

# The Relationship Between Ambient CO<sub>2</sub> Levels and Vehicle Emissions in Promoting Sustainable Campus Transportation



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**ABSTRACT:** Atmospheric CO<sub>2</sub> concentrations continue to increase, exacerbating the risk of global climate change and contributing to the deterioration of public health. This condition is primarily driven by escalating anthropogenic activities, particularly in the transportation sector, which relies on combustion engines, as observed in Indonesia. However, the relationship between vehicle emissions and ambient CO<sub>2</sub> concentrations remains insufficiently characterised. This research examined the association between vehicle emissions and ambient CO<sub>2</sub> concentrations at three monitoring locations within a campus in Indonesia. Measurements were conducted over 10 weekdays, and simultaneous full traffic counts and calibrated CO<sub>2</sub> monitoring were performed. Emission intensity was estimated using national emission factors standardised per unit distance. Regression analysis and analysis of covariance (ANCOVA) incorporating wind speed as a covariate were applied. Results showed a statistically positive relationship between vehicle emissions and CO<sub>2</sub> concentrations across all locations ( $p$  consistently  $< 0.001$  with model  $R^2$  ranging from 67.4% to 70.8%). Wind speeds also had a significant influence ( $p$  ranging from 0.020 to 0.001). Based on ANCOVA, motorcycles consistently exhibited the strongest influence relative to other vehicles ( $p < 0.001$ ). These findings underscore the need for policies to regulate motorcycle traffic within campus to reduce emissions, improve air quality, and safeguard public health.

**KEYWORDS:** Ambient carbon dioxide, vehicle emission, correlation analysis, campus transportation, emission reduction commitment

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## I. INTRODUCTION

The concentration of carbon dioxide in the air is a major concern for environmental experts worldwide, as it triggers global warming (Withey et al., 2019). Although debates occurred related to the phenomenon of global warming and its connection to the increase in greenhouse gases in the atmosphere, observational data and simulations have proven that the increase of greenhouse gas emissions, especially CO<sub>2</sub>, indeed need to be monitored and reduced to control the risk of temperatures increasing on the Earth surface (Huang et al., 2012). One of the main causes of the increase in carbon dioxide concentration in ambient air is human activity (Adams and Nsiah, 2019). Therefore, Indonesia, as one of the countries with a very large population, has committed to reducing CO<sub>2</sub> emissions until 2030 based on the Paris Agreement (Hartono et al., 2021)

As parts of achieving the target, scholars have conducted studies on CO<sub>2</sub> concentrations in ambient air and investigated the contributing emitter factors (Eko Cahyono et al., 2022). Among these sources, motor vehicles represent a major contributor, particularly given the sustained growth in vehicle fleets over the past decade. This condition happens more

severely in emerging countries including Indonesia and other countries (Lestari et al., 2022). Many university students and young adults rely heavily on motor vehicles for their daily mobility needs, including commuting to campus (Khalifa et al., 2024; Oktari et al., 2022). As a result, some campuses have become dominated by motorcycles and cars. The condition poses significant sustainability challenges, as campuses are expected to exemplify sustainable transport systems among other environments. University campuses have been proposed as ideal micro-urban environments because they function like small cities with defined access points, allowing better control of confounding variables compared to broader urban settings (Naaman et al., 2024)

Therefore, positioning the university campuses as living laboratories for the implementation of sustainable transportation systems represents a strategic approach. An important initial question that arises is to what extent vehicular emissions generated within a specific area significantly influence the ambient air quality of that area. In this study, the area in question refers to the campus environment, which, as previously described, occupies a strategic position as a semi

controlled micro-urban setting and a potential testbed for transportation policy intervention

Despite this rationale, a clear and empirically grounded understanding of the association of ambient CO<sub>2</sub> concentrations and vehicular emissions remains limited. A clearly defined relationship would enable relevant stakeholders to simulate the potential magnitude of ambient CO<sub>2</sub> reduction resulting from the implementation of specific vehicle control strategies within a certain area. To address this gap, this study aims to examine and quantitatively model the correlation between direct vehicle emissions and ambient CO<sub>2</sub> concentrations using simultaneous road-based measurements. By integrating real-time traffic emission estimation with on-site ambient CO<sub>2</sub> monitoring at a campus area in Indonesia, this study develops a regression-based empirical model that characterizes the strength of their relationship. The resulting model provides a predictive framework that enables the estimation of ambient CO<sub>2</sub> responses under varying traffic emission scenarios, thereby offering a practical tool to support transportation and emission policies

## II. THEORETICAL ANALYSIS

Climate change is a complex issue that requires collaboration across multiple sectors and is already affecting the environment, human health, and the economy (Nunes, 2023). According to the scientific consensus, the increase of atmospheric CO<sub>2</sub> concentrations is the primary driver of the climate change, with the Industrial Revolution and extensive use of fossil fuels serving as key factors (Filonchik *et al.*, 2024). Therefore, reducing CO<sub>2</sub> emissions is crucial to tackling climate change effect (Mateo Pla *et al.*, 2021). Among other CO<sub>2</sub> emission contributing sectors, road transportation is one of the top contributors (Zhou *et al.*, 2022). This sector accounts for approximately 24% of total energy consumption and contributes to CO<sub>2</sub> emissions from exhaust gases (Solaymani, 2019). Meanwhile, a sharp rise in privately owned vehicles in emerging countries is identified in recent years, leading to a more problematic condition (Sogbe *et al.*, 2025).

CO<sub>2</sub> emissions from motor vehicles can quickly spread and cause poor air quality on the roadside. The process through which vehicular emissions are transported and diluted in the atmosphere is inherently complex and governed by multiple interacting processes (Wang *et al.*, 2025). These include atmospheric dispersion mechanisms, surrounding vegetation, meteorological conditions and traffic flow dynamics (Gustafsson *et al.*, 2024). In atmospheric science, this relationship is described through dispersion theory, where pollutant concentrations at a given location depend on the balance between emission intensity, atmospheric mixing, advection by wind, and surface characteristics (Patiño *et al.*, 2024). Therefore, road emissions calculation is a substantial step in defining the relationship.

Several approaches have been developed to estimate the CO<sub>2</sub> emissions from road traffic. One approach estimates emissions at broader regional or national levels using aggregated fuel sales data within a defined area. The latter requires more detailed information, including vehicle characteristics and the distance travelled by individual vehicles, to calculate CO<sub>2</sub> emissions (Zhou *et al.*, 2022). For

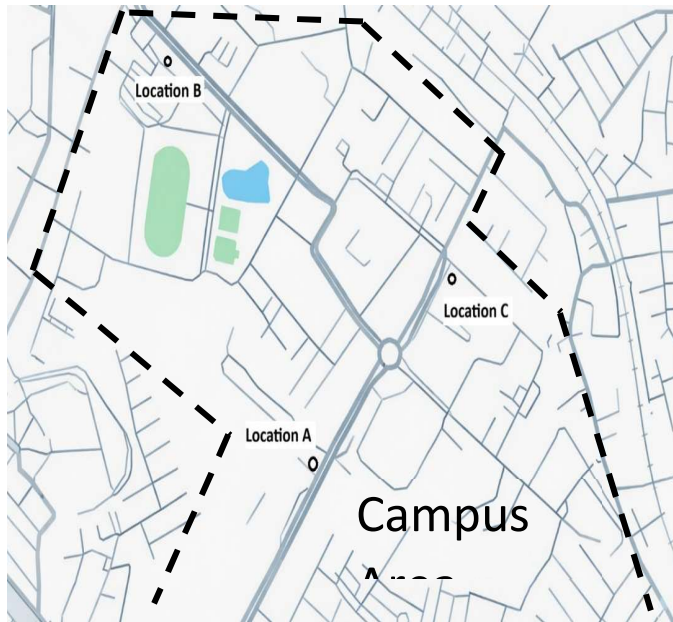
micro-level vehicle emission estimation, emissions can be measured by sampling the exhaust gases from each type of vehicle passing through the road segment. This method has a fairly good accuracy if the sample size meets statistical representation, although on busy roads, achieving this sample size can be difficult and costly (Cai *et al.*, 2017). Another method is to install on-board emission measurement devices on vehicles, allowing these devices to accurately record the vehicle's emissions throughout its journey. However, this method cannot capture the overall emission picture of a road segment and is more suitable for obtaining the emission factor of a specific vehicle (Smit and Kingston, 2019). To obtain an overview of the emissions from all vehicles on a particular road segment, remote sensing technology can be used, which records exhaust emissions based on infrared scanning (Smit *et al.*, 2019)

Besides estimating vehicular road emissions, scholars also conducted field measurements of carbon concentrations on roads to investigate their dispersion patterns. Previous study has found that pollutant concentrations generally decrease with increasing distance from traffic sources and are influenced by meteorological conditions such as temperature and wind dynamics (Joerger and Pryor, 2018). Other study has shown that the interaction between highways and surrounding urban structures can substantially modify airflow and dispersion processes, thereby influencing the spatial distribution of near-road pollutants and the resulting exposure levels in nearby environments (Tong *et al.*, 2012). These studies have primarily focused on pollutant dispersion patterns and near-road concentration gradients rather than quantitatively linking the magnitude vehicle emissions with measured ambient CO<sub>2</sub> concentrations. Consequently, empirical evidence that characterizes the emission-concentration relationship at a localized scale remains limited.

## III. METHODOLOGY

### A. General Steps of the Research

The activities conducted in this study are divided into three main parts: the process of calculating emissions based on the number of vehicles, measuring CO<sub>2</sub> concentrations in ambient air, and analysing the correlation between the two. The campus area of University of Lampung in Indonesia was used as the study area, where this campus has three entrance roads with different characteristics, making it sufficiently representative for the study. The types of vehicles were categorized into three groups: motorcycles, cars (including all types of sedans, minivans, and pick-ups), and buses/trucks (including buses and trucks of various sizes). The calculation of vehicle volume and the measurement of CO<sub>2</sub> concentration were conducted at three designated locations on the three entrance roads to the campus area, as shown in Figure 1 as Location A, Location B, and Location C.



**Figure 1** Map of University of Lampung Showing the Selected Locations

University of Lampung is a campus in the city of Bandar Lampung, Indonesia, covering 62.8 hectares with an elevation of 15 meters above sea level. The main campus area has three entrances. Location A is the main gate, while Location B as the second entrance has the same road width and capacity, and Location C as the third entrance is a narrower road connected to a student residential area.

Location A represents the busiest access point, as it is directly connected to one of the main arterial roads in the city. Consequently, most vehicles entering and exiting the campus pass through this gate. The surrounding area consists of office buildings, residential areas, and the main campus parking facilities, contributing to its high traffic intensity.

Location B is situated at the rear side of the campus and is connected to a provincial road. However, traffic volume at this entrance is relatively lower because it is not directly linked to the city centre or major residential zones. This location is characterized by a greener environment, surrounded by campus parks and several campus buildings with comparatively lower occupancy level.

Location C functions as an access road to a densely populated student housing area. It is surrounded by residential buildings and highly occupied lecture halls, resulting in substantial motorcycle traffic. However, due to its narrower road width, this entrance is less favourable for cars and is generally unsuitable for buses or trucks.

### B. Calculation of Vehicle Emission Intensity

The emission factors and coefficients used in this study strictly adhere to the Indonesian Regulation of the Minister of Environment No. 12 Year 2010. Motorcycles and cars were assumed to use gasoline fuel, while buses and trucks were assumed to use diesel, in accordance with the dominant fuel usage pattern for these vehicle categories in Indonesia. Specifically, the coefficients are as follows:  $C_{fw}$  (fuel weight

coefficient,  $\text{kg L}^{-1}$ ) values are 0.75 for motorcycles, 0.8 for cars, and 0.85 for buses/trucks;  $C_{fc}$  (fuel consumption coefficient,  $\text{km L}^{-1}$ ) values are 28 for motorcycles, 10 for cars, and 4 for buses/trucks; and  $EF_{fb}$  (emission factor,  $\text{g kg}^{-1}$  fuel) values are 3180 for motorcycles, 3176 for cars, and 3172 for buses/trucks (Table 1). To ensure the reliability of the results, vehicle activity was continuously recorded using complete enumeration during the monitoring period to minimize sampling bias.

**Table 1** Emission Factors and Coefficients

Coefficients	Motorcycle	Car	Bus / Truck
$C_{fw}$ ( $\text{kg L}^{-1}$ )	0.75	0.8	0.85
$C_{fc}$ ( $\text{km L}^{-1}$ )	28	10	4
$EF_{fb}$ ( $\text{g kg}^{-1}$ fuel)	3180	3176	3172

In this study, vehicle emissions were estimated as emission intensity per unit distance travelled. This standardized metric was used for subsequent statistical analysis to evaluate their association with ambient  $\text{CO}_2$  concentrations. To avoid uncertainties related to actual trip length within the campus area, the travelled distance was set to 1 meter. Accordingly, the emission intensity per unit distance is formulated as shown in Equation (1) (Labib et al., 2018; Pan et al., 2016)

$$E_{pm} = V \times \frac{C_{fw}}{C_{fc} \times 1000} \times EF_{fb} \quad (1)$$

where:

$E_{pm}$  = emission per meter ( $\text{g m}^{-1}$ )

$V$  = vehicle volume (units)

$C_{fw}$  = fuel weight coefficient ( $\text{kg L}^{-1}$ )

$C_{fc}$  = fuel consumption coefficient ( $\text{km L}^{-1}$ )

$EF_{fb}$  = fuel-based emission factor ( $\text{g kg}^{-1}$  fuel)

The vehicle volume at the three monitoring locations was recorded manually by an observer team who worked on shifts, with four people at each point. This observer team was supported by two supervisors to randomly verify the observers' counting results. The vehicle count was conducted from 08:30 to 17:30 for 10 days in July and August 2023, with the vehicle volume recorded every hour.

The collected data were analysed using several statistical approaches to evaluate the relationship between estimated vehicle emissions and measured ambient  $\text{CO}_2$  concentrations. It is important to clarify that vehicle emissions and ambient  $\text{CO}_2$  concentrations represent fundamentally different physical quantities. Vehicle emissions constitute an emission flux (mass per unit distance or time), whereas ambient concentration represents a volume mixing ratio (ppm) measured at a fixed location (Zhou et al., 2022). The relationship between these quantities is mediated by atmospheric dispersion processes and meteorological parameters, including wind speed, atmospheric stability, mixing height and background  $\text{CO}_2$  concentrations (Wang et al., 2025).

In this study, wind speed was incorporated as a covariate in the linear regression model to partially account for dispersion effects. However, other atmospheric parameters such as stability class and mixing height were not available during the measurement period. Therefore, the regression

results should be interpreted as an empirical association under the observed meteorological conditions rather than a direct physical emission-to-concentration conversion. The exclusion of other atmospheric variables constitutes a limitation of this study.

To further evaluate the contributions of different vehicle emission sources such as motorcycles, cars and buses/trucks, to ambient CO<sub>2</sub> concentrations, analysis of covariance (ANCOVA) was applied. ANCOVA was used to test the null hypothesis that there were no significant differences in the contributions of these sources. This analysis provided a statistical basis for determining whether certain emission sources had a more pronounced impact on CO<sub>2</sub> concentrations compared to others. Prior to ANCOVA, the underlying statistical assumptions were assessed to ensure model validity. Where necessary, appropriate corrective measures were considered to maintain the robustness of the analysis.

### C. Ambient Carbon Dioxide Measurement.

Ambient air quality was assessed through direct in situ measurement over a 10-day observation period and was synchronized with vehicle volume counting to enable direct temporal comparison between traffic related emissions and ambient CO<sub>2</sub> concentrations. The monitoring used a non-dispersive infrared (NDIR) CO<sub>2</sub> sensor mounted on a stable support structure in each measurement locations. The NDIR principle determines CO<sub>2</sub> concentration based on the selective absorption of infrared radiation by CO<sub>2</sub> molecules and is widely applied in atmospheric monitoring due to its stability, selectivity, and suitability for field deployment. Previous studies have demonstrated that NDIR-based sensors provide reliable ambient CO<sub>2</sub> measurements when appropriate calibration and environmental corrections are applied (Liu *et al.*, 2022; Martin *et al.*, 2017).

Before deployment, the instrument was calibrated in accordance with procedures recognized by Indonesian National Accreditation Committee (KAN), at a 95% confidence level. The calibration results indicated that at a certified reference concentration of 1020 ppm, the instrument recorded 1018 ppm, corresponding to a correction value of 2 ppm. The sampling protocol followed the Indonesian National Standard (SNI) 19-7119.9-2005 concerning ambient air sampling procedures. Measurement at the three selected locations were positioned 1.5 – 2 meters from the roadside and at a height of 2 – 3 meters above ground level to represent pedestrian level exposure condition while minimizing immediate tailpipe interference. CO<sub>2</sub> concentrations were recorded at 15 minutes intervals, yielding 36 data points per day at each location. For subsequent analysis, hourly concentration values were calculated as the average of the four measurements obtained within each hour. As a result, nine hourly CO<sub>2</sub> concentration data points were generated per day, producing a total of 90 observations over the 10-day monitoring period for each location.

## IV. RESULTS AND DISCUSSION

### A. General Overview

CO<sub>2</sub> concentration measurements were conducted at Location A, B and C using measurement instrument as described in the previous section from 8:30 am to 5:30 pm. During the measurement period, relative humidity ranges from 50 – 65%, temperature ranged from 27 – 32 degrees Celsius, and wind speed did not exceed 2.5 m/s. Measurements were carried out over 10 days, all of which were weekdays, in July (non-active academic period) and August (active academic period) of 2023. During the measurement, vehicle volume was simultaneously counted manually by a counting team, covering all vehicles entering and exiting the campus area, classified into three categories: motorcycles, cars (including sedans, minivans, pick-ups, and jeeps), and buses or trucks. Most of these vehicles travelled at the same speed, between 20 – 30 km/h, although a small portion travelled slower or faster.

It should be noted that vehicle emissions were estimated using nationally regulated emission factors, which represent average values for conventional internal combustion engine vehicles. These factors did not explicitly for variations in vehicle age, engine condition, technological improvements, or instantaneous driving dynamics. In addition, although the observed vehicle speeds were within relatively narrow range (20 – 30 km h<sup>-1</sup>), speed-dependent emission variations were not explicitly incorporated in the calculation. Therefore, the emission estimates represent standardized approximations of relative emission intensity rather than real-time exhaust measurements. These assumptions constitute a limitation of the study and should be considered when interpreting the emission-concentration relationships reported in this research.

Ambient CO<sub>2</sub> concentrations are also influenced by atmospheric dispersion processes, in which wind speed and local turbulence affect the dilution and transport of emitted gases. Under higher wind speeds or stronger atmospheric mixing, emitted CO<sub>2</sub> tends to disperse more rapidly (Solaymani, 2019). Conversely, under calm conditions, pollutants may accumulate locally and produce higher ambient concentrations. Additionally, the day and night cycles also have an impact, where CO<sub>2</sub> concentrations generally increase at night due to microbial and plant activity, while during the day, CO<sub>2</sub> concentrations tend to decrease with the increasing intensity of sunlight under normal conditions when there are no dominant emitters in the area (Liu *et al.*, 2020). To avoid bias from this time variation, the range between 8:30 am and 5:30 pm was chosen as the monitoring period when CO<sub>2</sub> concentrations tend to be more stable.

### B. Emission Calculation and Analysis

The accuracy of the estimated vehicle emissions depends on the accuracy of the vehicle volume calculations. In this research, the vehicle volume calculation was performed continuously over the specified duration. This approach is expected to enhance the validity of the data and the model that will be developed. The vehicle volume at the three measurement locations over 10 days can be seen in Figure 2, where the values displayed represented the number of vehicles entering and exiting the campus area. Figure 2(a) illustrates the number of motorcycles entering and exiting the campus over

the 10-day observation period at Locations A, B, and C, showing a generally similar pattern across the three sites. However, the vehicle counts during the first three days were relatively lower compared to the subsequent days. Figure 2(b) presents the number of cars recorded, while Figure 2(c) shows the counts of buses and trucks. Subsequently, the data was used to calculate the emission intensity in each location.

The average number of motorcycles entering the campus area per hour was 2,650 units, with a distribution of 51% at Location A, 13% at Location B, and 36% at Location C. The average number of cars entering per hour was 500 units, with a distribution of 59% at Location A, 30% at Location B, and 11% at Location C. Meanwhile, the average number of buses or trucks was 11 units per hour, with a distribution of 49% at Location A, 43% at Location B, and only 8% at Location C. This number was significantly higher compared to the vehicle volume calculations at another university in Indonesia, which recorded 39,000 motorcycles and 3,200 cars in one year (Handayani et al., 2024).

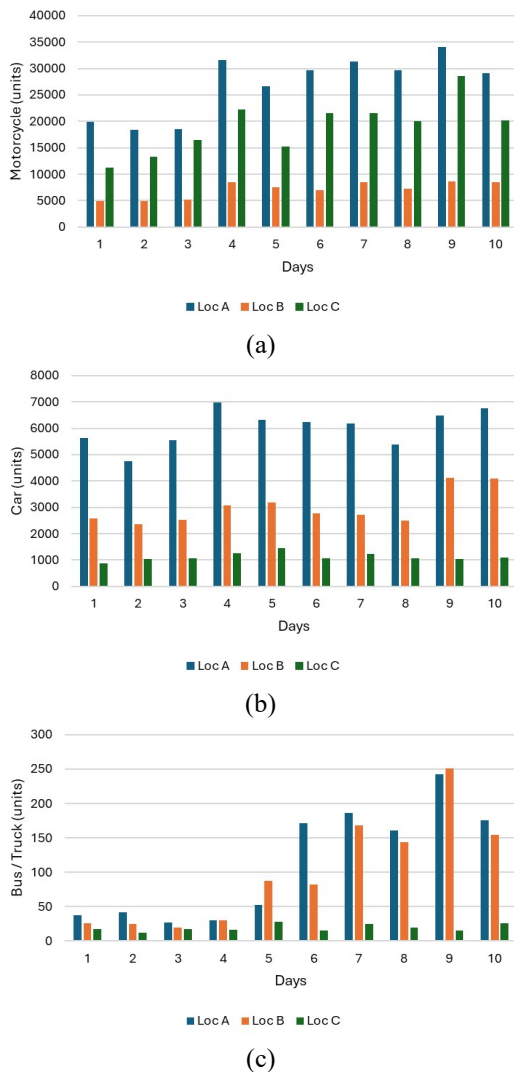


Figure 2 Volume of Vehicles in Three Monitoring Locations (a) Location A (b) Location B (c) Location C

The highest number of vehicles of all types entered and exited through Location A. This was naturally because Location A was the main gate connected to the main street in Bandar Lampung. Location B saw the fewest motorcycles, but it had more cars and buses/trucks compared to Location C. Location C had a high number of motorcycles, almost approaching the numbers at Location A, but it had a minimal number of cars and buses/trucks. One reason for this was that Location C was relatively narrow, making it less preferred by car users and unsuitable for buses/trucks. The high number of motorcycles was because Location C directly connected to a student housing area.

From the first to the fifth day, academic activities had not yet started. The number of motorcycles differed significantly, as this type of vehicle was predominantly used by students. However, the number of cars did not show significant differences before and after classes resumed, as they were mainly used by university staff, whose presence remained consistent even when classes were not in session. The difference in bus and truck volume was noticeable because most campus buses did not operate when classes were not in session.

Vehicle emissions per meter had been calculated based on Equation (1), and the results are depicted in the graph in Figure 3. In general, it is obvious that emissions per meter were highest at Location A, followed by Location C, and the lowest was Location B. At Location A and C, the majority of emissions came from motorcycles, while at B, cars emitted more CO<sub>2</sub> than the other two types of vehicles. Although buses and trucks had the highest emission factors, their emissions were the lowest at all locations due to their small numbers.

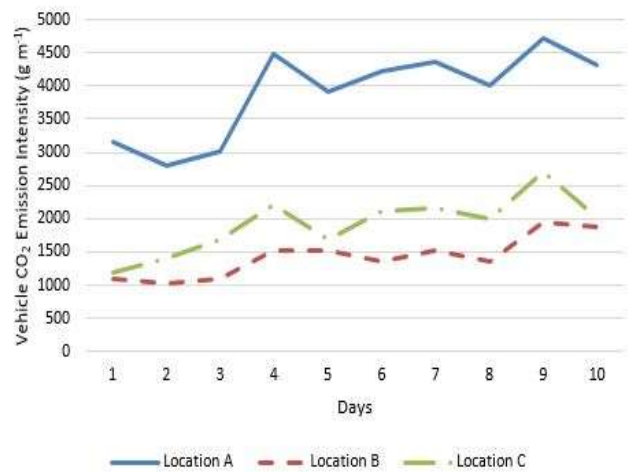
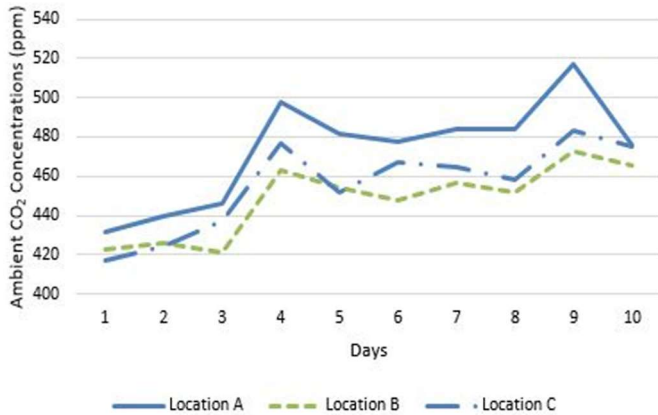


Figure 3 Vehicle Emission Intensity by Calculation

C. Carbon Dioxide Measurement Results and Analysis.

CO<sub>2</sub> concentration measurements in ambient air were conducted at the same locations as the vehicle volume measurement locations. The average CO<sub>2</sub> concentration pattern over the 10-day data collection period can be seen in Figure 4, which shows similarities with the emission pattern based on calculations, although not exact. The figure also

shows noticeable temporal variations in emissions per meter across the observation days. Emissions at all locations increased sharply in Day 4 due to events and congestions during the day, followed by slight decline on Days 5 – 6, and then fluctuated again toward the end of observation period. Among the three locations, Location A shows the biggest variability in emissions per meter, indicating that this location may experience more dynamic emissions conditions compared to Locations B and C. This finding is consistent with previous study showing that CO<sub>2</sub> concentrations at different locations within a campus area could exhibit distinct dynamics and were strongly influenced by human activities within their micro-environment (Wang et al., 2024)



**Figure 4** Measured Ambient CO<sub>2</sub> Concentrations

The average CO<sub>2</sub> concentration at Location A was 473.5 ppm, at Location B was 448.1 ppm, and at Location C was 455.5 ppm. The highest CO<sub>2</sub> concentration was recorded on the ninth day at midday at Location A, reaching 558 ppm, while the lowest value was found on the third day at Location B, with 405 ppm in the late afternoon. Overall, the measured CO<sub>2</sub> concentrations consistently exceeded 400 ppm, indicating a substantial anthropogenic contribution relative to pre-industrial level (200 – 300 ppm) and has the potential to contribute to global warming (Eko Cahyono et al., 2022). Temperature warming can lead to serious losses in human wellbeing, economic productivity and natural ecosystems, making this phenomenon one of the foremost concerns among environmental scientist today (You et al., 2022). For example, extreme weather events associated with global warming may result in significant loss of life and cause substantial disruptions to economic activities (Shi et al., 2018).

While from a public health standpoint, even outdoor concentrations in this range are not immediately hazardous, sustained increases in CO<sub>2</sub> concentration may indicate broader air quality deterioration (Bikis, 2023). The condition may lead to the decrease of human health where the increase of CO<sub>2</sub> concentrations to around 500 ppm in recent years has been associated with decreased cognitive ability, concentration, and overall physical health in humans (Jacobson et al., 2019). Furthermore, from an environmental perspective, persistent elevation above global baseline (≈411 ppm) suggests localized emission accumulation that may contribute to regional greenhouse gas loading (Karnauskas et al., 2020). Elevated CO<sub>2</sub> concentrations can also influence plant metabolic processes, altering photosynthesis, respiration and carbon

allocation. Changes in plant metabolism under higher CO<sub>2</sub> concentrations may affect the capacity of vegetation, with potential implications for ecosystem function and carbon cycling (Adirededy et al., 2024).

The CO<sub>2</sub> concentration data was then tested for normality to assess its suitability for further analysis. The normality test found that the CO<sub>2</sub> concentration data distribution met the requirements for regression and ANCOVA, with a P value greater than alpha 0.05, unless for data in Location A based on Ryan Joiner method (Table 2).

**Table 2** Ambient CO<sub>2</sub> Data Normality Test Result

Test	p – value		
	Location A	Location B	Location C
Anderson Darling	0.181	0.200	0.190
Ryan Joiner	0.027	0.100	0.100
Kolmogorov Smirnov	0.160	0.150	0.150

*D. Ambient CO<sub>2</sub> Concentrations and Vehicle Emissions Correlation Analysis*

This section will explain the correlation between ambient CO<sub>2</sub> concentration and vehicle emissions based on the data obtained. Multilinear regression analysis with wind speed as a covariate was chosen to examine the relationship. The model equations are presented in Equation (2), (3) and (4) for Location A, B and C respectively. The detail results of the regression analysis of each location are presented in Table 3.

$$CO_2 = 368 + 0.276 E. tot - 14.4 WS \tag{2}$$

$$CO_2 = 392 + 0.416 E. tot - 8.81 WS \tag{3}$$

$$CO_2 = 443 + 0.216 E. tot - 35.6 WS \tag{4}$$

**Table 3** Multi Linear Regression Results

Parameter	Location A	Location B	Location C
R <sup>2</sup> (%)	67.4	70.8	69.2
Adj. R <sup>2</sup> (%)	66.6	70.2	68.5
Model significance (p-value)	< 0.001	< 0.001	< 0.001
E.tot coefficient	0.276 (p < 0.001)	0.416 (p < 0.001)	0.216 (p < 0.001)
WS coefficient	-14.4 (p = 0.020)	-8.81 (p = 0.005)	-35.6 (p = 0.001)
VIF (max)	-1.2	1.255	1.629
Notable Diagnostic	Several influential obs. (Cook’s D up to 0.44)	Some moderate influential obs.	One highly influential obs. (Cook’s D = 0.43)

The multiple linear regression results indicated that total vehicle emissions (E.tot) and wind speed (WS) jointly explained a substantial proportion of the variability in ambient CO<sub>2</sub> concentrations at all three monitoring locations. The models were statistically significant ( $p < 0.001$ ) across locations, with R<sup>2</sup> values ranging from 67.4% (Location A) to 70.8% (Location B), indicating moderate to strong explanatory power for field-based environmental data. The consistent significance of E.tot ( $p < 0.001$  at all locations) confirmed that vehicular emissions intensity is a primary driver of local CO<sub>2</sub> concentrations. At the same time, the negative coefficients for wind speed at all locations demonstrated the critical role of atmospheric dispersion processes in modulating measured concentrations.

At location A, which is characterized by high traffic intensity, dense built-up surroundings, and frequent congestion near campus main gate, the emission coefficient ( $\beta=0.276$ ) was positive and highly significant, while wind speed showed moderate but significant negative effect. This suggested that while emissions strongly increase ambient CO<sub>2</sub> concentrations, dispersion conditions partially offset accumulation. The relatively enclosed roadside configuration and queuing behaviour likely promoted short term pollutant buildup, explaining R<sup>2</sup> (67.4%). However, several influential observations (Cook's D approaching 0.44) indicated episodic conditions. It represented peak hour congestion or very low wind speed that amplify the CO<sub>2</sub> concentrations spikes.

Location B exhibited the highest R<sup>2</sup> (70.8%) and the strongest emissions coefficient ( $\beta=0.416$ ), indicating a more pronounced sensitivity of ambient CO<sub>2</sub> to emission intensity. Despite being more open spatially and surrounded by vegetation, the statistical relationship between emissions and CO<sub>2</sub> concentrations appeared more stable and less affected by extreme influential observations compared to Location A. The wind speed effect was weaker than other locations, suggesting that played the secondary role relative to emission magnitude in this setting. This might reflect smoother traffic flow and fewer micro scale turbulence effects, resulting in a clearer emission – concentration signal.

In contrast, Location C demonstrated the strongest wind speed effect, indicating that the atmospheric dispersion was more dominant to control factors in this location. Although emissions remain significant, their magnitude was smaller than at Location A and B. The road geometry, narrower corridor, dominance of motorcycles and proximity to vegetation likely enhanced wind-driven dilution and vertical mixing. The presence of one highly influential observation (Cook's D = 0.43) suggested occasional extreme accumulation events under very low wind condition, which affected the concentrations.

From a validity perspective, several indicators supported robustness: (1) all predictors were statistically significant; (2) multicollinearity was minimal (VIF < 2 across locations); (3) R<sup>2</sup> values were consistent and within a realistic range for environmental field studies; and (4) diagnostic plots did not indicate severe structural violations. While some influential observations were present, they appeared to represent real world episodic conditions rather data errors. Overall, the models were statistically valid and environmentally interpretable, demonstrating that ambient CO<sub>2</sub> concentrations

in the study area were influenced by the interaction between emission intensity and micro-scale meteorological dispersion processes.

To further examine the effect of vehicle composition on ambient CO<sub>2</sub> concentrations, an analysis of covariance (ANCOVA) was conducted including wind speed as a covariate. This analysis aimed to evaluate whether different vehicle categories significantly influence ambient CO<sub>2</sub> concentrations (Table 4)

**Table 4** Analysis of Covariance Results

Parameter	Location A	Location B	Location C
R <sup>2</sup> (%)	66.85	78.64	69.64
Adj. R <sup>2</sup> (%)	62.66	75.93	65.53
S (Residual SD)	20.51	11.64	14.01
Wind Speed	F=12.86 p = 0.001	F=7.63 p = 0.007	F=19.74 p = 0.000
WS Coefficient	-23.46	-8.56	-22.97
E.MC	F=6.61 p = 0.000	F=24.73 p = 0.000	F=15.51 p = 0.000
E.Car	F=3.20 p = 0.028	F=3.11 p = 0.031	F=1.03 p = 0.386
E.BT	F=0.73 p = 0.535	F=1.38 p = 0.255	F=0.46 p = 0.712

Vehicle volumes for each category were classified into four levels: low, middle-low, middle-high and high, based on quartile distribution. These categorical volume levels were treated as independent variables in the ANCOVA model, with ambient CO<sub>2</sub> concentrations as the dependent variable. The ANCOVA results generally confirmed and strengthened the findings obtained from the previous multiple regression analysis. Wind speed remained a significant covariate, where the magnitude of the WS coefficient in Location A and C showed that these locations were more sensitive to meteorological dilution effects compared to Location B. This condition may be related to differences in micro-environmental characteristics such as road geometry and surrounding buildings which could influence air circulation and pollutant dispersion.

The R<sup>2</sup> values ranged from 66.85% to 78.64% indicated that a substantial proportion of variability in ambient CO<sub>2</sub> concentrations could be explained by the combination of vehicle emissions and wind speeds. The remaining unexplained variability may be associated with atmospheric CO<sub>2</sub> background, local vegetation absorption, and other meteorological factors such as atmospheric stability mixing height that were not explicitly included in the model.

The findings strengthen result from prior analysis that motorcycles are the primary contributors to the increase of ambient CO<sub>2</sub> concentrations in the monitoring locations. This is consistent with previous research conducted at another university in Indonesia, which reported that motorcycles are the preferred mode of transportation among student for commuting in campus and further became the biggest contributor of vehicle emissions (Handayani et al., 2024). Although cars also contribute to emissions, their statistical significance was weaker compared to motorcycles. In Location

C, cars emission was not significant due to its low volume in monitoring period. Meanwhile, bus and trucks were not significant in all locations.

Students' transportation choices are largely influenced by affordability and flexibility of movement. As a result, students with motorcycles predominantly use them in daily activities, whereas those without private vehicles typically depend on bus services (Risdiyanto *et al.*, 2022). Meanwhile, walking and cycling are less favored by most students, which may be attributed to the hot tropical climate that make these activities less comfortable, as well as long travel distances that discourage active mobility choices (Yumita *et al.*, 2021). Given this proportion, shifting motorcycle usage toward a more optimized utilization of campus bus represents a highly reasonable strategy for future implementation. It can reduce fuel consumption (Johar *et al.*, 2025), alleviate traffic congestion and improve air quality (Chen *et al.*, 2021).

Therefore, university management should consider implementing policies aimed at reducing motorcycle use within campus area by requiring motorcycles to park at centralized parking facilities located near entrances, while encouraging students to continue their trips within the campus using campus bus services. In parallel, promoting the gradual transition towards environmentally friendly vehicles could further supports emission reduction efforts. A combined approach integrating these notions is likely to yield more effective outcomes. In addition, the improvements to pedestrian facilities and bicycle lanes, may encourage a modal shift toward greener mobility options over the long term. Collectively, these interventions would contribute to the development of a more sustainable and healthier campus environment for the entire academic community. Although implementing such changes requires considerable investment and time, it has the potential to produce significant improvements toward a more sustainable campus transportation system (Hu and Schneider, 2015)

#### IV. CONCLUSION

This study examined the relationship between vehicle emissions and ambient CO<sub>2</sub> concentrations at three monitoring locations within a university campus area. The results consistently demonstrated a statistically significant positive relationship between estimated vehicle emissions and ambient CO<sub>2</sub> concentrations across all locations ( $p < 0.001$ ), with regression models explaining approximately 67% - 71% of the observed variation. These findings indicate that traffic-related emissions constitute a major contributor to localized CO<sub>2</sub> accumulation within the campus environment. Wind speeds were also found to significantly influence ambient CO<sub>2</sub> concentrations, highlighting the role of atmospheric dispersion in regulating pollutant accumulation. Lower wind speeds tended to correspond with higher CO<sub>2</sub> concentrations due to reduced dilution of emitted gases. Among vehicle categories, motorcycles exhibited the strongest influence on ambient CO<sub>2</sub> concentrations, based on ANCOVA. This finding highlights that vehicle volume, rather than the emission factor alone, determines overall contribution. Despite having lower emission factor, motorcycles dominate total emissions due to their high frequency of mobility. Measured ambient CO<sub>2</sub>

concentrations consistently exceeded global thresholds and occasionally surpassed 500 ppm, raising concerns about greater environmental risks as well as potential impacts on public health within campus. Although not immediately hazardous, it requires mitigation strategies to prevent long-term impacts. Based on the findings of this study, restricting motorcycles use within the campus area may represent an appropriate policy. However, such a policy should be accompanied by the provision of comfortable and environmentally friendly public transportation, as well as improvements in non-motorized mobility infrastructure including pedestrian facilities and bicycle lanes

#### AUTHOR CONTRIBUTIONS

**A. Y. T. Panuju:** Conceptualization, Data Collection, Methodology, Writing – original draft, Writing – review & editing. **E. P. Wahono:** Methodology, Writing – review & editing. **S. R. Sulistiyanti:** Validation, Writing – review & editing. **G. A. Ibrahim:** Conceptualization, Supervision, Writing – review & editing.

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