Sustinere
Journal of Environment and Sustainability
Volume 10 Number 1 (2026) 20-32

Print ISSN: 2549-1245 Online ISSN: 2549-1253
Website: https://sustinerejes.com E-mail: sustinere.jes@uinsaid.ac.id

RESEARCH PAPER

Traffic-related impacts on air quality around student housing in Malang, Indonesia

Muhammad Evan Wahyudi Putra[1], Ridwan Muhamad Rifai[2*],
Mohammad Palwa Priya Rajendra[2]
[1]*Civil Engineering Study Programme, State University of Malang, Indonesia*
[2]*Environmental Engineering Study Programme, State University of Malang, Indonesia*

Article history:
Received 3 August 2025 | Accepted 17 November 2025 | Available online 30 April 2026

Abstract. Urban air pollution from traffic emissions poses a significant risk to students residing in student communal housing (SCH) near major roadways. This study investigates the impact of peak hour traffic on ambient air quality around SCH in Malang City, focusing on carbon dioxide (CO_2), total volatile organic compounds (TVOC), and fine particulate matter ($PM_{2.5}$). Measurements were taken at 40 SCH locations during both daytime and nighttime peak hours. The study employed Geographic Information Systems (GIS) for spatial modelling to visualise pollutant distribution and used linear regression to develop a distance recommendation model. The results revealed a strong correlation between CO_2 and TVOC concentrations and traffic volume, whereas $PM_{2.5}$ levels were more influenced by atmospheric conditions. The air quality index (AQI) classification indicated a shift toward "moderate" pollution levels during the night, particularly in dense urban areas. Indicative empirical regression modelling suggested setback distances of approximately 280 m for $PM_{2.5}$ and 1,500 m for CO_2. In comparison, an anomalous result of 9,000 m for TVOC highlights significant modelling uncertainty, likely caused by confounding non-traffic sources. Despite its limitations and the need for further validation, this study contributes valuable, policy-relevant insights for urban planning, especially concerning SCH or resident zoning. The findings underscore the necessity of considering both emission intensity and microclimatic factors in residential planning near major roads.

Keywords: Air Quality Index (AQI); Geographic Information Systems (GIS); Student communal housing; Traffic emissions; Urban pollution

1. Introduction

The transportation sector is a primary source of urban air pollution globally, a trend that is also prominent in Indonesia. Worldwide, road transport is responsible for a significant share of atmospheric pollutants. In many cities, it is the primary contributor to nitrogen dioxide (NO_2) and an essential source of particulate matter ($PM_{2.5}$) (Anenberg et al., 2019; World Health Organization, 2021). This global issue is acutely evident in Indonesia, where major cities are experiencing a significant rise in air pollution. Indeed, this sector accounts for 70% of total emissions, more than other industries (Buanawati et al., 2017). Consequently, motor vehicle emissions are a significant source of atmospheric pollutants, including carbon monoxide (CO), NO_2, sulphur dioxide (SO_2), and particulate matter ($PM_{2.5}$ and PM_{10}) (Aziz et al., 2020; Yusrianti,

*Corresponding author. E-mail: ridwan.muhamadrifai.ft@um.ac.id
DOI: https://doi.org/10.22515/r8c8p248

2015). In response to the substantial health and environmental impacts of these pollutants, the Indonesian government has established ambient air quality standards through the Ministry of Health Regulation No. 2/2023 to protect public health (KEMENKES, 2023).

Residential buildings, both private and communal, situated alongside roads are at high risk of pollutant exposure. A recent study revealed that air pollution contributes to over 123,000 deaths annually in Indonesia, ranking it as the country's fifth leading risk factor for mortality (Hidajat et al., 2023). This situation is exacerbated during peak hours, when increased traffic volume leads to higher exhaust emissions in the ambient air (Putra & Sudibyakto, 2013). Therefore, managing air pollution from motor vehicles is a critical concern for urban air quality management, given the substantial contribution of vehicle emissions to urban air pollution (Hidayah et al., 2021).

The intrusion of ambient air pollutants into buildings is highly probable, especially considering that approximately 59.2% of houses have inadequate ventilation, and 88.5% are poorly constructed (Murniati, 2020). Buildings with minimal maintenance are particularly susceptible to the accumulation of harmful pollutants. This is a significant issue, as exposure to these pollutants can lead to severe health problems, including acute respiratory distress syndrome (ARDS) and chronic obstructive pulmonary disease (COPD) (A'yun & Umaroh, 2023; Maharani & Aryanta, 2023). Studies have also demonstrated that buildings located near major roads are vulnerable to the infiltration of traffic-related pollutants, such as CO, NOx, SOx, $PM_{2.5}$, PM_{10}, and VOCs, which may contribute to the development of ARDS among residents (Handika & Driejana, 2013; Yusrianti, 2015).

Student Communal Housing (SCH) poses a higher risk than other housing types. Most SCHs are located along roadsides, and students often prefer accommodations with easy vehicle access (Amilia & Iriyani, 2020; Rahmenda et al., 2017). Physiological and environmental factors magnify this vulnerability, as young adults are more susceptible to air pollution, and housing quality significantly impacts indoor pollutant concentrations (Holden et al., 2023). Student time-activity patterns compound this risk, as studies show they spend a significant portion of their day indoors, where they face prolonged exposure to pollutants that infiltrate from high-traffic outdoor environments (Liu et al., 2022). This preference can lead to a decreased quality of life and an increased public health burden, particularly since 94.5% of students in SCHs reside in densely populated areas with poor air circulation (Sari & Pradana, 2024). Consequently, SCHs are highly vulnerable to the adverse effects of air pollution from motor vehicle activities in urban areas (H. Huang et al., 2020).

Previous research in Indonesian university cities has successfully linked traffic volume to degraded air quality (Nurmaningsih, 2018; Nurmaya et al., 2024). However, a significant research gap remains. These studies have not specifically investigated SCHs as a unique, high-risk residential environment. Furthermore, there is a lack of research modelling pollutant distribution to determine a safe setback distance for residential buildings from major roads, and insufficient data to differentiate exposure levels between daytime and nighttime peak traffic hours. Filling these gaps requires a focused analysis that measures key pollutants and visualises their spatial distribution to inform evidence-based planning recommendations.

This study focuses on three key pollutants: CO_2, total volatile organic compounds (TVOC), and $PM_{2.5}$. These specific pollutants were selected as they are primary components of vehicular emissions and serve as key indicators of traffic air pollution. $PM_{2.5}$ is a critical metric due to its significant adverse health effects (World Health Organization, 2021), while TVOCs are established as direct indicators of fuel combustion and evaporation from traffic (Yang et al., 2022), and CO_2 is effective for tracing the dispersion of vehicle exhaust in urban environments (Y. Huang et al., 2025). The same condition has also been observed in Indonesia. Research in Jakarta has shown that road transportation contributes significantly to the total emissions, accounting for 46% of $PM_{2.5}$, 34% of CO_2 (a greenhouse gas), and 75% of TVOC (Lestari et al., 2020). Although these

pollutants play essential roles in determining health risks and are strongly correlated with traffic activity, relatively few studies have examined them compared to more commonly studied pollutants such as NO_2, SO_2, and CO. Therefore, this study is crucial for evaluating the risks and impacts of vehicle pollution on the ambient air quality of SCHs adjacent to main roads. It aims to do so by examining traffic volume, analysing air distribution patterns, and utilising visualisation modelling to recommend appropriate distances between main roads and SCHs for future construction planning.

To achieve these objectives, a three-pronged methodological approach will be employed: direct measurement of CO_2, TVOC, and $PM_{2.5}$ on the road; calculation of traffic volume and assessment of emissions during day and night peak hours; and visualisation of the AQI distribution between the road and surrounding areas using Geographic Information Systems (GIS) software. Based on this framework, this study proposes the following hypothesis: higher traffic volumes significantly increase the concentrations of CO_2, TVOC, and $PM_{2.5}$ in roadside environments, thereby increasing exposure risks for SCH located closer to main roads than those situated at greater setback distances.

2. Methods

2.1 Sampling location

The sampling and measurements for this study were conducted in Malang City, a prominent centre for higher education in Indonesia. A multi-stage sampling method was employed to select 40 SCH locations. First, several urban villages with high student housing density were purposively selected as the primary sampling areas. Figure 1 illustrates the areas of Sumbersari, Lowokwaru, Dinoyo, and Ketawang Gede. Then, within these selected urban villages, a list of eligible SCHs was compiled based on the key criterion of being located within a 500-meter radius from the nearest main road. From this final list, 40 SCH were chosen using a random number generator to ensure an unbiased sample.

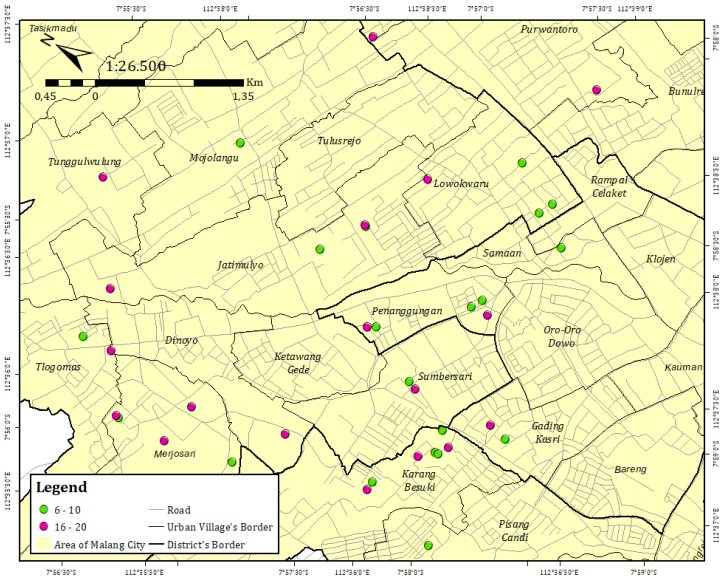


Figure 1. Distribution of sampling points in Malang City used in this study. Note that the colour of the sampling point denotes the sampling time.

2.2 Traffic volume measurement

Traffic volume was measured using MultipleCounter, an iOS-based traffic counting software. A direct observation method was employed at the 40 selected sampling locations, which were divided into two measurement periods: daytime peak hours (06:00 to 10:00) and nighttime peak hours (16:00 to 20:00). Each period was divided into four one-hour sub-sections.

The types of vehicles measured included motorcycles and cars. Previous studies in Southeast Asian and other urban contexts have also identified private cars and motorcycles as the primary contributors to total traffic volume and vehicular emissions, with heavy vehicles playing a secondary role due to their lower frequency of existence (Mustapha et al., 2011; Shafie & Mahmud, 2020). Focusing on motorcycles and cars provides a representative picture of traffic-related exposure for roadside student housing populations, while minimising potential data distortion from infrequent heavy-vehicle counts.

Commented [CPE1]: Replaced by Musthofa (wrong name order)

2.3 Air quality measurement

Ambient air quality was measured during the peak hours described above, with four repetitions for each parameter per sub-section. The measurements focused on the chemical parameters CO_2, TVOC, and $PM_{2.5}$, as listed in the Ministry of Health Regulation No. 2/2023. These measurements were conducted in the ambient area of the SCHs and on their nearest main road within a 500-meter radius, following Indonesian standards (SNI 19-7119.6-2005) and direct reading methods (Kristensson et al., 2004; Oktaviani & Prasasti, 2016).

All parameters were measured using a Bosean TZ01 Air Quality Monitor. According to the manufacturer's specifications, this instrument has a measurement accuracy of ±10% for $PM_{2.5}$, ±50 ppm for CO_2, and ±15% for TVOC. To ensure data reliability, the air quality monitor was calibrated before each daily measurement session following the manufacturer's guidelines, which included stabilising the sensor and performing a zero-point calibration in a clean-air environment away from pollution sources.

2.4 Data analysis

The results of the ambient air parameter measurements from the nearest main road to each SCH were used to calculate the air quality index (AQI) for each pollutant. These data, together with the main road locations, served as a base layer in GIS software to model the AQI distribution as a heatmap. Spatial analysis was performed using the Kernel Density feature to model the distribution of pollutants based on concentrations calculated from point sources (Li et al., 2016). This process generated two AQI distribution heatmaps, corresponding to daytime and nighttime peak hours. The AQI was determined using Equation (1), with the categories defined in thresholds were then converted into AQI levels using formulae derived from empirical real-time measurement data. For $PM_{2.5}$, the US EPA's seven categories were consolidated into four levels, i.e., good, moderate, unhealthy, and hazardous (Saad et al., 2017).

2.5 Simple modelling

The measurement results of ambient air parameters around the main roads and SCHs were tested for each parameter using Pearson correlation with α = 0.05. Significant results were then analysed using a multivariate regression approach, in which β represented the substantial para-

Table 1.

$$CI_p = \left[\left(C_p - BP_{Lo}\right) \times \frac{I_{Hi} - I_{Lo}}{BP_{Hi} - BP_{Lo}}\right] + BP_{Lo} \quad (1)$$

where CI_p is the pollutant index, C_p is the pollutant concentration, BP_{Lo} is the lower threshold concentration of the index category, BP_{Hi} is the upper threshold concentration of the index category, I_{Lo} is the lower threshold index value, and I_{Hi} is the upper threshold index value. Since threshold values for CO_2 and TVOCs are not specified in either the Indonesian regulation (Ministry of Environment and Forestry Regulation No. P.14/2020) or by the United States Environmental Protection Agency (US EPA), reference values were adopted from the Hong Kong Environmental

Protection Department and the Department of Occupational Safety and Health Malaysia. These thresholds were then converted into AQI levels using formulae derived from empirical real-time measurement data. For $PM_{2.5}$, the US EPA's seven categories were consolidated into four levels, i.e., good, moderate, unhealthy, and hazardous (Saad et al., 2017).

2.6 Simple modelling

The measurement results of ambient air parameters around the main roads and SCHs were tested for each parameter using Pearson correlation with $\alpha = 0.05$. Significant results were then analysed using a multivariate regression approach, in which β represented the substantial parameters, and distance was a mandatory parameter. The resulting equation was used as a baseline for empirical regression modelling (Alhindawi et al., 2020). This stage visualises the AQI distribution to inform the planning of safe building distances.

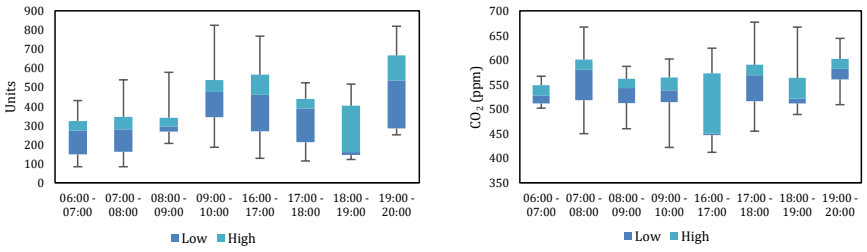
Table 1. Category of area of SCH air quality index (AQI)

AQI	Status	CO_2 (PPM)	TVOC (mg/m³)	$PM_{2.5}$ (µg/m³)
100 – 76	Good	340 – 600	0 – 0.281	0 – 7.14
75 – 51	Moderate	601 – 1000	0.282 – 0.843	7.15 – 53.57
50 – 26	Unhealthy	1000 – 1500	0.844 – 1.389	53.58 – 64.29
25 – 0	Hazardous	1501 - 5000	1.39 – 9.687	64.30 – 214.29

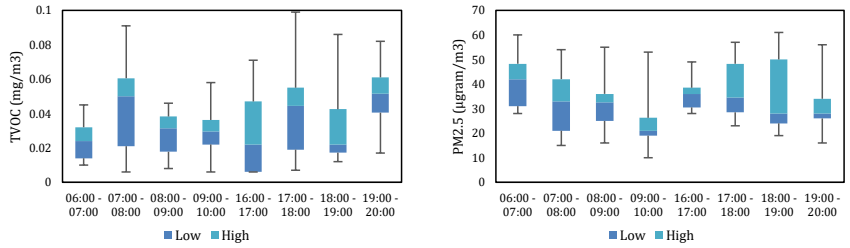
3. Results and discussion

3.1. Road pollution distribution affected by traffic volume

Traffic volume fluctuated throughout the measurement period, with significant peaks observed from 09:00 to 10:00, 16:00 to 17:00, and 19:00 to 20:00. Lower traffic volumes were recorded between 06:00 and 08:00. From 18:00 to 19:00. Interestingly, these peaks do not align with the typical morning rush hours (06:00 to 08:00). Student behaviour may also contribute to this deviation in Malang, where many students start their daily activities later or rely on non-motorised transport such as walking, a pattern similarly observed in other university cities like Solo and Semarang (Nurmaningsih, 2018; Rahmenda et al., 2017). These mobility patterns likely contribute to the observed traffic fluctuations, as indicated by the wide interquartile ranges in Figure 2(a). To statistically assess the relationship between the observed traffic fluctuations and the measured pollutants, a Pearson correlation analysis was conducted. This analysis quantified the linear relationships between total traffic volume and ambient CO2, TVOC, and $PM_{2.5}$ concentrations. The detailed results of this correlation, including the correlation coefficients (r) and significance levels (p-values), are presented in Table 2.



(a) (b)



(c) (d)

Figure 2. Distribution pattern of traffic volume (a), CO_2 concentration (b), TVOC concentration (c), and $PM_{2.5}$ concentration (d), for each peak hour

Table 2. The output of Pearson's correlation between three parameters and traffic volume (the *p*-values are shown in brackets)

	CO_2	TVOC	$PM_{2.5}$	Traffic volume
CO_2	1	0.903 (< 0.001)	0.299 (0.228)	0.205 (0.413)
TVOC	0.903 (< 0.001)	1	0.469 (0.050)	0.245 (0.328)
$PM_{2.5}$	0.299 (0.228)	0.469 (0.050)	1	0.129 (0.610)
Traffic volume	0.205 (0.413)	0.245 (0.328)	0.129 (0.610)	1

CO_2 concentrations remained relatively stable but showed slight elevations between 07:00 and 08:00, 17:00 and 18:00, and 19:00 and 20:00. While the correlation between CO_2 and traffic volume was weak (r = 0.205), the strong correlation between CO_2 and TVOC (r = 0.903) suggests a common emission source, primarily vehicle combustion (Lestari et al., 2020; Putra & Sudibyakto, 2013). This pattern also indicates that CO_2 accumulates over time due to its low reactivity in the ambient environment, especially under stagnant conditions.

TVOC levels exhibited greater variability and were more closely linked to traffic fluctuations, particularly between 07:00–08:00 and 16:00–18:00, as shown in Figure 2(c). This is supported by a moderate correlation with traffic volume (r = 0.245), suggesting that TVOC emissions are influenced by multiple traffic-related sources, such as fuel evaporation and incomplete combustion (H. Huang et al., 2020; Kristensson et al., 2004). The highest TVOC concentrations occurred between 19:00 and 20:00, which could indicate an accumulation from earlier traffic or reduced dispersion due to night-time meteorological conditions.

In contrast, $PM_{2.5}$ concentrations followed a different pattern. As seen in Figure 2(d), concentration levels were higher between 06:00 and 07:00 and from 17:00 to 19:00, with a notable dip from 09:00 to 10:00, despite traffic volume peaking at that time. The weak correlation between $PM_{2.5}$ and traffic volume (r = 0.129) suggests that vehicle emissions do not solely influence its behaviour. Instead, atmospheric factors probably play a critical role in $PM_{2.5}$ distribution and accumulation, often separating its concentration from the daily patterns of local traffic emissions (Kumari & Toshniwal, 2020). This finding is consistent with other studies where daytime $PM_{2.5}$ peaks were affected by low mixing layer height and cooler temperatures, which trap particulates near the ground (Nurmaya et al., 2024). However, it must be noted that this study did not collect meteorological data. Therefore, this explanation remains an inference based on established literature rather than a direct finding.

This study found a complex link between traffic and air pollution. The daily patterns of CO_2 and TVOC rose and fell in line with traffic, suggesting vehicle emissions were the primary source.

However, the result of Pearson's correlation was surprisingly weak. This likely happened because other factors other than real-time traffic were at play. For example, pollutants can become trapped and accumulate in urban "street canyons," obscuring the direct link to traffic volume in statistical analyses (Fu et al., 2017). The chemical stability of these gases also allows them to accumulate under microclimatic conditions, further weakening the statistical association with immediate traffic counts (Saha et al., 2022). The concentration of $PM_{2.5}$ was even more disconnected from traffic patterns. These findings show that while traffic is a key source, its statistical impact can be masked by other factors, highlighting the need to include local weather data in future air quality studies (Vardoulakis et al., 2018).

3.2. AQI proportion level during day and night

The AQI classifications revealed notable differences between day and night. During the day, 80% of AQI readings were categorised as "good" and 20% as "moderate" (Figure 3). At night, the proportion of "good" air quality decreased to 67%, while "moderate" levels rose to 33% (Figure 4). Although this study found that neither period reached "unhealthy" or "hazardous" levels, the shift toward "moderate" at night indicates a worsening trend in air quality.

This night-time deterioration is consistent with increased traffic intensity, as shown in Figure 2, and is supported by elevated concentrations of TVOC and CO_2. The night-time period also corresponds with reduced atmospheric dispersion capacity due to lower wind speeds and the formation of temperature inversions, which trap pollutants near the surface (Aziz et al., 2020; Li et al., 2016).

Furthermore, the increase in "moderate" AQI at night may be influenced by the social and behavioural patterns unique to Malang City. As a city dominated by students, daily activities often extend into the evening, leading to persistent vehicle movement and prolonged pollutant exposure near roadside residences (Nurmaningsih, 2018; Rahmenda et al., 2017). Previous studies in dense urban residential zones have reported similar AQI deterioration during night-time hours (Lestari et al., 2020).

Although the AQI remained within the "good" to "moderate" range, the observed night-time deterioration signals potential health risks, particularly for vulnerable populations like students in poorly ventilated buildings. When combined with factors such as low airflow, minimal filtration, and poor building maintenance, indoor air quality can worsen, increasing the risk of chronic respiratory symptoms (A'yun & Umaroh, 2023; Murniati, 2020). These results emphasise the importance of assessing diurnal variability and average AQI values when developing environmental health policies and guidelines for SCH development.

3.3. AQI distribution area by heatmap

The GIS heatmap visualisations of AQI distribution highlight temporal variations in air quality patterns between day and night. During the day, most of Malang City, particularly areas like Tunggulwulung, Dinoyo, Tulusrejo, and Merjosari, maintained a "good" AQI. These areas, located farther from the city centre and high-traffic corridors, are represented by cooler colour gradients in the heatmap (Figure 5), indicating lower pollutant concentrations. In contrast, areas such as Sumbersari, Karangbesuki, and Samaan showed "moderate" levels, reflecting exposure to traffic emissions.

Interestingly, the increase in night-time AQI did not perfectly correspond with peak traffic volume in the late afternoon (Figure 6). This indicates that the persistence and accumulation of pollutants, especially CO_2 and TVOC, can continue even after traffic has subsided. Pollutants from combustion can linger due to reduced photochemical activity and atmospheric mixing at night (Kristensson et al., 2004).

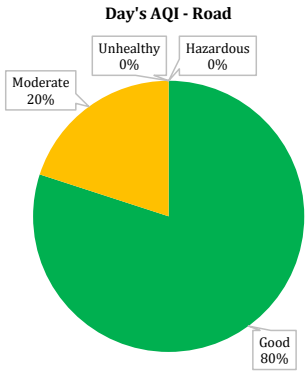


Figure 3. AQI proportion during the day

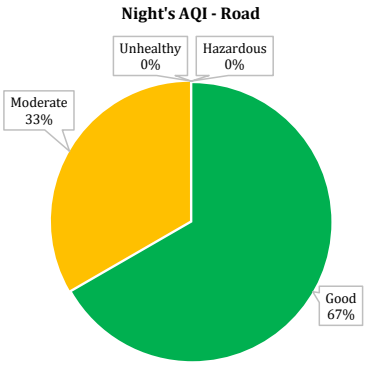


Figure 4. AQI proportion during the night

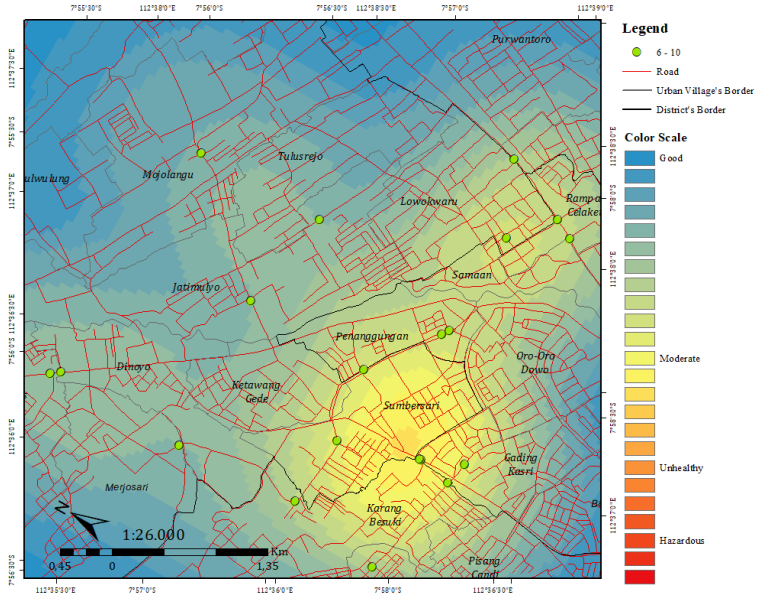


Figure 5. Spatial distribution of AQI amount during the day peak hours

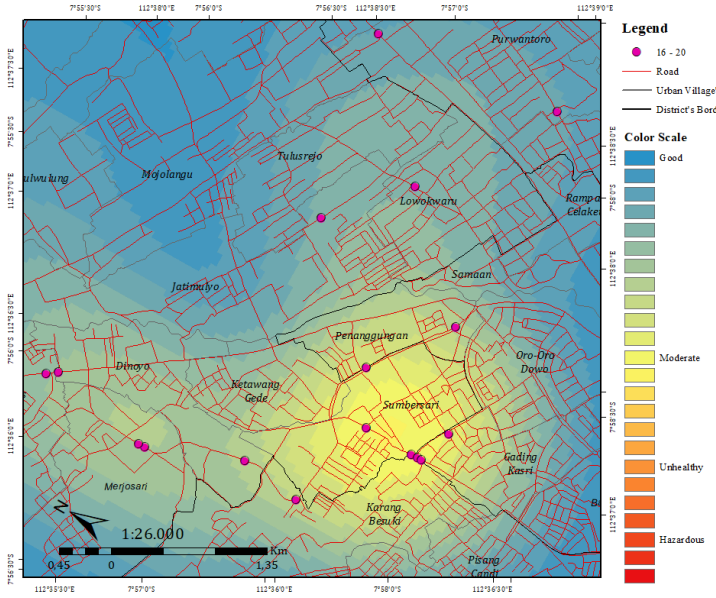


Figure 6. Spatial distribution of AQI amount during night peak hours

The "moderate" AQI levels in central urban zones like Sumbersari and Penanggungan may also be attributed to building density and poor airflow, which aligns with the finding that pollutants accumulate in poorly ventilated housing (Murniati, 2020). The concentration of "moderate" AQI zones at night suggests that pollution tends to persist and intensify in urban cores rather than spreading uniformly, likely due to dense building layouts and limited airflow. This accumulation may also reflect sustained night-time activity around universities and commercial centres (Nurmaningsih, 2018; Rahmenda et al., 2017). Similarly, a study found that TVOCs and CO_2 emissions remained elevated in dense urban residential zones despite deterioration in vehicle counts, emphasising the delayed dispersion effect (Lestari et al., 2020).

The diurnal AQI variation reflects a complex interplay between traffic patterns, urban structure, and atmospheric behaviour. While AQI levels remained "good" to "moderate," the night-time deterioration warrants attention to ventilation standards in SCHs and traffic management near residential areas to minimise the risks of prolonged exposure for the student population.

3.4. Empirical regression modelling for distance recommendation

Pollution distribution modelling using linear regression was employed to estimate recommended safe distances between the main road and SCHs based on CO_2, TVOC, and $PM_{2.5}$ concentrations. The results revealed variations in pollutant behaviour, which align with each pollutant's distinct chemical and physical characteristics (H. Huang et al., 2020; Kristensson et al., 2004).

As shown in Figures 7, 8, and 9, CO_2 required over 1,500 meters to reach the "good" AQI category, reflecting its persistent and less-reactive nature. For $PM_{2.5}$, the required distance was the shortest, at approximately 280 meters. Surprisingly, TVOC exhibited contrasting behaviours. While it is known to dissipate quickly, the model indicated that under high-emission conditions ("hazardous" category), they required up to 9,000 meters for full recovery. This result should be interpreted with caution, as it diverges significantly from general expectations for VOCs, which

are typically associated with short-range exposure (Kristensson et al., 2004). This extreme value should not be interpreted as a realistic safe distance but rather as a strong indicator of both the limitations of the linear regression model and the presence of significant confounding emission sources. A linear model is highly susceptible to outliers, and a single anomalously high data point can drastically skew the regression line. On the other hand, such high readings are common for TVOCs in cities, as they are emitted from numerous non-traffic sources such as commercial solvent use, industrial processes, and consumer products, which create localised hotspots not accounted for in this study's modelling (Yang et al., 2022). Therefore, this finding highlights a critical area for more targeted future research.

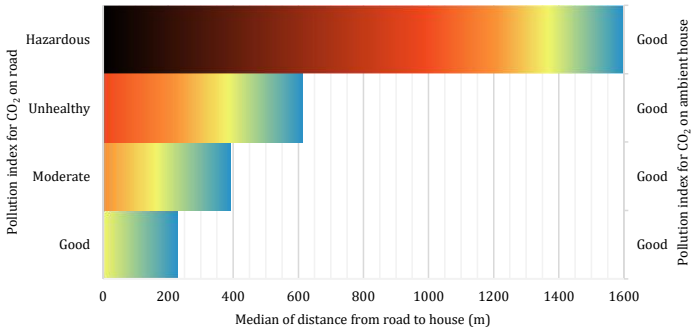


Figure 7. Distance recommendation modelling for CO_2 based on linear regression

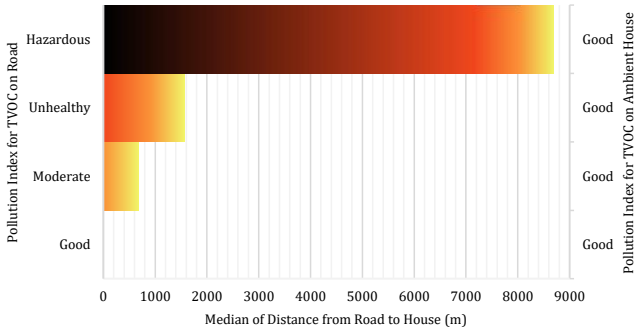


Figure 8. Distance recommendation modelling for TVOC based on linear regression

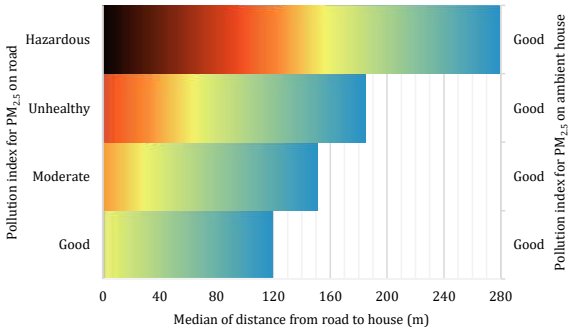


Figure 9. Distance recommendation modelling for $PM_{2.5}$ based on linear regression

The World Health Organization (WHO) provides clear, health-based targets that help put this study's findings into perspective. For $PM_{2.5}$, the WHO's strict guideline recommends that the annual average concentration should not exceed five $\mu g/m^3$(World Health Organization, 2021). Our model's finding that a 280-meter setback is needed to reach safe levels suggests that students in housing closer to the road are likely exposed to pollution levels exceeding this critical global health standard. It is important to note that the WHO does not set similar ambient air quality guidelines for CO_2 or TVOC as a total mixture, because these health risks depend heavily on specific sources and the exact chemicals present. Therefore, even though the $PM_{2.5}$ guideline cannot provide the most direct and consequential benchmark for policy, it underscores the need for health-protective planning for new student housing as a preliminary estimation.

3.5. Limitations and future research

Several limitations should be acknowledged. While Malang City was chosen as a representative urban setting, the data collection was limited to one month, restricting the ability to capture seasonal variations, which are known to affect $PM_{2.5}$ levels (Nurmaya et al., 2024). The one-month timeframe was selected to establish baseline diurnal variations during a stable academic semester, when student residential activity and traffic intensity are relatively consistent. Another limitation is the exclusion of meteorological parameters such as temperature, humidity, and wind speed, which are known to influence pollutant dispersion and concentration (Y. Huang et al., 2025; Kumari & Toshniwal, 2020). The study focused on CO_2, TVOCs, and $PM_{2.5}$ due to their prevalence in vehicle emissions and established health impacts (Lestari et al., 2020; Yusrianti, 2015), but other relevant pollutants like NO_2, SO_2, and NO_3 were omitted. Additionally, the linear regression model assumes uniform distribution and does not account for confounding emission sources or meteorological variations (Alhindawi et al., 2020; Saad et al., 2017), which may affect the accuracy of the distance recommendations.

Nevertheless, this research offers significant practical and scientific value. It provides a clearer understanding of diurnal air quality dynamics in dense student residential areas. It offers visual models that help policymakers and urban planners identify high-risk zones. Future research should incorporate extended observation periods covering multiple seasons to better account for climatic variability. Integrating meteorological parameters such as temperature, humidity, and wind speed would also improve the precision of pollutant distribution models, especially for $PM_{2.5}$. Furthermore, incorporating direct health data from SCH residents could strengthen the linkages among outdoor air pollution, indoor air quality, and health outcomes.

4. Conclusion

This study evaluated the impact of traffic emissions on the air quality around SCH during peak hours in Malang City. By integrating traffic volume data, ambient pollutant measurements (CO_2, TVOCs, and $PM_{2.5}$), and GIS modelling, the research identified significant temporal and spatial variations in air quality, particularly between day and night.

A key finding is that CO_2 and TVOC levels are closely connected to traffic volume in the visualisation but not in Pearson's correlation, while $PM_{2.5}$ is disconnected from both. This result indicated that meteorological factors and others probably influenced these relationships. Although most AQI values remained within the "good" and "moderate" categories, a noticeable decline was observed at night, indicating a higher risk of pollutant buildup and exposure, particularly in poorly ventilated buildings. The heatmap models confirmed that central urban areas like Sumbersari maintain persistent "moderate" AQI levels due to dense infrastructure and high nocturnal activity. Furthermore, linear regression modelling indicated safe distances of around 280 metres for $PM_{2.5}$, 1,500 metres for CO_2, and 9,000 metres for TVOCs from "hazardous" main roads. These figures must be interpreted not as policy-ready values, but as preliminary estimates from an empirical regression model that require significant further validation.

While the study has limitations, including a short data-collection period and the exclusion of some prominent pollutants such as NO_2 and SO_2, it provides valuable insights for urban planners and public health stakeholders. Recommendations include enhancing building ventilation, establishing minimum safe distances for new developments near main roads, and incorporating night-time air quality trends into policy frameworks. Future research should extend the observation period and include meteorological and health data to develop a more comprehensive understanding of the long-term impacts of roadside pollution on urban student populations.

Acknowledgment

Universitas Negeri Malang funded this research through the Non-APBN Research Grant No. 21.2.51/UN32/KP/2025.

References

Alhindawi, R., Nahleh, Y. A., Kumar, A., & Shiwakoti, N. (2020). Projection of greenhouse gas emissions for the road transport sector based on multivariate regression and the double exponential smoothing model. *Sustainability (Switzerland)*, *12*(21), 9152. https://doi.org/10.3390/su12219152

Amilia, S., & Iriyani (2020). Pengaruh lokasi, harga dan fasilitas terhadap keputusan sewa kamar kost mahasiswa Fakultas Ekonomi Universitas Samudra. *Jurnal Manajemen dan Keuangan*, *8*(3), 267–280. https://doi.org/10.33059/jmk.v8i3.2328

Anenberg, S., Miller, J., Henze, D., & Minjares, R. (2019). *A global snapshot of the air pollution-related health impacts of transportation sector emissions in 2010 and 2015*. www.theicct.org

A'yun, I. Q., & Umaroh, R. (2023). Polusi udara dalam ruangan dan kondisi kesehatan: Analisis rumah tangga Indonesia. *Jurnal Ekonomi dan Pembangunan Indonesia*, *23*(1), 16–26. https://doi.org/10.21002/jepi.2022.02

Aziz, M. F., Abdurrachman, A., Chandra, I., Majid, L. I., Vaicdan, F., & Salam, R. A. (2020). Pemantauan konsentrasi gas (CO_2, NO_2) dan partikulat ($PM_{2.5}$) pada struktur horizontal di kawasan Dayeuhkolot, cekungan udara Bandung Raya. *Jurnal Sains Dirgantara*, *18*(1), 1–12. https://doi.org/10.13140/RG.2.2.11223.42407

Buanawati, T. T., Huboyo, H. S., & Samadikun, B. P. (2017). Estimasi Emisi Pencemar Udara Konvensional (Sox, Nox, Co, dan Pm) Kendaraan Pribadi Berdasarkan Metode International Vehicle Emission (Ive) di Beberapa Ruas Jalan Kota Semarang. *Jurnal Teknik Lingkungan*, *6*(3), 1–12.

Fu, X., Liu, J., Ban-Weiss, G. A., Zhang, J., Huang, X., Ouyang, B., Popoola, O., & Tao, S. (2017). Effects of canyon geometry on the distribution of traffic-related air pollution in a large urban area: Implications of a multi-canyon air pollution dispersion model. *Atmospheric Environment*, *165*, 111–121. https://doi.org/10.1016/j.atmosenv.2017.06.031

Handika, R., & Driejana, D. (2013). Polusi udara dalam rumah sekitar jalan raya: Intrusi NO_2 dari transportasi dan gangguan pernapasan pada penghuni rumah. *Dampak*, *10*(2), 119. https://doi.org/10.25077/dampak.10.2.119-132.2013

Hidajat, D., Febry Gilang Tilana, & I Gusti Bagus Surya Ari Kusuma. (2023). Dampak polusi udara terhadap kesehatan kulit. *Jurnal Kedokteran Unram*, *12*(4), 371-378. https://doi.org/10.29303/jk.v12i4.4565

Hidayah, E. N., Rosyid, M. A. A., & Pulansari, F. (2021). Pengaruh jenis kendaraan bermotor terhadap peningkatan konsentrasi nitrogen dioksida (NO_2) di sekitar Bundaran Dolog. *Jurnal Envirotek*, *13*(1), 73–77. https://doi.org/10.33005/envirotek.v13i1.107

Holden, K. A., Lee, A. R., Hawcutt, D. B., & Sinha, I. P. (2023). The impact of poor housing and indoor air quality on respiratory health in children. *Breathe*, *19*(2), 230058. https://doi.org/10.1183/20734735.0058-2023

Huang, H., Hu, H., Zhang, J., & Liu, X. (2020). Characteristics of volatile organic compounds from vehicle emissions through on–road test in Wuhan, China. *Environmental Research*, *188*, 109802. https://doi.org/10.1016/J.ENVRES.2020.109802

Huang, Y., Wang, H. B., Mak, H. M. W., Chu, M., Ning, Z., Organ, B., Chan, E. F. C., Liu, C.-H., Mok, W.-C., Gromke, C., Shon, H. K., Lei, C., & Zhou, J. L. (2025). Suitability of using carbon dioxide as a tracer gas for studying vehicle emission dispersion in a real street canyon. *Journal of Environmental Sciences*, *155*, 832–845. https://doi.org/10.1016/j.jes.2024.06.036

KEMENKES (2023). *Peraturan Menteri Kesehatan Nomor 2 Tahun 2023 tentang Peraturan Pelaksanaan Peraturan Pemerintah Nomor 66 Tahun 2014 tentang Kesehatan Lingkungan*. https://peraturan.bpk.go.id/Details/245563/permenkes-no-2-tahun-2023

Kristensson, A., Johansson, C., Westerholm, R., Swietlicki, E., Gidhagen, L., Wideqvist, U., & Vesely, V. (2004). Real-world traffic emission factors of gases and particles measured in a road tunnel in Stockholm, Sweden. *Atmospheric Environment*, *38*(5), 657–673. https://doi.org/10.1016/J.ATMOSENV.2003.10.030

Kumari, P., & Toshniwal, D. (2020). Impact of lockdown on air quality over major cities across the globe during COVID-19 pandemic. *Urban Climate*, *34*, 100719. https://doi.org/10.1016/j.uclim.2020.100719

Lestari, P., Damayanti, S., & Arrohman, M. K. (2020). Emission inventory of pollutants (CO, SO_2, $PM_{2.5}$, and NOx) in Jakarta Indonesia. *IOP Conference Series: Earth and Environmental Science*, *489*(1), 012014. https://doi.org/10.1088/1755-1315/489/1/012014

Li, H., Fan, H., & Mao, F. (2016). A visualization approach to air pollution data exploration-A case study of air quality index (PM2.5) in Beijing, China. *Atmosphere*, *7*(3). https://doi.org/10.3390/atmos7030035

Liu, Z., Li, Y., & Zhao, L. (2022). Monitoring and analysis of indoor air quality in graduate dormitories in Northern China. *Atmosphere*, *13*(12), 1941. https://doi.org/10.3390/atmos13121941

Maharani, S., & Aryanta, W. R. (2023). Dampak buruk polusi udara bagi kesehatan dan cara meminimalkan risikonya. *Jurnal Ecocentrism*, *3*(2), 47–58. https://doi.org/10.36733/jeco.v3i2.7035

Murniati, N. (2020). Sick building syndrome in Indonesia and Singapore: A comparative study. *Proceedings of the 3rd International Conference on Vocational Higher Education (ICVHE 2018)*. https://doi.org/10.2991/assehr.k.200331.153

Mustapha, B.A., Blangiardo, M., Briggs, D. J., & Hansell, A.L. (2011). Traffic air pollution and other risk factors for respiratory illness in schoolchildren in the Niger-Delta Region of Nigeria. *Environmental Health Perspectives*, *119*(10), 1478–1482. https://doi.org/10.1289/ehp.1003099

Nurmaningsih, D. R. (2018). Analisis kualitas udara ambien akibat lalu lintas kendaraan bermotor di kawasan Coyudan, Surakarta. *Al-Rad: Jurnal Teknik Lingkungan*, *3*(2), 46–53. https://doi.org/10.29080/alard.v3i2.336

Nurmaya, E. M., Murti, S. H., & Nurjani, E. (2024). Kajian pencemaran lingkungan terhadap kesehatan masyarakat akibat gas buangan CO kendaraan bermotor di kawasan Universitas Gadjah Mada. *Jurnal Paradigma*, *5*(1), 16-38. https://doi.org/10.22146/jpmmpi.v5i1.91392

Oktaviani, D., & Prasasti, corie indria. (2016). The physical and chemical air uality, worker's characteristics, and respiratory symptoms among printing workers in Surabaya. *Jurnal Kesehatan Lingkungan*, *8*, 195. https://doi.org/10.20473/jkl.v8i2.2016.195-205

Putra, E. B. D., & Sudibyakto, H. A. (2013). Pengaruh kepadatan kendaraan bermotor terhadap konsentrasi karbon monoksida ambien (Studi kasus Jalan Taman Siswa Yogyakarta). *Jurnal Bumi Indonesia*, *2*(4).

Rahmenda, A., Awaluddin, M., & Laila Nugraha, A. (2017). Pembuatan aplikasi sebaran lokasi kos berbasis WebGIS menggunakan Google Map API (Studi kasus: Area kampus Universitas Diponegoro). *Jurnal Geodesi Undip Januari, 6*(1), 12-20, https://doi.org/10.14710/jgundip.2017.15022

Saad, S. M., Shakaff, A. Y. M., Saad, A. R. M., Yusof, A. M., Andrew, A. M., Zakaria, A., & Adom, A. H. (2017). Development of indoor environmental index: Air quality index and thermal comfort index. *AIP Conference Proceedings*, *1808*(1), 020043. https://doi.org/10.1063/1.4975276

Saha, L., Kumar, A., Kumar, S., Korstad, J., Srivastava, S., & Bauddh, K. (2022). The impact of the COVID-19 lockdown on global air quality: A review. *Environmental Sustainability*, *5*(1), 5–23. https://doi.org/10.1007/s42398-021-00213-6

Sari, K. A. L. H., & Pradana, A. H. (2024). Kajian kondisi Pemukiman Joyo Raharjo RW 02 Malang. *Pawon: Jurnal Arsitektur*, *8*(1), 53–66. https://doi.org/10.36040/pawon.v8i1.9169

Shafie, S. H., & Mahmud, M. (2020). Urban air pollutant from motor vehicle emissions in Kuala Lumpur, Malaysia. *Aerosol and Air Quality Research*, *20*(12), 2793–2804. https://doi.org/10.4209/aaqr.2020.02.0074

Vardoulakis, S., Kettle, R., Cosford, P., Lincoln, P., Holgate, S., Grigg, J., Kelly, F., & Pencheon, D. (2018). Local action on outdoor air pollution to improve public health. *International Journal of Public Health*, *63*(5), 557–565. https://doi.org/10.1007/s00038-018-1104-8

World Health Organization (2021). *WHO global air quality guidelines: Particulate matter ($PM_{2.5}$ and PM_{10}), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide.* https://www.who.int/publications/i/item/9789240034228

Yang, Y., Liu, B., Hua, J., Yang, T., Dai, Q., Wu, J., Feng, Y., & Hopke, P. K. (2022). Global review of source apportionment of volatile organic compounds based on highly time-resolved data from 2015 to 2021. *Environment International*, *165*, 107330. https://doi.org/10.1016/j.envint.2022.107330

Yusrianti. (2015). Studi literatur tentang pencemaran udara akibat aktivitas kendaraan bermotor di Jalan Kota Surabaya. *Al-Ard: Jurnal Teknik Lingkungan*, *1*(1), 11–20. https://doi.org/10.29080/alard.v1i1.29