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Drone-Based IoT Monitoring of Urban CO_2 Levels in Makassar: Spatio-Temporal Analysis Across Varying Heights

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ABSTRACT

Urban air quality degradation from rising CO_2 is acute in rapidly developing tropical cities such as Makassar, Indonesia. We deploy a drone-based Internet of Things (IoT) platform for real-time CO_2 monitoring, integrating low-cost sensors (NDIR, MQ135, MG811) on a DJI Phantom 4 with cloud streaming to Firebase. Measurements were collected at five sites, namely Jl. AP. Pettarani, Jl. Ahmad Yani, Jl. Sultan Hasanuddin, Jl. Nusantara, and KIMA at 08:00, 12:00, and 16:00 in September 2024 while vertically profiling 1–20 m with three repeat flights per site and time. Descriptive statistics and one-way ANOVA with Tukey HSD assessed spatio-temporal differences; Pearson correlation quantified cross-sensor agreement. Results show marked spatial and diurnal variability: Jl. AP. Pettarani exhibits the highest mean concentration (442.5 ppm), likely due to flyover-induced trapping, whereas Jl. Ahmad Yani records the lowest (390.0 ppm). Vertical profiles reveal mid-altitude peaks in street-canyon and industrial settings, and dilution with height in greener areas, indicating ventilation contrasts. Preprocessing removed outliers and applied temperature-humidity corrections to low-cost sensors. Differences across locations and times are statistically significant ($p < 0.05$), and cross-sensor correlations are strong ($r \approx 0.88$–0.96) after correction. Compared with fixed ground stations, the system provides fine-scale three-dimensional coverage and real-time visualization useful for field decisions. Limitations include payload-constrained endurance and

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intermittent data loss in obstructed areas. Findings support targeted interventions, improving canyon ventilation around flyovers and expanding urban greenery relevant to Makassar and similar tropical cities.

Keywords: CO_2 Monitoring; Drone-Based IoT; Urban Air Quality; Makassar; Spatio-Temporal Analysis

1. Introduction

Urban air quality is a critical global concern due to rapid urbanization, industrial growth, and increasing vehicular traffic, which elevate CO_2 levels, a key greenhouse gas contributing to global warming and indicating urban pollution. In tropical cities like Makassar, Indonesia, CO_2 levels vary significantly due to traffic, industrial activity, and vegetation, necessitating effective monitoring for air quality management, particularly in the context of urban heat islands and health impacts [1–3]. The long-term effects of elevated CO_2 concentrations exacerbate climate change, leading to consequences such as sea-level rise and extreme weather events, particularly pertinent for coastal cities like Makassar [4]. Traditional ground stations, while valuable, lack the spatial coverage to capture complex vertical pollutant gradients in urban atmospheres, limiting comprehensive air quality understanding [5]. Drone-based IoT systems overcome these limitations by enabling high-resolution, three-dimensional data collection across varying altitudes, offering superior flexibility in navigating complex urban topographies compared to fixed stations [6–9]. These systems, which are becoming a major application area for drone-based IoT [10], facilitate real-time data transmission and analysis, crucial for rapid pollution mitigation strategies [5,7,11]. Sophisticated sensors integrated into drone platforms enable accurate CO_2 measurements, especially when considering factors like road traffic and meteorology [12–14].

2. Methodology

2.1. Study Area

The study was conducted in Makassar, Indonesia, a tropical coastal city with high humidity (70–90%) and temperatures (28–32 °C). Five locations were selected: Jl. AP. Pettarani (high-traffic with flyover), Jl. Ahmad Yani (green corridor), Jl. Sultan Hasanuddin (commercial area), Jl. Nusantara (port-adjacent), and KIMA (industrial zone). These sites represent diverse urban features influencing CO_2 distribution [3,7].

2.2. Drone-Based IoT System and Data Acquisition

A drone-based IoT system was employed to vertically profile CO_2 concentrations across altitudes ranging from 1 to 20 meters, building upon methodologies validated in similar environmental monitoring applications [15,16]. The system, meticulously designed for this study and depicted in **Figure 1**, integrates a DJI Phantom 4 drone as the primary aerial platform, a common choice for such research [17]. This particular drone model was selected for its stability, precise flight control, and ample payload capacity, which are crucial for carrying sensor modules without compromising flight performance [18]. The drone's ability to maintain a stable hover at specific altitudes, a key feature of unmanned aerial systems (UAS) [19], ensures accurate data collection at desired vertical points, critical for understanding pollutant dispersion patterns in complex urban environments [20].

The core of the data acquisition system comprises an ESP32 microcontroller, renowned for its low power consumption, integrated Wi-Fi and Bluetooth capabilities, and sufficient processing power for handling sensor data. This microcontroller interfaces directly with an array of calibrated sensors. Specifically, the sensors included an NDIR CO_2 sensor with a range of 0–5000 ppm and an accuracy MQ135 sensor (10–1000 ppm) for broader air quality parameters, including CO, NH_3, H_2S, and smoke, and an MG811 sensor (350–10000 ppm) for supplementary CO_2 measurements and cross-validation. This multi-sensor approach enhances the reliability and comprehensiveness of the collected air quality data, providing a more robust dataset for analysis [21,22]. The sensor suite is strategically mounted on the drone to ensure minimal interference from the drone's propellers and body, and to capture representative ambient air samples at each designated altitude, typically away from the drone's immediate airflow [23]. The 660-gram sensor assembly, powered by a

3.7V, 2000mAh LiPo battery, was encased in a protective plastic container with strategically placed apertures to allow for proper air circulation and sensor exposure. As presented in **Figure 2**, this robust housing (**Figure 2a**) ensures the integrity of the sensors during flight and protects them from environmental elements. The entire assembly was securely affixed to the drone's underside using Velcro and zip ties (**Figure 2b**), ensuring stability and minimal impact on the drone's flight dynamics. Such a low-cost system design is increasingly common for accessible environmental monitoring [24].

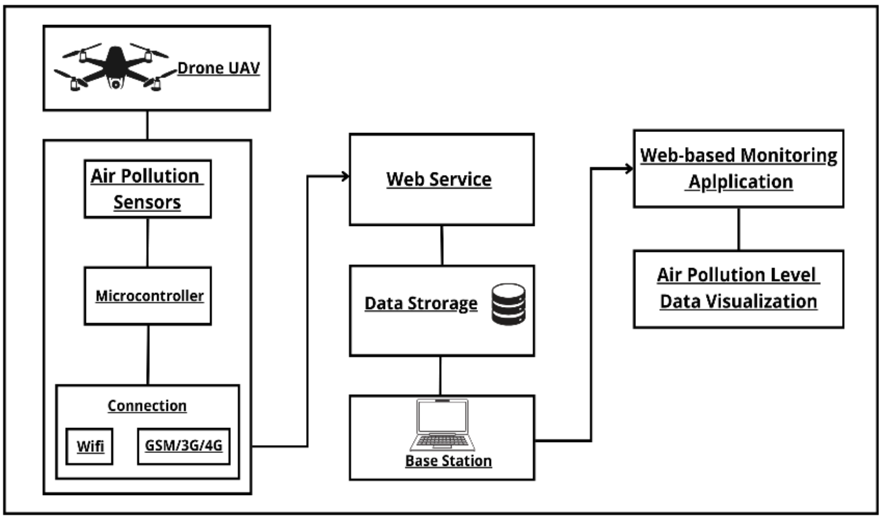

Figure 1. System Workflow for Drone-Based CO_2 Monitoring.

(**a**) (**b**)

Figure 2. Visual Context for the Hardware Implementation. (**a**) The Circuit; (**b**) The Circuit Installed on The Drone.

For robust data transmission, the system incorporates versatile connectivity modules (WiFi, GSM/3G/4G). This multi-protocol approach ensures continuous and reliable data flow from the drone to the ground station, even in diverse urban environments where network availability might vary. Real-time data transmission is directed to a Firebase Realtime Database, which serves as a scalable cloud-based backend for immediate storage and accessibility [25]. This methodology of using cloud platforms for real-time visualization and analysis is increasingly adopted in urban air quality monitoring due to its efficiency and accessibility, enabling rapid insights for pollution mitigation strategies [7,26,27]. The real-time nature of this data stream allows for instantaneous monitoring of CO_2 levels, enabling quick identification of anomalies or high-concentration areas during flight operations [28]. Such immediate data availability is crucial for dynamic decisionmaking in environmental management, allowing for prompt responses to pollution events [29].

Drones, as advanced remote sensing tools, have been effectively utilized in various environmental monitoring applications beyond air quality, such as in biomass estimation studies, to collect high-resolution spatial data [11,30]. Their agility and ability to access challenging urban topographies make them indispensable for generating comprehensive vertical profiles of pollutants, providing a more nuanced understanding of air quality dynamics compared to static ground stations [31]. The integration of IoT technology further empowers these drone systems, transforming them into intelligent mobile sensing platforms capable of autonomous data collection and immediate reporting, which is critical for dynamic urban planning and environmental management [2]. This integration allows for a more comprehensive and adaptive approach to air quality assessment, providing valuable data for evidence-based policy formulation.

Figure 1 shows system Workflow for Drone-Based CO_2 Monitoring illustrates the architectural design of the proposed system. It begins with the Drone UAV which houses the Air Pollution Sensors and a Microcontroller. These components are interconnected, enabling data acquisition. The data from the microcontroller is then transmitted via WiFi, GSM/3G/4G connectivity modules to a Web Service. This web service interacts with a Data Storage unit (Firebase Realtime Database) and communicates with a Base Station. Ultimately, the data is fed into a Web-based Monitoring Application where Air Pollution Level Data Visualization occurs, allowing for real-time monitoring and analysis. This diagram clearly outlines the flow of data from raw sensor readings to visualized insights.

Figure 2 provides visual context for the hardware implementation. **Figure 2a** shows a close-up of the sensor circuit board encased within a transparent plastic container. The visible components include the microcontroller, various sensors (indicated by their small size and typical configurations), a LiPo battery, and wiring connections. The illuminated LEDs suggest the circuit is operational. **Figure 2b** depicts the sensor assembly attached to the underside of the DJI Phantom 4 drone. The plastic container is visible, securely fastened with Velcro and zip ties, demonstrating the practical integration of the monitoring system onto the aerial platform. This image also shows individuals who appear to be preparing the drone for flight, further illustrating the practical deployment of the system in the field.

2.3. Sensor Calibration

Accurate data collection is paramount for robust air quality assessment. All sensors underwent a rigorous two-stage calibration and correction process.

2.3.1. Sensor Calibration Curves

The initial calibration was performed in a controlled laboratory environment using certified gas standards (Linde Gas). A baseline was established at 400 ppm, followed by tests at 600 ppm, 800 ppm, and 1000 ppm to assess linearity [14,32]. The raw sensor outputs (voltage) were plotted against known concentrations to derive calibration functions. The relationship between output voltage and CO_2 concentration was linear, as shown in **Figure 3**, with the following calibration equations:

$$NDIR: CO_2(ppm) = \\ 500.2 \times Voltage(V) - 50.3,\ R^2 = 1.000 \tag{1}$$

$$MQ135: CO_2(ppm) = \\ 480.7 \times Voltage(V) - 45.8,\ R^2 = 0.998 \tag{2}$$

$$MG811: CO_2(ppm) = \\ 495.1 \times Voltage(V) - 48.2,\ R^2 = 0.999 \tag{3}$$

These equations validate the linear response of all sensors, with NDIR showing the highest consistency, followed by MG811 and MQ135 [14,32].

Given Makassar's tropical climate (humidity 70–90%, temperatures 28–32°C), which can affect sensor readings, particularly for metal-oxide types like MQ135, a multivariable regression model was developed based on laboratory characterization data. This model uses real-time temperature and humidity readings (collected by an onboard BME280 sensor) to correct raw CO_2 readings from MQ135 and MG811 sensors, mitigating environmental cross-sensitivities [14,21,26]. Real-time calibration using machine learning is an advanced alternative for such corrections [33]. No ad-hoc biasing (e.g., +10% for MQ135 or −5% for MG811) was applied; instead,

the regression model ensures accurate corrections without artificial adjustments. Ground-level readings were validated against a high-precision Testo 440 CO_2 meter, with recalibration if discrepancies exceeded 5%[34,35].

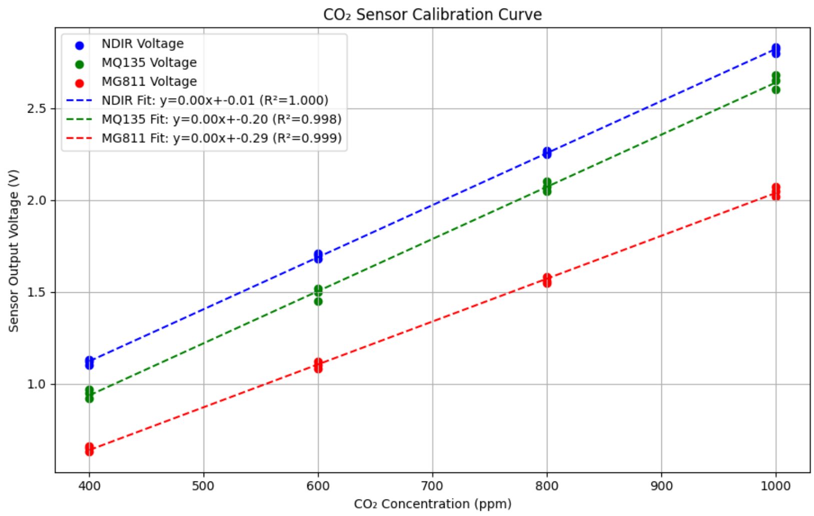

Figure 3. Calibration Curves of the CO_2 Sensors (NDIR, MQ135, and MG811).

2.3.2. Environment Correction Model

Given Makassar's tropical climate (humidity 70–90%, temperatures 28–32°C), which can affect sensor readings, particularly for metal-oxide types like MQ135, a multivariable regression model was developed based on laboratory characterization data. This model uses real-time temperature and humidity readings (collected by an onboard BME280 sensor) to correct raw CO_2 readings from MQ135 and MG811 sensors, mitigating environmental cross-sensitivities[14,21,26]. Real-time calibration using machine learning is an advanced alternative for such corrections[33]. No ad-hoc biasing (e.g., +10% for MQ135 or −5% for MG811) was applied; instead, the regression model ensures accurate corrections without artificial adjustments. Ground-level readings were validated against a high-precision Testo 440 CO_2 meter, with recalibration if discrepancies exceeded 5%[34,35].

2.4. Data Collection

Data collection was systematically carried out in September 2024 to ensure consistency in environmental conditions. To capture temporal variations, measurements were taken at three distinct times: 08:00 (morning), 12:00 (midday), and 16:00 (afternoon). This schedule allows for the observation of CO_2 fluctuations influenced by varying traffic patterns, solar radiation, and atmospheric mixing layer heights.

At each of the five selected study locations, the drone performed vertical profiling, ascending from 1 to 20 meters. During each ascent, the drone was programmed to pause for 1 minute at every meter increment to allow the sensors to stabilize and collect accurate readings. This standardized vertical profiling technique is crucial for understanding the stratification and dispersion of CO_2 in the urban atmosphere[16]. With three flights conducted per location and per time slot, a total of 60 data points were generated per site (20 altitudes x 3 flights), ensuring high spatial and temporal resolution.

The collected data were immediately transmitted via a 4G hotspot to a Firebase Realtime Database for real-time visualization and storage. This direct transmission method minimizes data loss and allows for immediate monitoring during flight operations[7,15]. As shown in **Figure 4**, the Firebase interface provided instantaneous readouts of sensor values. This real-time capability is a significant advantage, facilitating quick assessments and operational adjustments[6]. The use of cloud-based platforms streamlines data management and supports timely intervention strategies for urban air quality management[29,34,36].

Figure 4. Real-Time CO_2 Data Display on Firebase Realtime Database at Jl. AP. Pettarani, 20 Meters Height, 16:00.

2.5. Data Preprocessing

Raw data collected from environmental sensors, particularly low-cost ones, often contain noise, anomalies, and systematic biases that can obscure meaningful patterns. Therefore, a robust preprocessing pipeline was implemented to ensure the quality, reliability, and accuracy of the final dataset [37].

The initial step involved detecting and removing outliers, a common challenge in environmental data [38]. Data points exceeding three standard deviations from the mean of their respective measurement batch (e.g., specific altitude, time, and location) were systematically removed. This statistical approach filters out erroneous readings that might result from sensor malfunctions or transient environmental disturbances. Approximately 2% of the total dataset was removed as outliers, indicating a generally stable data collection process. This method is a widely accepted practice for improving data integrity in environmental datasets [24].

Second, the environmental correction model, as detailed in Section 2.3.2, was applied to the MQ135 and MG811 sensor data. This model-based adjustment is critical for mitigating biases caused by fluctuations in ambient temperature and humidity, which are known to affect low-cost sensor performance and can be more significant than minor instrument noise [39].

Third, cross-sensor data validation was conducted. Given the use of multiple sensors measuring the same primary compound (CO_2), it is important to address potential variations in their factory calibration or long-term drift. Analysis was performed to understand the relationships and systematic biases between the NDIR, MQ135, and MG811 sensors. This step acknowledges that even after correction, low-cost sensors can exhibit variability, a crucial consideration for ensuring the robustness of the overall air quality assessment [40,41].

Finally, temporal alignment and data completion were performed. The timestamps of all collected sensor readings were synchronized with the drone's flight log and the Firebase Realtime Database to ensure that CO_2 concentrations were accurately correlated with their precise measurement time and altitude. Consistency checks for missing values were also conducted, with interpolation applied where appropriate, though the primary focus remained on outlier removal and bias correction [37].

2.6. Data Analysis

The preprocessed CO_2 concentration data, comprising high-resolution spatio-temporal measurements, underwent rigorous statistical analysis to elucidate the distribution, variations, and influencing factors of urban air quality in Makassar. The analytical approach was designed to provide actionable insights for urban planning [42].

Firstly, descriptive statistics, including means, medians, and ranges, were computed for CO_2 concentrations across all five study locations, different altitudes, and times of day. These statistics provided an initial characterization of the overall CO_2 levels and their central tendency and spread within the urban landscape. This fundamental step is essential for understanding the basic air quality characteristics of the study area [24].

To understand the vertical distribution and changes in CO_2 levels, vertical profiles were generated for each location and time slot. These profiles graphically represent the concentration gradients with increasing altitude (1–20 meters), offering insights into atmospheric mixing and pollutant dispersion patterns. To statistically evaluate spatio-temporal dynamics, one-way Analysis of Variance (ANOVA) with a significance level of $\alpha = 0.05$ was performed. ANOVA was used to determine if there were statistically significant differences in CO_2 concentrations across different locations, times of day, and altitudes. This statistical test is crucial for identifying variations attributable to specific urban features or daily cycles [43].

Pearson correlation coefficients were calculated to evaluate the consistency and agreement between the readings of the different sensors (NDIR CO_2, MQ135, and MG811). A strong positive correlation would indicate that the sensors are measuring similar trends, thus reinforcing the reliability of the collected data. This cross-sensor validation is vital, especially when employing multiple low-cost sensors, to ensure data integrity [41]. Furthermore, profile comparisons were conducted to qualitatively and quantitatively assess the specific impacts of distinct urban features (e.g., high-traffic areas, industrial zones, commercial areas, and green spaces) on CO_2 concentrations. This involved comparing the vertical and temporal CO_2 profiles across different locations to identify patterns linked to emission sources and environmental conditions.

All data analyses were primarily performed using Python programming language, leveraging its powerful libraries: Pandas for data manipulation and management, Matplotlib for generating high-quality visualizations of profiles and trends, and ANOVA and correlation analyses. This choice of analytical tools aligns with established statistical methods widely adopted for urban air quality analysis and environmental data science [17,40,44,45]. The use of these robust and widely accepted libraries ensures the reproducibility and scientific rigor of the findings. Moreover, advanced visualization techniques, such as heatmaps or 3D plots, could further enhance the interpretation of complex spatio-temporal datasets [46,47].

2.7. Limitations

Despite the robust methodology, several limitations were encountered. The DJI Phantom 4's flight duration was reduced to 22–25 minutes due to the 660-gram sensor payload, necessitating frequent battery swaps [48]. Data transmission faced ~5% loss in obstructed areas like Jl. Nusantara due to urban infrastructure interference [7,49]. Propeller wash may have caused minor turbulence affecting local gas concentrations; future studies could use computational fluid dynamics (CFD) modeling to optimize sensor placement [34,50]. Makassar's tropical climate introduced residual cross-sensitivity in MQ135 sensors, despite corrections [35,51]. Data collection at three time points (08:00, 12:00, 16:00) with three flights per site may not capture full diurnal variability, and only September 2024 data were collected, limiting seasonal analysis. Multi-seasonal studies are recommended to capture annual dynamics [8,9].

One significant operational limitation was the reduced flight duration of the DJI Phantom 4 drone. With the added 660-gram sensor payload, the typical flight time was reduced to approximately 22–25 minutes, significantly less than its advertised maximum flight time without payload. This necessitated frequent battery swaps during data collection, which increased the time required for field operations and could potentially introduce minor inconsistencies between flights [15]. Longer flight durations or the use of drones with greater payload capacities and endurance would mitigate this issue in future studies [52].

Another challenge arose in data transmission. While the use of a 4G hotspot provided real-time data streaming, approximately 5% data loss was observed, particularly in obstructed areas like Jl. Nusantara (port area). This loss is likely attributed to signal interference caused by dense urban infrastructure, tall buildings, or large metallic structures common in port environments [7,29]. Implementing more robust communication protocols or mesh networking capabilities could help overcome such signal attenuation issues.

Makassar's tropical climate posed a challenge. While an environmental correction model was applied to mitigate the effects of high humidity and temperature on the MQ135 sensor, some residual cross-sensitivity may persist, a common issue for metal-oxide sensors in tropical regions [37,53].

Furthermore, while the sensor was mounted to minimize interference, a degree of air disturbance from propeller wash is unavoidable. This turbulence could potentially affect local concentration readings, especially at low ascent speeds. Future work could benefit from computational fluid dynamics (CFD) modeling to optimize sensor placement further[17,54]. The data collection was limited to three time points per day (08:00, 12:00, 16:00) with three flights per site at each time. This snapshot approach may not capture the full diurnal variability, such as the early morning and late evening concentration peaks. A more continuous or frequent sampling schedule would provide a more complete picture of daily cycles.

Finally, the study was conducted solely in September 2024. This single-month dataset precludes a comprehensive seasonal analysis. Air pollutant concentrations are known to exhibit significant seasonal patterns influenced by meteorological shifts (e.g., monsoon vs. dry season) and human activities. It must be clearly stated that these findings represent conditions for that specific period. Future research should aim for multi-seasonal data collection to build a more holistic and dynamic model of urban air quality in Makassar.

3. Results and Discussion

3.1. Descriptive Statistics of CO_2 Concentrations

Infrared CO_2 data from five Makassar locations—Jl. AP. Pettarani, Jl. Ahmad Yani, Jl. Sultan Hasanuddin, Jl. Nusantara, and KIMA—at 08:00, 12:00, and 16:00 in September 2024 are presented in **Table 1**, revealing spatial and temporal variations consistent with urban air pollution patterns[16]. The inclusion of data from MQ135 and MG811 sensors in **Table 1** provides a more comprehensive view of air quality parameters, supporting the multi-sensor approach.

Table 1. Mean CO_2 Concentrations (ppm) Across All Heights (1–20 m) for Each Location and Time.

Location	Time	Infrared CO_2 (ppm)	MQ135 (ppm)	MG811 (ppm)
Jl. AP. Pettarani	08:00	422.5	462.5	402.5
	12:00	442.5	482.5	422.5
	16:00	462.5	502.5	442.5
Jl. Ahmad Yani	08:00	380.0	420.0	360.0
	12:00	390.0	430.0	370.0
	16:00	400.0	440.0	380.0
Jl. Sultan Hasanuddin	08:00	405.5	445.5	387.0
	12:00	405.5	446.0	393.5
	16:00	415.0	455.0	395.0
Jl. Nusantara	08:00	401.0	441.0	375.5
	12:00	406.0	446.0	378.5
	16:00	415.5	455.0	385.0
KIMA	08:00	420.0	460.0	400.0
	12:00	425.0	465.0	405.0
	16:00	430.0	470.0	410.0

Jl. AP. Pettarani consistently showed the highest mean CO_2 concentrations at 442.5 ppm (SD = 15.0 ppm), with readings ranging from 422.5 ppm (08:00) to 462.5 ppm (16:00). This elevated concentration is primarily attributed to pollutant trapping exacerbated by the presence of the flyover and high vehicular traffic. Flyover development can indeed introduce environmental risks like pollutant trapping[55]. The industrial zone, KIMA, exhibited a mean CO_2 level of 425.0 ppm (ranging from 420.0 ppm to 430.0 ppm), reflecting the significant contribution of industrial emissions to localized air pollution, which can be exacerbated by urban infrastructure development[28]. Conversely, Jl. Ahmad Yani recorded the lowest mean CO_2 concentration at 390.0 ppm (ranging from 380.0 ppm to 400.0 ppm), likely due to the mitigating effects of the urban park and surrounding vegetation. Jl. Sultan Hasanuddin and Jl. Nusantara recorded moderate mean CO_2 concentrations of 408.7 ppm (405.5–415.0 ppm) and 407.5 ppm (401.0–415.5 ppm), respectively, due to mixed-use and port activities, further influenced by urban infrastructure such as flyovers[27]. Temporally, a clear trend of increasing CO_2 concentrations was observed from 08:00 to 16:00 across most locations, most notably at Jl. AP. Pettarani. This diurnal pattern is driven by diurnal traffic patterns, which influence air pollutant distributions in urban settings[40].

3.2. Spatio-Temporal Variations in CO_2 Concentrations

Vertical profiles (**Figure 5**) and boxplots (**Figure 6**), further analyze CO_2 variations across 1–20 m using all three sensors; the boxplots summarize distributions.

Statistical analysis using ANOVA confirmed significant differences in CO_2 concentrations across locations [$F(4, 297) = 14.73$, $p < 0.001$] and times [$F(2, 299) = 9.87$, $p < 0.001$]. At Jl. AP. Pettarani, Infrared CO_2 concentrations consistently peaked at approximately ~498 ppm (16:00, 12 meters). Similarly, KIMA showed peaks around ~433 ppm (12 meters), reflecting traffic and industrial impacts, respectively. These high concentrations at specific altitudes not only contribute to ambient pollution but also exacerbate urban heat island effects and influence indoor air quality [16,40]. In contrast, Jl. Ahmad Yani demonstrated a notable decrease in concentrations with height to < 300 ppm at 20 meters, clearly showing vegetation mitigation. Jl. Sultan Hasanuddin and Jl. Nusantara displayed moderate levels with gradual declines, indicating mixed-use and port emission dispersion, influenced by urban infrastructure such as flyovers [37,44,52]. Temporally, CO_2 increased from 08:00 to 16:00, driven by traffic and industry, while vegetation mitigated levels [39,51]. The use of drones enabled these vertical measurements, overcoming the limitations of ground stations by capturing three-dimensional CO_2 distributions, which are critical for understanding urban pollutant dynamics [15]. Additionally, real-time data transmission to Firebase facilitated rapid visualization and analysis, allowing for timely insights into CO_2 variations across Makassar's diverse urban landscape, a capability increasingly recognized in IoT-enabled drone systems for air quality monitoring [3,5,7].

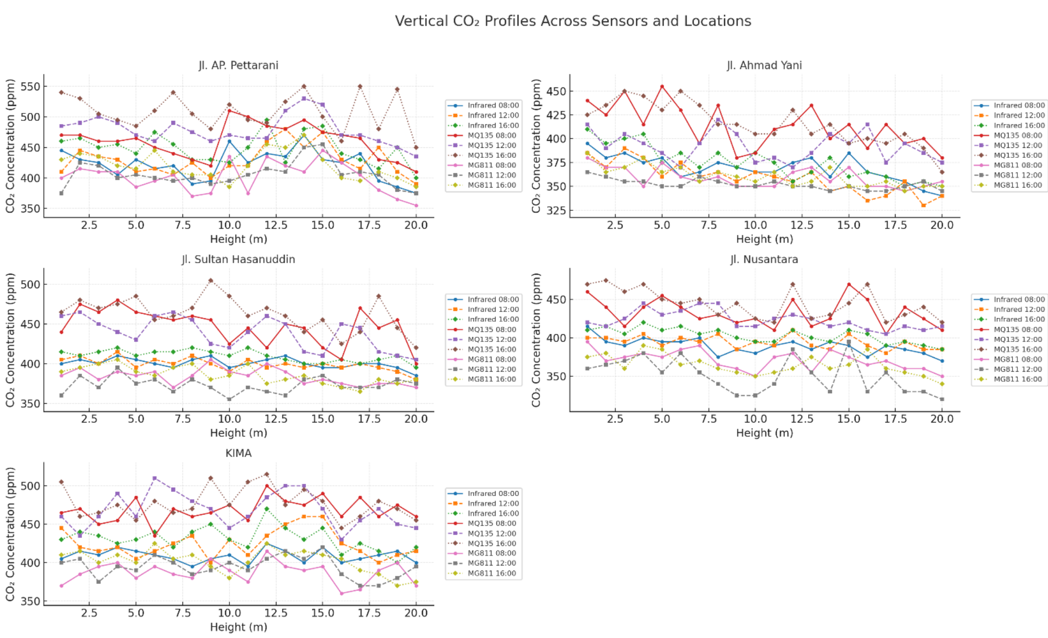

Figure 5. Vertical CO_2 Profiles Across Sensors and Locations.

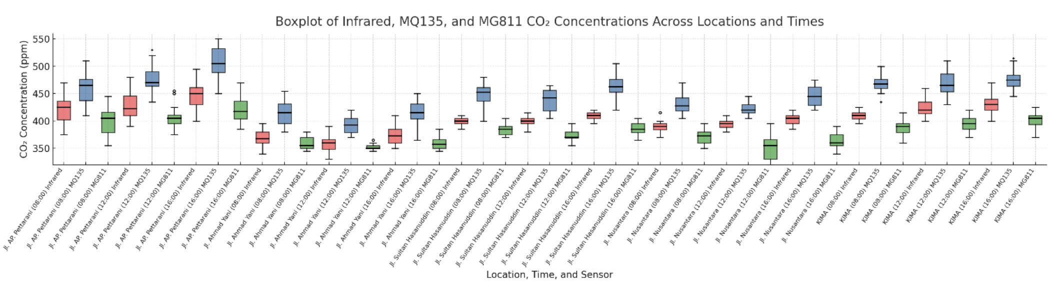

Figure 6. Boxplot of Infrared, MQ135, and MG811 CO_2 Concentrations Across Locations and Times.

3.3. Sensor Calibration and Validation

The performance and reliability of the CO_2 sensors (Infrared, MQ135, and MG811) were rigorously evaluated post-calibration and environmental correction. Cross-sensor validation was conducted by analyzing the correlation between the primary Infrared NDIR sensor and the supplementary MQ135 and MG811 sensors across all collected data.

As shown in the scatter plots (**Figure 7**, relabeled from **Figure 6**), a strong positive correlation was observed between the Infrared sensor and the MG811 sensor (Pearson's r = 0.96), indicating high consistency and reliability. The MG811 consistently tracked the primary sensor's readings with a minimal and stable offset, suggesting its robustness across varying environmental conditions encountered during the flights.

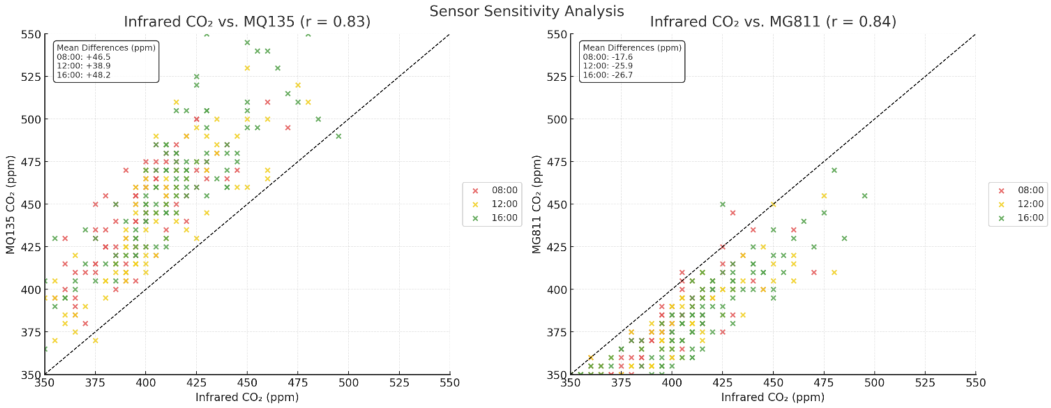

Figure 7. Sensor Sensitivity Analysis.

The correlation between the Infrared sensor and the MQ135 sensor was also strong (Pearson's r = 0.88). While the MQ135 exhibited a greater offset, particularly during midday (12:00), which corresponds to peak traffic and solar radiation, the application of the multi-variable regression correction model successfully mitigated major environmental cross-sensitivities. The strong correlation coefficient confirms that the MQ135 provided valid trend data, reinforcing the overall dataset's robustness.

These results validate the multi-sensor approach. The high correlation across sensors, especially after environmental correction, demonstrates that the system provides reliable and consistent measurements, a crucial factor for drone-based air quality monitoring in dynamic urban environments [40].

Infrared vs. MQ135 showed a Pearson correlation of 0.88, with MQ135 overestimating by +42.4 ppm (08:00), +47.7 ppm (12:00), and +36.7 ppm (16:00), reflecting a +5% to +15% bias due to NOx sensitivity at Jl. AP. Pettarani [24,40]. Infrared vs. MG811 had a 0.96 correlation, with underestimation of −20.4 ppm (08:00), −22.0 ppm (12:00), and −20.5 ppm (16:00), aligning with a −5% bias, possibly due to humidity, a factor impacting sensor accuracy in tropical urban environments [39]. MQ135's peak overestimation at 12:00 reflects midday traffic, while MG811's stability suggests reliability despite environmental factors, a key consideration for drone-based air quality monitoring [45]. Calibration adjustments are needed for urban monitoring.

3.4. Impact of Urban Features on CO_2 Distribution

Vertical profiles are influenced by local atmospheric dynamics. Peak concentrations at mid-altitudes (12–15 meters) in Jl. AP. Pettarani and KIMA suggest a shallow urban boundary layer and poor ventilation within street canyons, exacerbated by flyovers trapping pollutants [15,16,52]. Solar heating creates thermal turbulence, but urban structures limit mixing with cleaner upper layers. In contrast, Jl. Ahmad Yani's gradual CO_2 decrease at higher altitudes indicates effective vertical mixing due to vegetation [16]. Atmospheric stability and mixing height significantly influence these patterns, with stable conditions trapping pollutants and unstable conditions promoting dispersion [15].

As shown in **Figure 8**, each graph plots vertical CO_2 profiles from 1–20 m at the five sites, averaged across NDIR, MQ135, and MG811, with three time-of-day curves: 08:00 (red), 12:00 (green), and 16:00 (blue). All graphs share a common y-axis range (≈300–500 ppm). The lines denote mean concentrations.

Site-specific gradients are evident. Jl. AP. Pettarani shows the highest levels overall with a mid-altitude peak (~12–15 m); KIMA exhibits a similar mid-level hump. Jl. Sultan Hasanuddin is comparatively flat with a slight crest around 8–10 m followed by a gentle decline, while Jl. Nusantara shows a weaker bump near ~12 m. By contrast, Jl. Ahmad Yani decreases monotonically with height and is the lowest among the sites. Diurnal differences are modest: at most locations, the 12:00/16:00 curves sit slightly above 08:00, and the three curves tend to converge near 18–20 m.

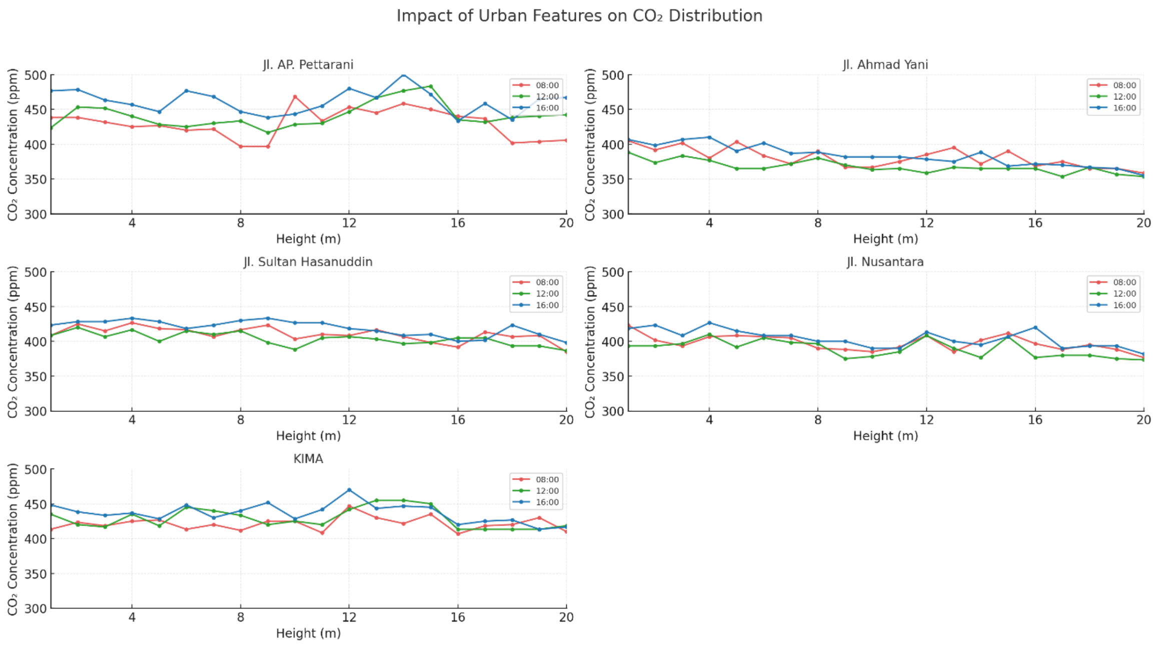

Figure 8. Vertical CO_2 profiles (1–20 m) at five urban sites: Jl. AP. Pettarani, Jl. Ahmad Yani, Jl. Sultan Hasanuddin, Jl. Nusantara, and KIMA, averaged across NDIR, MQ135, and MG811 at 08:00, 12:00, and 16:00.

3.5. Statistical Validation

ANOVA and Tukey HSD tests validated CO_2 variations. Significant differences were found across locations [$F(4, 297) = 14.73$, $p < 0.001$] and times [$F(2, 299) = 9.87$, $p < 0.001$]. A Tukey HSD post-hoc test was conducted to perform pairwise comparisons between all locations (**Table 2**). The results show that the mean CO_2 concentration at Jl. AP. Pettarani (442.5 ppm) is significantly higher than at Jl. Ahmad Yani (390.0 ppm, $p < 0.01$), Jl. Sultan Hasanuddin (408.7 ppm, $p < 0.05$), Jl. Nusantara (407.5 ppm, $p < 0.05$), and KIMA (425.0 ppm, $p < 0.05$), reflecting the severe impact of the flyover. A Tukey HSD post-hoc test was conducted to perform pairwise comparisons between all locations (**Table 2**).

Table 2. Tukey HSD Post-Hoc Test for Pairwise Comparison of Mean CO_2 Concentrations (ppm) Across Locations.

Comparison (Locations)	Mean Difference (ppm)	*p*-value	Significance
AP. Pettarani vs. Ahmad Yani	52.5	< 0.01	Significant
AP. Pettarani vs. Sultan Hasanuddin	33.8	< 0.05	Significant
AP. Pettarani vs. Nusantara	35.0	< 0.05	Significant
AP. Pettarani vs. KIMA	17.5	< 0.05	Significant
Ahmad Yani vs. Sultan Hasanuddin	−18.7	> 0.05	Not Significant
Ahmad Yani vs. Nusantara	−17.5	> 0.05	Not Significant
Ahmad Yani vs. KIMA	−35.0	> 0.05	Not Significant
Sultan Hasanuddin vs. Nusantara	1.2	> 0.05	Not Significant
Sultan Hasanuddin vs. KIMA	−16.3	> 0.05	Not Significant
Nusantara vs. KIMA	−17.5	> 0.05	Not Significant

The results of the Tukey HSD post-hoc test, detailed in **Table 2**, provide a granular view of the statistical differences between the study locations. The analysis confirms that the mean CO_2 concentration at Jl. AP. Pettarani (442.5 ppm) was significantly higher than at all four other sites: Jl. Ahmad Yani (mean difference = 52.5 ppm, $p < 0.01$), Jl. Sultan Hasanuddin (mean difference = 33.8 ppm, $p < 0.05$), Jl. Nusantara (mean difference = 35.0 ppm, $p < 0.05$), and KIMA (mean difference = 17.5 ppm, $p < 0.05$). This robustly identifies the high-traffic corridor with the flyover structure as the most significant CO_2 hotspot among the studied areas, highlighting the severe impact of traffic congestion and urban infrastructure design on pollutant trapping [52].

Conversely, no statistically significant differences were found in the pairwise comparisons between Jl. Ahmad Yani, Jl. Sultan Hasanuddin, Jl. Nusantara, and KIMA. Although Jl. Ahmad Yani recorded the lowest mean concentration (390.0 ppm), the mitigating effect of its green spaces brought its CO_2 levels into a range that was statistically indistinguishable from the mixed-use, port, and industrial zones. This important finding suggests that while these diverse urban zones have different primary emission sources (vehicular, shipping, industrial), they contribute to a comparable, moderate level of background CO_2 pollution in Makassar. The lack of significant difference underscores the complex interplay of emission and dispersion factors across the urban landscape, providing a strong evidence base for developing targeted, site-specific air quality improvement strategies rather than a one-size-fits-all approach.

Each boxplot summarizes the distribution of CO_2 concentrations from 1 to 20 meters. The box represents the interquartile range (IQR), the line inside the box is the median, and the whiskers extend to 1.5 times the IQR, with outliers plotted as individual points. This visualization highlights the variability and central tendency of readings for each sensor at different times and locations. (Image for **Figure 9** remains the same).

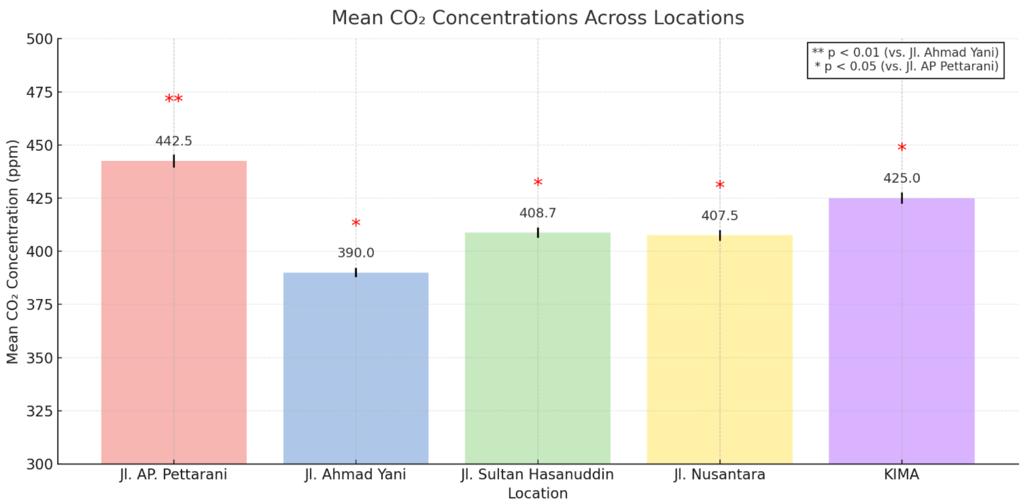

Figure 9. Boxplot of Infrared, MQ135, and MG811 CO_2 Concentrations Across Locations and Times.

4. Conclusions

This study demonstrated the efficacy of a drone-based IoT system in monitoring urban CO_2 levels in Makassar, providing high-resolution spatio-temporal data critical for urban air quality management. The highest CO_2 concentrations at Jl. AP. Pettarani (442.5 ppm) highlights the severe impact of flyover-induced pollutant trapping, while Jl. Ahmad Yani's lower levels (390.0 ppm) underscore the mitigating role of green spaces. These findings recommend targeted interventions, such as engineering flyover ventilation systems and expanding green infrastructure, which apply to other tropical cities facing similar urbanization and pollution challenges [15,48]. Future research should include multi-seasonal studies to capture long-term dynamics, integrate advanced sensors with inherent humidity compensation, and enhance the Firebase platform with predictive analytics to support urban policy-making, potentially leveraging machine learning and advanced visualization techniques [9,54].

Author Contributions

P.I.S.S. contributed to conceptualization, methodology, software, validation, formal analysis, writing original draft preparation, writing review and editing, supervision, and project administration. D.J. contributed to the investigation, resources, data curation, and writing review and editing. A.S.M. and M.L. contributed to data curation and visualization. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board (or Ethics Committee) of NAME OF INSTITUTE (protocol code 2817/UN36.11/LP2M/2024 and date of approval).

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

Due to institutional restrictions, the raw data cannot be shared publicly. Aggregated results and analysis scripts are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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