

## Evaluation of Ambient PM<sub>2.5</sub> Levels in The Campus Area Using Information from A Low-Cost Sensor Device

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### Abstract

*This study assesses ambient PM<sub>2.5</sub> concentrations alongside temperature and humidity at two campus sites, UPN and UGM, utilising a Low-Cost Sensor (LCS) IoT-based device. LCS-IoT provides a cost-effective and sustainable solution for air quality monitoring, addressing the shortcomings of costly traditional sensors. Data indicates considerable daily fluctuations in PM<sub>2.5</sub> concentrations; UPN documented morning peaks surpassing 100 µg/m<sup>3</sup> at approximately 08:00 AM, but UGM exhibited lower peaks, remaining below 45 µg/m<sup>3</sup> during the same timeframe. This discrepancy is associated with the positioning of UGM's sensors within the campus's Green Open Space (RTH)/vegetation zone, whereas UPN is situated adjacent to a bustling roadway. This observation highlights the effectiveness of green spaces and vegetation in reducing PM<sub>2.5</sub> pollution. The temperature trend at both analogue locations peaked at 31-33°C during the day. Relative humidity exhibits an inverse correlation with temperature, peaking at 80-90% during the early morning and declining to a low of 59-70% during the day. The research findings underscore the significance of air quality monitoring within the campus environment and the necessity for specific mitigation strategies to safeguard the health of the academic community. Extended research with prolonged measuring periods is recommended for a more thorough comprehension.*

**Keywords:** Air Pollution, Low-Cost Sensor, PM<sub>2.5</sub>, Campus Area.

## 1. INTRODUCTION

Air pollution has emerged as a significant concern that has attracted worldwide attention due to its extensive effects on human health and ecosystems (Santoso et al., 2024a; Tian & Gai, 2023). Among several air contaminants, suspended particles with a diameter under 2.5 micrometres, referred to as Particulate Matter 2.5 (PM<sub>2.5</sub>), are of significant concern (Haghighbayan et al., 2025). PM<sub>2.5</sub>, derived from multiple sources including vehicular emissions, industrial processes, biomass combustion, and natural occurrences, possesses the capacity to infiltrate the respiratory system and enter the circulation, hence presenting considerable health hazards (Manisalidis et al., 2020).

Elevated levels of PM<sub>2.5</sub> in the atmosphere have been consistently associated with heightened morbidity and mortality rates (Anwar et al., 2021; Damor et al., 2021). Both acute and chronic exposure to PM<sub>2.5</sub> can initiate or exacerbate numerous respiratory ailments, including asthma, chronic bronchitis, and chronic obstructive pulmonary disease (Czernański et al., 2024; Jiang et al., 2024). Moreover, PM<sub>2.5</sub> constitutes a significant risk factor for cardiovascular diseases, including stroke and myocardial infarction, and is associated with an elevated risk of lung cancer and developmental abnormalities in children (Giles et al., 2011). Besides its health implications, PM<sub>2.5</sub> also

exacerbates environmental issues, including diminished visibility, acid rain, and climate change, which collectively influence quality of life and ecosystem sustainability (Myhre et al., 2013).

The PM<sub>2.5</sub> predicament in developing nations, especially in Southeast Asia, is frequently more intricate and formidable (Dahari et al., 2021; Lung et al., 2022). Accelerated population expansion, unregulated urbanisation, a rising volume of cars, and heightened industrial activity frequently result in PM<sub>2.5</sub> levels that significantly beyond the safety thresholds established by international health organisations (Santoso et al., 2024b; Wang et al., 2019). Research indicates that numerous cities in Southeast Asia often encounter hazardous PM<sub>2.5</sub> pollution levels, rendering it a critical public health concern (Chi et al., 2022).

The utilisation of low-cost Internet of Things (IoT)-based sensors (LCS) for PM<sub>2.5</sub> measurement is on the rise in developing nations to enhance air quality monitoring and management (Santoso et al., 2025). LCS provides a more cost-effective and adaptable alternative to conventional air quality monitoring stations, which are costly and scarce (Huda et al., 2024). This IoT-based system facilitates extensive deployment and real-time data provision, allowing for detailed air quality monitoring and swift responses to pollution events (Blessy et al., 2023). Nonetheless, assessing the authenticity and trustworthiness of data produced by LCS, particularly in campus settings that frequently possess distinct characteristics, is crucial to guarantee the validity of information utilised in policymaking.

The restricted availability of air quality and meteorological monitoring instruments at the research sites (Luo et al., 2020), specifically the UPN and UGM campuses, has led to insufficient data for many applications. The scarcity of PM<sub>2.5</sub> data in the campus vicinity, resulting from a lack of monitoring efforts, is anticipated to undermine environmental management, particularly concerning air quality.

The deployment of LCS to measure ambient PM<sub>2.5</sub> concentration provides an alternate method for monitoring and regulating air quality at the study site. The research site was selected among the UPN and UGM campus areas, noted for their distinctiveness. The distinctiveness arises from the varying land use features surrounding the university, while the UPN campus is predominantly encircled by residential neighbourhoods and thoroughfares. Concurrently, the IoT-based LCS at UGM campus is situated in areas predominantly characterised by green open spaces or vegetation. These two separate traits will offer valuable information into potential major variances in PM<sub>2.5</sub> concentrations at these locations. Conversely, the campus is significantly susceptible to air pollution due to its elevated population density and the presence of motorised vehicles, including motorbikes and cars. Exposure to air pollution, especially PM<sub>2.5</sub>, poses significant risks to the academic community on campus unless countered with effective mitigation strategies. One mitigating measure is to monitor and regulate the ambient PM<sub>2.5</sub> concentrations in the campus vicinity.

Low-cost IoT-based sensor instruments have the advantage of being cheaper and providing continuous, real-time data. Compared to national standard instruments like HVAS, AQMS, or BAM 1020, the cost is certainly quite high. Therefore, the utilization of this IoT-based LCS becomes an alternative for measuring air quality, particularly PM<sub>2.5</sub> (Prayoga et al., 2025; Santoso et al., 2025). The novelty of this research lies in the fact that there haven't been many studies using IoT-based LCS to monitor and analyze PM<sub>2.5</sub> at the research campus location, making the findings of this study a novel contribution and filling a research gap. The objectives of this study are: 1) To measure the concentration of PM<sub>2.5</sub>, temperature, and ambient humidity at two campus locations,

2) To evaluate the daily variations of these parameters, and 3) To analyze the differences in PM<sub>2.5</sub> conditions between a location near a highway (UPN) and a location with Green Open Space (UGM).

## 2. RESEARCH METHODOLOGY

### 2.1 Study Location

The research sites are two locations: the UPN Veteran Yogyakarta campus and the UGM campus, both situated in Depok District, Sleman Regency, Yogyakarta. Both campuses share same characteristics: they are situated in the suburbs of Yogyakarta, which exhibit relatively high mobility and population density. The substantial concentration of buildings and commercial activity, including trade, significantly contributes to heightened traffic intensity, which is a source of PM<sub>2.5</sub> emissions.

The UPN Campus is situated at UTM coordinates 435107 and 9141780. The UGM Campus is situated at UTM coordinates 431857 and 9141022. The IoT-based LCS is installed on the side of a district road at the UPN campus, but in the UGM campus, it is situated in a predominantly open green space. This may be analogous to the correlation between PM<sub>2.5</sub> characteristics in the UPN area and population density, as well as in UGM inside the green space region. The LCS installation at the two locations was carried out at a height of 2 meters from the ground surface.

### 2.2 Data Used and Measurement Techniques

The data used in this study are PM<sub>2.5</sub>, temperature, and humidity. The measurement technique used was to install an IoT-based LCS at two research locations. Next, for 24 hours, the device will capture data directly thru sensors and send it to the server, making it accessible via Android or laptop. Next, the data already stored on the cloud server is downloaded and analyzed. The measurement duration is 24 hours with data recorded every 30 minutes. This research is still preliminary as an initial step in utilizing an IoT-based LCS to measure PM<sub>2.5</sub>, so the measurement duration data is still limited to only 24 hours. Although the measurement duration is only 24 hours, the sensor is able to capture data every 30 minutes, resulting in a significant amount of recorded data. Thus, these data can be processed proportionally. Furthermore, to obtain more optimal results, future research can be conducted with a longer measurement duration.

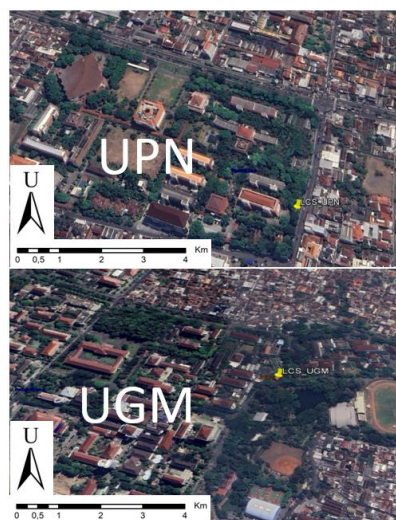


Figure 1. Location of Low-Cost Sensor Installation at UPN and UGM Campuses  
Image source: Google Earth,2025

### 2.3. Validation of IoT-based LCS using AQMS

The data quality from Low-Cost Sensors (LCS) is a crucial issue, so this study cannot ignore the calibration process. Calibration was performed using the Collocation technique, which involves comparing PM2.5 data measured by the LCS and AQMS instruments. The AQMS instrument is owned by the Ministry of Environment and Forestry (KLHK) and is installed at the Environmental Agency (DLH) of Yogyakarta City. Calibration using the collocation technique is done by operating the LCS instrument near the AQMS, and then simultaneously, within the same time frame (ideally 14 days), both instruments will record PM2.5 data. The recording results from both instruments were then analyzed using the parameters shown in Table 1.

Table 1. Criteria for LCS colocation testing

No	Criteria for field performance testing of colocation		Acceptance criteria
1	Presisi	a. Standar Deviation (SD)	$\leq 5 \mu\text{g}/\text{m}^3$
		b. Coefisien Variation (CV)	$\leq 30\%$
2	Bias	a. Slope	$1,0 \pm 0,35$
		b. Intercept	$-5 \leq b \leq 5 \mu\text{g}/\text{m}^3$
3	Linieritas	Coefisien determination ( $r^2$ )	$\geq 0,70$
4	Error	Root Mean Square Error (RMSE)	$\text{RMSE} \leq 7 \mu\text{g}/\text{m}^3$

### 2.4. Design and Construction of a Low-Cost IoT-Based Sensor Device

The working system of the Low-Cost Instrument IoT for air quality monitoring begins with the data collection stage. At this stage, the main sensors, namely the temperature, humidity, and PM2.5 sensors, work in real-time to capture environmental parameters. The next step is data processing. Data from the three sensors is sent to the processing unit to be formatted and combined into a single structured data package. The final step is data visualization and storage. The processed data is displayed to the user thru a visual interface in the form of real-time graphs, allowing users to directly monitor environmental conditions.

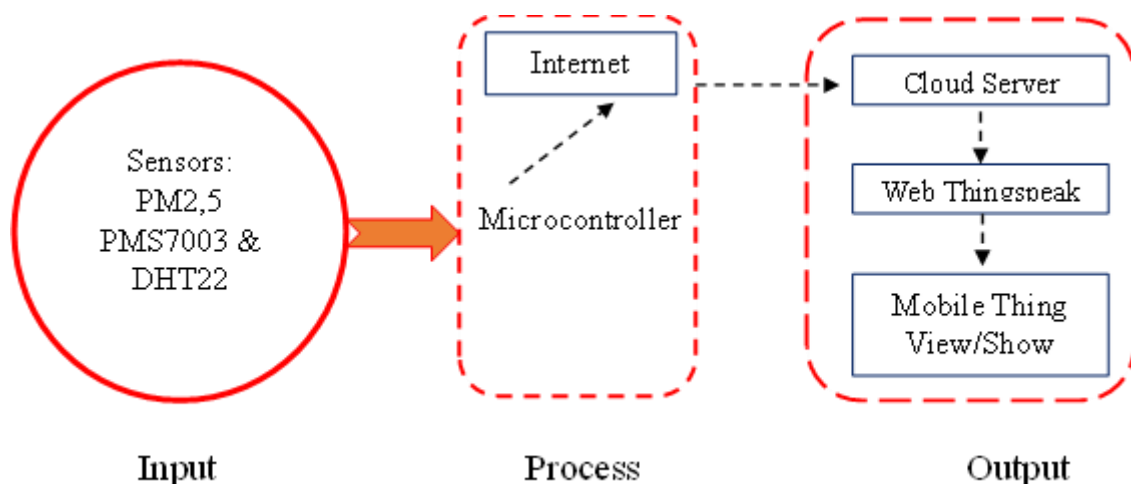


Figure 2. Flowchart of the Low-Cost Instrument IoT System for PM<sub>2</sub> Air Quality Monitoring. 5,  
Temperature and Humidity  
Image source: Santoso et all, 2025

This engineered Low-Cost Sensor (LCS) IoT system is intended to monitor air quality through the utilisation of temperature, humidity, and PM2.5 sensors. Data from each sensor is gathered through the MQTT communication protocol, facilitating real-time

data transmission from IoT devices to the central system. The data flow diagram illustrates that each data type (temperature, humidity, and PM2.5) is sourced from distinct MQTT topics: `airquality/temperature` for temperature, `airquality/humidity` for humidity, and `airquality/PM2.5` for PM2.5 particle concentration.

### 3. RESULT AND DISCUSSION

The problem of air pollution, especially PM2.5, cannot be ignored. The impact and effects on humans and the environment are very significant and are already being felt. On the other hand, all parties must be aware of the need to immediately mitigate the negative impacts of air pollution. One way to mitigate air pollution is by implementing good air quality management, which includes providing measuring instruments, consistent monitoring, annual reports, and appropriate policies. These steps must be taken continuously to achieve the goal of maintaining good air quality.

#### 3.1. Measurement Results for PM2.5, Temperature, and Humidity

Measurements of the research variables, including PM2.5, humidity, and temperature, were taken using a Low-Cost Sensor for 24 hours. The device displayed measurement readings from the sensor every 30 minutes on an LCD screen or web interface.

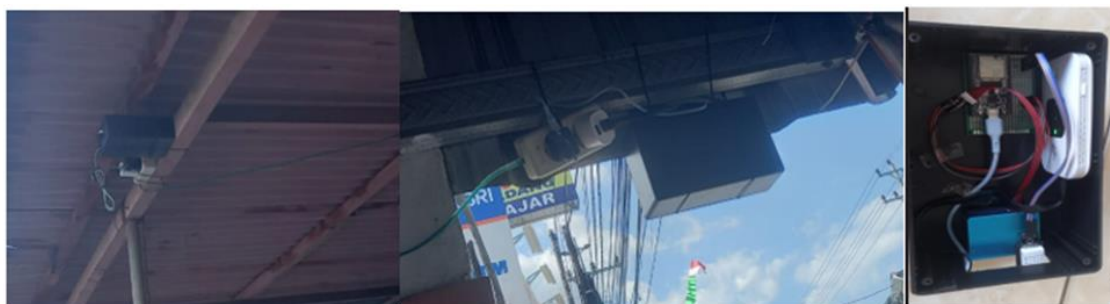


Figure 3. LCS installation at the research site  
Image source: Field documentation, 2024

The summary results of the measurements are presented in Table 2 and Table 3.

Table 2. Descriptive analysis of measurements at UPN

Statistik	PM2.5	Temperature	Humidity
mean	28.41	28.04	73.76
std	16.04	2.41	10.21
min	15.17	24.92	58.23
max	101.00	32.48	87.95

The mean PM2.5 concentration at UPN (28.41  $\mu\text{g}/\text{m}^3$ ) exceeded that at UGM (17.77  $\mu\text{g}/\text{m}^3$ ). This suggests that the air quality at UPN is generally poorer regarding fine particulate matter. PM2.5 variations were more pronounced at UPN, evidenced by a higher standard deviation (16.04  $\mu\text{g}/\text{m}^3$ ) relative to UGM (10.21  $\mu\text{g}/\text{m}^3$ ). The peak PM2.5 concentration observed at UPN (101.00  $\mu\text{g}/\text{m}^3$ ) was markedly greater than that at UGM (44.83  $\mu\text{g}/\text{m}^3$ ), signifying a substantial pollution event at UPN. Simultaneously, the minimum PM2.5 concentration at UPN (15.17  $\mu\text{g}/\text{m}^3$ ) surpassed that at UGM (4.67  $\mu\text{g}/\text{m}^3$ ), suggesting that PM2.5 levels at UGM may have the capacity to decline further (Refer to Table 2 and Table 3).

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Table 3. Descriptive analysis of measurements at UGM

Statistik	PM <sub>2.5</sub>	Temperature	Humidity
mean	17.77	28.49	79.31
std	10.21	2.21	7.96
min	4.67	25.22	67.32
max	44.83	32.95	91.82

The mean temperature of UGM (28.49 °C) is marginally elevated compared to UPN (28.04 °C). This disparity suggests that the temperature at UGM is generally somewhat higher. The standard deviation of temperature at UPN (2.41) exceeds that at UGM (2.21°C), suggesting that daily temperature variations at UPN are marginally more volatile. The temperature range, defined as the difference between the maximum and minimum values, is comparable at both locations, with UPN spanning from 24.92°C to 32.48°C, and UGM from 25.22°C to 32.95°C (refer to Table 1 and Table 2).

The average humidity of UGM (79.31°C) exceeds that of UPN (73.76°C), signifying that UGM typically maintains a higher humidity level. The standard deviation of humidity at UPN (10.21°C) is marginally greater than that at UGM (7.96°C). The peak humidity at UGM (91.82°C) surpasses that at UPN (87.95°C), whilst the minimum at UPN (58.23°C) is inferior to that at UGM (67.32°C). This signifies an expanded humidity range at UPN (Refer to Table 1 and Table 2).

This research indicates that the two places possess markedly distinct environmental attributes. UPN exhibits more severe PM<sub>2.5</sub> air quality challenges, characterised by elevated average and peak concentration values, along with increased variability. Concurrently, UGM typically exhibits reduced PM<sub>2.5</sub> concentrations, somewhat elevated temperatures, and increased humidity. This discovery can provide a foundation for more research into the processes contributing to variations in air quality and microclimate between the two sites. Both locations exhibit a pattern of diurnal changes in PM<sub>2.5</sub> concentration. There are intervals during which both lines exhibit parallel movement, suggesting that specific environmental causes may concurrently influence air quality in both regions. Nonetheless, substantial disparities exist in the intensity and timing of pollution peaks.

The highest PM<sub>2.5</sub> concentration was recorded at UPN at approximately 8:00 AM, exceeding 100  $\mu\text{g}/\text{m}^3$ . This level was markedly elevated compared to the peak linked with UGM at that time, as well as any other peak seen throughout the day at either site. The substantial surge in PM<sub>2.5</sub> at UPN at 08:00 AM can be attributed to its proximity to a heavily trafficked route, particularly during work and school hours. Furthermore, it may also result from the sensor's state, which could be unstable due to readings that significantly deviate from the average. This necessitates some modifications and rectifications (refer to Figure 4).



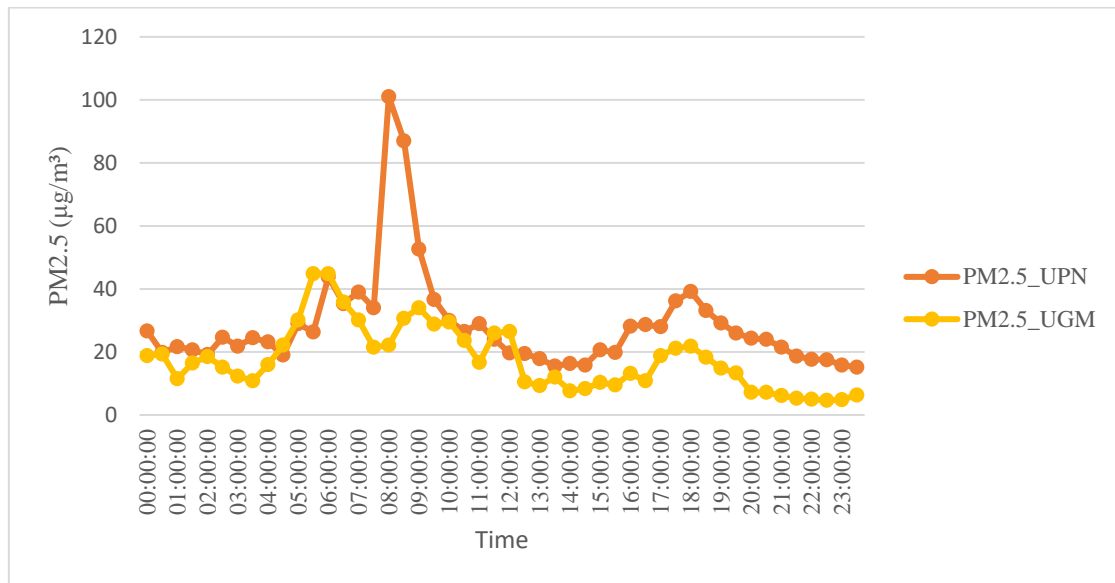


Figure 4. Comparison Graph of Daily PM2.5 at UPN and UGM  
Image source: data analysis, 2025

UGM also showed an increase in PM2.5 in the morning, peaking around 06:00 AM to 07:00 AM, although at a lower concentration (around 40-45  $\mu\text{g}/\text{m}^3$  compared to UPN). After the morning peak, PM2.5 levels at UGM tended to decrease and remain relatively stable throughout the day until the afternoon at a lower level. On the other hand, PM2.5 at UPN showed a more varied pattern with a lower second peak in the afternoon (around 05:00 PM - 06:00 PM), which could also be linked to rush hour and increased traffic. After 8:00 PM, both locations showed a decrease in PM2.5 concentration, reaching their lowest levels toward midnight.

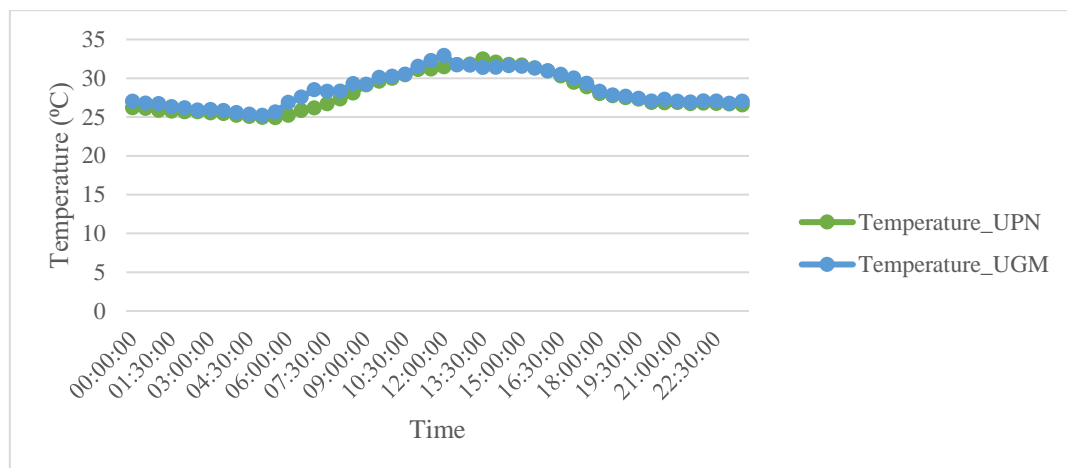


Figure 5. Daily Temperature Comparison Chart at UPN and UGM  
Image source: data analysis, 2025

Figure 5 illustrates the daily temperature variations at two sites, UPN and UGM, across a whole 24-hour cycle, from midnight to late evening. Both locations exhibit remarkably similar, nearly identical temperature patterns, with the Temperature\_UPN (green) and Temperature\_UGM (blue) data lines sometimes overlapping. This pattern commences in the early morning hours (12:00 AM to 05:00 AM), when temperatures range from 26 to 27°C, representing the day's minimum. In the morning, the temperature steadily increased, culminating between 12:00 PM and 02:00 PM at 32–33°C.

Subsequent to the noon zenith, the temperature progressively diminished until dusk, persisting in its decline until nightfall, ultimately reverting to a range of 26–27°C by midnight. The striking resemblance between these two sites indicates that UPN and UGM are affected by the same regional air mass, with external elements like solar radiation and atmospheric conditions impacting both in a nearly identical manner.

No substantial changes in microclimate parameters influencing average temperature were observed between the two locations, hence they can be regarded as typical of one another in terms of temperature. The minor discrepancies noted may result from sensor variations or negligible microclimate differences; however, the data overall suggest a significant degree of local climate consistency between the two locations.

Figure 6 presents a comparative graph of daily relative humidity patterns (in %) between two locations, UPN and UGM, during a 24-hour duration, commencing at midnight and concluding in the late evening. Both locations exhibit comparable humidity patterns; however, Humidity\_UGM (yellow) consistently registers somewhat higher levels than Humidity\_UPN (orange) throughout the day.

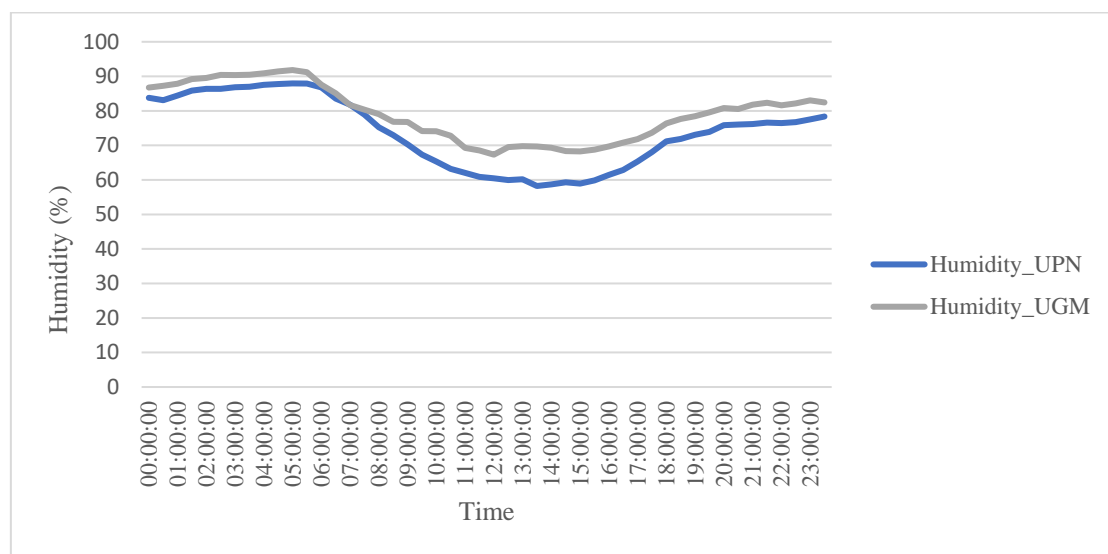


Figure 6. Daily Humidity Comparison Chart at UPN and UGM  
Image source: data analysis, 2025

During the early morning hours (about 12:00 AM to 05:00 AM), both locations exhibit elevated humidity levels, fluctuating between 80% and 90%. This signifies that during these hours, the air is typically saturated with water vapour. Humidity subsequently commenced a slow decline as temperatures increased in the morning. The drop persisted until noon or early afternoon, attaining its nadir between 2:00 PM and 3:00 PM, with humidity levels at 60-70% for UPN and slightly exceeding 70% for UGM. Following its nadir, humidity commenced a slow ascent once more in the afternoon. The rise persisted into the evening, with humidity levels reverting to approximately 80-85% shortly before midnight.

This pattern aligns with the typical daily humidity cycle, wherein humidity is inversely related to temperature: as temperature increases, humidity generally decreases, and vice versa (Sherwood et al., 2010). The persistent little discrepancy between UGM and UPN may suggest microclimatic variables, like increased vegetation, water bodies, or topographical differences that influence water vapour retention at UGM relative to UPN.



### 3.2. Correlation Between PM2.5, Temperature, and Humidity

This initial research has successfully provided interesting findings toward achieving optimal air quality management in the study areas, namely the UPN and UGM campuses. Measurements of PM2.5, air temperature, and humidity were conducted well and provided sufficient information regarding the conditions of these variables at the study locations.

The correlation between PM2.5, temperature, and humidity at the study site provides insight into understanding that air pollution, particularly PM2.5, cannot form on its own. There are surrounding factors that can contribute both positively and negatively to ambient PM2.5 levels. In this study, the magnitude of PM2.5 can be determined by examining the correlation between variables.

The two heatmaps presented show the correlation analysis between Temperature, Humidity, and PM2.5 from two different datasets. In the first heatmap Figure 7. a), there is a moderate negative correlation between Temperature and Humidity (-0.41), indicating that higher temperatures tend to coincide with lower humidity. Temperature also shows a weak negative correlation with PM2.5 (-0.24), while Humidity has a moderate to strong negative correlation with PM2.5 (-0.47). This means that an increase in humidity is associated with a more significant decrease in PM2.5 concentration compared to the influence of temperature.

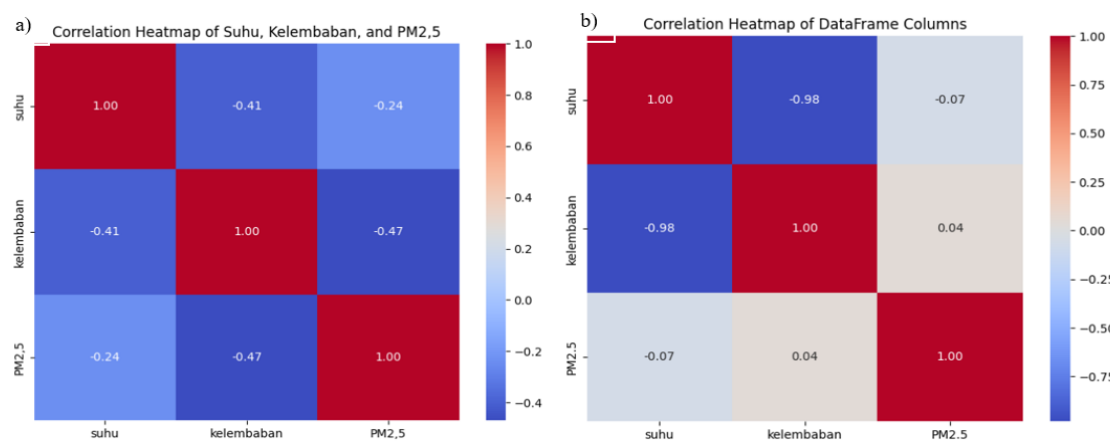


Figure 7. Heatmap correlation between PM2.5, temperature, and humidity a). UGM, b). UPN  
Image source: data analysis, 2025

Conversely, the second heatmap Figure 7.b) shows substantially varying correlation patterns. The correlation between Temperature and Humidity is very strong and negative (-0.98), indicating an almost perfect inverse relationship. Interestingly, the correlation between Temperature and PM2.5 weakens drastically to very negative (-0.07), showing almost no significant linear relationship. Meanwhile, Humidity and PM2.5 exhibit a very weak positive correlation (0.04), a significant change from the negative correlation observed in the first heatmap. The striking difference between these two heatmaps highlights how relationships between variables can vary depending on the dataset, particularly in the context of the interaction between Humidity and PM2.5.

### 3.3. Analysis of PM2.5 Conditions Based on Thresholds

The 24-hour variations in PM2.5 levels (microgrammes per cubic meter, or  $\mu\text{g}/\text{m}^3$ ) from UPN and UGM are shown in Figure 8 relation to the legal limitations. Around 8:00 AM, the PM2.5\_UPN curve reaches a notable peak of over  $100 \mu\text{g}/\text{m}^3$ , which is significantly higher than the restrictions imposed by the "US EPA" (about  $35 \mu\text{g}/\text{m}^3$ ) and

"Government Regulation No. 22 of 2021" (about  $55 \mu\text{g}/\text{m}^3$ ). Since exposure to PM<sub>2.5</sub> above  $100 \mu\text{g}/\text{m}^3$  can cause a variety of respiratory and cardiovascular health issues, particularly in vulnerable populations including children, the elderly, and asthmatics, this suggests extremely poor air quality during those hours. In contrast, PM<sub>2.5</sub>\_UGM exhibits comparatively lower levels, typically within regulatory limits, though it did momentarily peak at  $45 \mu\text{g}/\text{m}^3$  in the morning, still beyond the WHO-recommended threshold of roughly  $15 \mu\text{g}/\text{m}^3$ . Overall, these variations show that the air quality at at least one place (UPN) can reach extremely dangerous levels at specific times, particularly in the morning. If this exposure persists, it could have major health effects on the general public.

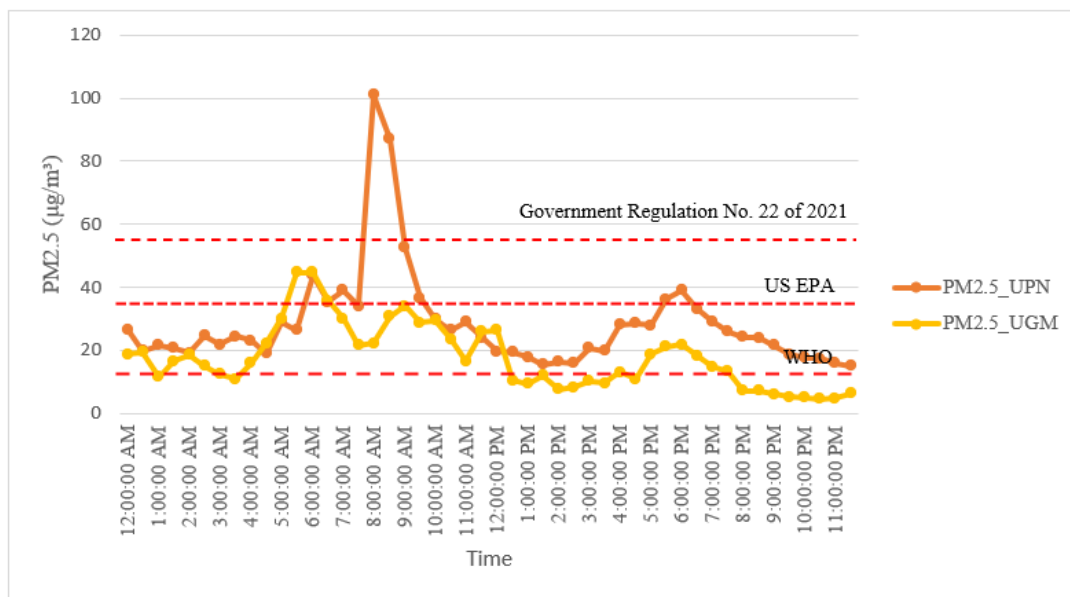


Figure 8. Graph of PM<sub>2.5</sub> conditions based on thresholds at UPN and UGM  
Image source: data analysis, 2025

From this analysis, it can be concluded that UPN experiences more serious PM<sub>2.5</sub> air quality issues, especially during peak morning hours. The peak value at UPN indicates that air quality sometimes borders on unhealthy levels. Although UGM also experiences fluctuations, its PM<sub>2.5</sub> levels tend to be lower and more controlled compared to UPN. This difference can be caused by various factors such as traffic density, the distance between the LCS installation locations and the highway, or even land use dominance. In fact, the LCS installation locations at UPN are more dominated by buildings, indicating population and transportation density. However, the LCS installation at UGM is located in an area largely dominated by green open spaces (RTH) surrounding UGM. This suggests that the presence of RTH can somewhat reduce PM<sub>2.5</sub> concentration, which aligns with this research. Some studies also confirm that the presence of vegetation and plants can reduce air pollution (Buraerah et al., 2023; Janhäll, 2015; Zhai et al., 2022).

In the end, this study has effectively addressed every research goal and offered insight into how LCS functions as a substitute tool that can be utilised to get beyond the limits of PM<sub>2.5</sub>, temperature, and humidity data. The study area's PM<sub>2.5</sub> air quality parameters have also been thoroughly identified. Further research with more LCS, a longer length of one week or several months, and the requirement for regular maintenance and calibration to provide the best measurement results might be suggested based on the study's findings.

#### 4. CONCLUSION

This study provides a comprehensive analysis of the temporal variations in PM2.5 concentration, temperature, and humidity at two campus sites, UPN and UGM, over the course of the day. It employs cost-effective IoT-based sensors that have demonstrated reliable performance in measuring ambient PM2.5 levels, temperature, and humidity at the research locations. Data indicate that PM2.5 levels exhibit notable daily variability, with UPN experiencing more pronounced morning concentration maxima, frequently surpassing 100 µg/m<sup>3</sup> around 8:00 AM. In contrast to UPN, PM2.5 concentrations at UGM exhibited a lower apex, remaining below 45 µg/m<sup>3</sup> approximately concurrently. This discrepancy can be attributed to the sensor installation sites at UGM, which are situated in regions predominantly characterised by Green Open Space (GOS) or campus vegetation, whereas at UPN, the sensors are positioned along a highway that frequently encounters traffic congestion during specific periods. This observation suggests that verdant open spaces and vegetation possess the capacity to serve as pollutant mitigators, especially for PM2.5, within the study area. The temperature patterns at both sites exhibit notable similarities, with minimum temperatures approximately 25-27°C in the early morning and reaching a zenith of 31-33°C during the day, roughly between 12:00 PM and 2:00 PM. Relative humidity also exhibits a distinct daily pattern inversely related to temperature, attaining its peak at approximately 80-90% in the early morning and its lowest levels around 59-60% for UPN and 68-70% for UGM during daytime. Persistent variations in humidity, with UGM generally exhibiting marginally higher levels, may suggest distinct microclimate features. These findings highlight the critical need for ongoing air quality surveillance within the campus environment, considering the potential health implications of contaminant variations, particularly PM2.5, on the academic community. This approach can establish a basis for formulating more precise mitigation strategies aimed at decreasing pollutant exposure during peak hours and in targeted locations, with the objective of fostering a healthier and more sustainable campus environment. To enhance the quality of the research and achieve a more thorough comprehension, it is advisable to undertake additional studies utilising extended measurement periods.

#### ACKNOWLEDGEMENT

The authors wish to convey their profound appreciation to all individuals and institutions that facilitated the effective completion of this research. Gratitude is expressed to LPPM UPN Veteran Yogyakarta for their comprehensive support of our research.

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