 urban air pollution forecasting using multivariate ensemble learning Accounting for evolving target distributions. *Chemosphere* [online]. 2024, vol. 364, 143097. [viewed 2025-05-14]. ISSN 0045-6535. Available from: doi:10.1016/J.CHEMOSPHERE.2024.143097
25. WRIGHT, C. Y., M. BENYON, R. D. DIAB, N. NAIDOO, N. KWATALA, S. KUNENE, C. BATINI, L. K. MICKLESFIELD, S. CAI, R. PANCHAL, S. B. ZONDO, B. LANGUAGE, B. WERNECKE, S. HAZELHURST, F. XAVIER GÓMEZ-OLIVÉ ir J. V. HEY. Assessing the human health risks of indoor PM2.5 exposure in urban and rural households in two provinces of South Africa. *Atmospheric Environment* [online]. 2025, vol. 343, 120996. [viewed 2025-05-14]. ISSN 1352-2310. Available from: doi:10.1016/J.ATMOSENV.2024.120996
26. WORLD HEALTH ORGANIZATION. *Ambient (outdoor) air quality and health* [online]. [viewed 2025-05-14]. Available from: https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health
27. UNITED STATES ENVIRONMENTAL PROTECTION AGENCY. *Health and environmental effects of particulate matter (PM)* [online]. 2025. [viewed 2025-05-14]. Available from: https://www.epa.gov/pm-pollution/health-and-environmental-effects-particulate-matter-pm
28. LIETUVOS APLINKOS APSAUGOS AGENTŪRA. *Rekomendacijos dėl savivaldybių aplinkos monitoringo programų plėtros: kietųjų dalelių $KD_{2,5}$ ir KD_{10} koncentracijos aplinkos ore matavimai ir vertinimas* [online]. 2024. [viewed 2025-05-14]. Available from: https://aaa.lrv.lt/media/viesa/saugykla/2024/1/mjlbPyY_EO4.pdf
29. OMIDVARBORNA, H. and P. KUMAR. Low-cost sensors for air quality monitoring. *Reference Module in Earth Systems and Environmental Sciences* [online]. 2025, 393–414. [viewed 2025-05-14]. Available from: doi:10.1016/B978-0-323-99762-1.00046-2
30. BHATTARAI, H., A.P.K. TAI, M. VAL MARTIN, D. H.Y. YUNG. Responses of fine particulate matter (PM2.5) air quality to future climate, land use, and emission changes: Insights from modeling across shared socioeconomic pathways. *Science of The Total Environment* [online]. 2024, vol. 948, 174611. [viewed 2025-05-14]. ISSN 0048-9697. Available from: doi:10.1016/J.SCITOTENV.2024.174611
31. RAI, A. C., P. KUMAR, F. PILLA, A. N. SKOULOUDIS, S. DI SABATINO, C. RATTI, A. YASAR, D. RICKERBY. End-user perspective of low-cost sensors for outdoor air pollution monitoring. *Science of The Total Environment* [online]. 2017, vol. 607–608, 691–705. [viewed 2025-05-14]. ISSN 0048-9697. Available from: doi:10.1016/J.SCITOTENV.2017.06.266
32. AGBROKO, Samuel O. and J. COVINGTON. A novel, low-cost, portable PID sensor for the detection of volatile organic compounds. *Sensors and Actuators B: Chemical* [online]. 2018, vol. 275, 10–15. [viewed 2025-05-14]. ISSN 0925-4005. Available from: doi:10.1016/J.SNB.2018.07.173
33. DE VITO, S., G. DI FRANCIA, E. ESPOSITO, S. FERLITO, F. FORMISANO, E. MASSERA. Adaptive machine learning strategies for network calibration of IoT smart air quality monitoring devices. *Pattern Recognition Letters* [online]. 2020, vol. 136, 264–271. [viewed 2025-05-15]. ISSN 0167-8655. Available from: doi:10.1016/J.PATREC.2020.04.032

34. GUIDOTTI, R., A. MONREALE, S. RUGGIERI, F. TURINI, F. GIANNOTTI, D. PEDRESCHI. A survey of methods for explaining black box models. *ACM Computing Surveys* [online]. 2018, vol. 51(5). [viewed 2025-05-15]. ISSN 15577341. Available from: doi:10.1145/3236009
35. BORREGO, C., M. COUTINHO, A. M. COSTA, J. GINJA, C. RIBEIRO, A. MONTEIRO, I. RIBEIRO, J. VALENTE, J. H. AMORIM, H. MARTINS, D. LOPES, A. I. MIRANDA. Challenges for a New Air Quality Directive: The role of monitoring and modelling techniques. *Urban Climate* [online]. 2015, vol. 14, 328–341. [viewed 2025-05-15]. ISSN 2212-0955. Available from: doi:10.1016/J.UCLIM.2014.06.007
36. CASTELL, N., F. R. DAUGE, P. SCHNEIDER, M. VOGT, U. LERNER, B. FISHBAIN, D. BRODAY, A. BARTONOVA. Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? *Environment International* [online]. 2017, vol. 99, 293–302. [viewed 2025-05-15]. ISSN 0160-4120. Available from: doi:10.1016/J.ENVINT.2016.12.007
37. YIN, P. Y., A. Y. YEN, S. E. CHAO, R. F. DAY, B. BHANU. A Machine Learning-Based Ensemble Framework for Forecasting PM2.5 Concentrations in Puli, Taiwan. *Applied Sciences (Switzerland)* [online]. 2022, vol. 12(5). [viewed 2025-05-15]. ISSN 20763417. Available from: doi:10.3390/app12052484
38. BURGUÉS, J. and S. MARCO. *Low Power Operation of Temperature-Modulated Metal Oxide Semiconductor Gas Sensors* [online]. 2018. [viewed 2025-05-15]. ISBN 1424-8220. Available from: doi:10.3390/s18020339
39. CORDERO, J. M., R. BORGE, A. NARROS. Using statistical methods to carry out in field calibrations of low cost air quality sensors. *Sensors and Actuators B: Chemical* [online]. 2018, vol. 267, 245–254. [viewed 2025-05-15]. ISSN 0925-4005. Available from: doi:10.1016/J.SNB.2018.04.021
40. BIANCARDI, M., Y. ZHOU, W. KANG, T. XIAO, T. GRUBESIC, J. NELSON, L. LIANG. Exploring spatiotemporal dynamics, seasonality, and time-of-day trends of PM2.5 pollution with a low-cost sensor network: Insights from classic and spatially explicit Markov chains. *Applied Geography* [online]. 2024, vol. 172, 103414. [viewed 2025-05-15]. ISSN 0143-6228. Available from: doi:10.1016/J.APGEOG.2024.103414
41. HEINTZELMAN, A., G. M FILIPPELLI, M. J MORENO-MADRIÑAN, J. S WILSON, L. WANG, G. K DRUSCHEL ir V. O LULLA. *Efficacy of Low-Cost Sensor Networks at Detecting Fine-Scale Variations in Particulate Matter in Urban Environments* [online]. 2023. [viewed 2025-05-20]. ISBN 1660-4601. Available from: doi:10.3390/ijerph20031934