

Atmospheric fingerprints of urbanization: satellite-based detection of nitrogen dioxide, sulfur dioxide and carbon monoxide dynamics in a tropical highland city

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ABSTRACT

Rapidly growing medium-sized cities in the tropics may exhibit complex spatial patterns of combustion-related air pollutants while remaining poorly represented by conventional ground-based monitoring networks. This study characterizes nitrogen dioxide (NO₂), sulfur dioxide (SO₂), and carbon monoxide (CO) over Malang City, East Java, Indonesia, using Sentinel-5P TROPOMI observations for selected periods in 2021 and 2025. Tropospheric column densities were processed in Google Earth Engine and converted to estimated ambient concentrations using a mixing-height formulation. The estimates were classified according to the Indonesian air pollution standard index and compared with available ministry in situ observations and Copernicus Atmosphere Monitoring Service (CAMS) reanalysis using regression, root mean square error, and mean absolute error. City-mean concentrations were lower in the analysed 2025 periods than in 2021 for NO₂ (5.36 to 4.60 µg/m³) and CO (1.571 to 1.465 µg/m³). Because the two years were not sampled in the same months, each difference was recomputed across every possible month subset. Only the CO difference proved robust (−6.7%, envelope −7.3% to −6.1%); the NO₂ difference was robust in direction but not in magnitude (−24.9% to −3.5%); and the apparent SO₂ decrease reversed to an increase when restricted to the months common to both years (−60% to +34%) and is therefore not reported as a difference. Spatial patterns differed among pollutants: NO₂ maxima occurred along northern and western built-up corridors, SO₂ was higher near the eastern and southern industrial periphery, whereas CO was relatively homogeneous, with a coefficient of variation below 2%. Agreement with in situ observations was weak for NO₂ and absent for SO₂, with no satellite–reference correlation reaching statistical significance ($p \geq 0.09$) and every confidence interval on r spanning zero, indicating that satellite-derived concentrations are more appropriately interpreted as spatial screening estimates. The principal contribution is a multi-pollutant characterization of Malang as a tropical highland city with limited ground-based monitoring, revealing contrasting spatial signatures of NO₂, SO₂, and CO. These findings demonstrate the potential of satellite observations to complement sparse ground-based monitoring in data-limited tropical urban environments.

Keywords: air quality, atmospheric fingerprint, remote sensing, tropospheric monitoring instrument, urbanization.

INTRODUCTION

Cities leave a distinct chemical signature in the atmosphere that can be observed from space. The concentration of fossil-fuel use, industrial

activities, and daily human movement within relatively limited urban areas creates persistent patterns in the overlying troposphere. These patterns are influenced by several characteristics of cities, including street networks, the location of industrial

facilities, vegetation distribution, and daily commuting cycles. Understanding these atmospheric signatures is increasingly important because ambient air pollution remains one of the major environmental risk factors associated with premature mortality worldwide (Fuller et al., 2022; Lelieveld et al., 2015). Global assessments have estimated that outdoor particulate and gaseous pollutants contribute to millions of premature deaths each year through cardiovascular, respiratory, and metabolic pathways (Cohen et al., 2017). Epidemiological studies have further demonstrated that prolonged exposure to air pollution can increase mortality risk even when pollutant concentrations remain below existing regulatory limits (Chen and Hoek, 2020). In urban areas, exposure to nitrogen dioxide has also been associated with a considerable proportion of newly developed cases of paediatric asthma worldwide (Anenberg et al., 2022). Although natural processes, including lightning, soil microbial processes, volcanic emissions, and biomass burning, contribute to atmospheric trace gases, anthropogenic activities generally represent the dominant sources in cities. High population density and intensive mobility can further increase both emission levels and spatial differences in human exposure (Sicard et al., 2021; World Health Organization, 2021).

The relationship between urban development and atmospheric composition cannot, however, be explained simply by the size of a city. Research involving large numbers of urban areas indicates that population density, urban compactness, and income characteristics interact in complex ways and may produce contrasting effects on atmospheric pollution (Bechle et al., 2011; Borck and Schrauth, 2021). Emission inventories likewise indicate substantial differences among regions in the relative contributions of transportation, residential fuel use, energy production, and industrial activities, with these contributions changing considerably over the last two decades (Crippa et al., 2023). Consequently, relying on a single pollutant provides only a limited representation of an urban airshed. The three pollutants considered in this study provide complementary information because they respond differently to emission sources and atmospheric processes. Nitrogen dioxide (NO_2), which has a relatively short atmospheric lifetime of only a few hours, is particularly useful as a near-source indicator of combustion. Its concentrations can therefore change sharply along major road corridors and within densely developed urban areas

(Bodah et al., 2022). Carbon monoxide (CO), in contrast, has a longer atmospheric lifetime and is more effectively retained within the atmospheric column. It represents incomplete combustion associated with transportation, household fuel use, and open burning, while also reflecting the influence of regional atmospheric transport (Borsdorff et al., 2023; Landgraf et al., 2016). Sulfur dioxide (SO_2) is more strongly associated with specific point sources, including power plants, refineries, and heavy industrial facilities, resulting in an urban signal that is often weaker, more variable, and episodic (Fioletov et al., 2023; Kamiński et al., 2021). When considered together, these three pollutants provide a multi-species perspective that can be interpreted as an atmospheric fingerprint. Such an approach offers greater potential to distinguish transportation, residential, industrial, and transported contributions than simply describing the overall magnitude of urban pollution.

Obtaining this atmospheric fingerprint is challenging when relying exclusively on conventional ground-based monitoring. Reference monitoring stations provide accurate measurements with high temporal resolution and are essential for regulatory purposes, but their measurements generally represent only a limited surrounding area. In addition, monitoring networks are often sparse, with station locations determined primarily by administrative considerations rather than by the spatial distribution of population exposure. This limitation is particularly important in Indonesia, where regional assessments have identified uneven monitoring coverage, discontinuous observations, and substantial gaps in secondary and tertiary cities despite rapid urban development (Lukman et al., 2025). When measurements are available from only a small number of stations, spatial interpolation cannot adequately capture variations occurring within individual urban areas. Consequently, air quality assessments may become disproportionately influenced by the few locations where monitoring instruments are available. Under these circumstances, satellite remote sensing provides an important means of obtaining spatially continuous information that can support a more comprehensive and policy-relevant assessment of urban air quality.

The Copernicus Sentinel-5 Precursor mission, equipped with the Tropospheric Monitoring Instrument (TROPOMI), has substantially expanded the ability to observe atmospheric pollutants at regional and urban scales. TROPOMI is

a nadir-viewing imaging spectrometer operating across the ultraviolet, visible, near-infrared, and shortwave-infrared spectral regions. It provides daily global observations with substantially improved spatial sampling compared with earlier satellite sensors (Veefkind et al., 2012). The accuracy of its retrieval products has also improved through successive algorithm developments. For example, the version 2.2 NO₂ product addressed previously identified low biases over polluted areas and showed improved consistency with ground observations and measurements from earlier satellite missions (van Geffen et al., 2022). Shortwave-infrared observations have additionally demonstrated the ability to provide useful vertical information on CO for atmospheric data assimilation applications (Borsdorff et al., 2023). Meanwhile, TROPOMI observations have expanded the global identification of major SO₂ emission sources, including both anthropogenic and volcanic sources (Fioletov et al., 2023). Comparisons with regional chemical transport model ensembles have further supported the application of TROPOMI column measurements to air quality research while highlighting the remaining uncertainties associated with estimating surface concentrations from atmospheric columns (Douros et al., 2023). At the same time, cloud-based geospatial computing platforms have considerably reduced the computational demands associated with processing multi-year satellite archives at the city scale (Gorelick et al., 2017).

Recent studies demonstrate the growing application of satellite observations for urban air quality analysis, although the geographical distribution and methodological focus of this research remain uneven. Machine-learning approaches have increasingly been used to estimate surface pollutant concentrations from satellite-derived atmospheric columns, particularly in Europe and East Asia where dense ground-monitoring networks provide sufficient training data (Kang et al., 2021; Shetty et al., 2024). Research has also demonstrated that the performance of these models is sensitive to the spatial and temporal resolution of predictor variables, indicating that the selection of analytical scale can significantly influence the resulting estimates (Zhalehdoost and Taleai, 2025). Sentinel-5P observations have successfully captured rapid changes in atmospheric emissions, most notably the substantial reductions in NO₂ associated with mobility restrictions during the COVID-19 pandemic across Europe and China (Bauwens et al., 2020; Liu et

al., 2020). Similar activity-related patterns have been identified at city and port scales in Spain and Egypt, further demonstrating the relationship between changes in human mobility and atmospheric pollutant concentrations (Baldasano, 2020; Kaamouch et al., 2025). Beyond short-term emission perturbations, TROPOMI has also been applied to assess the environmental implications of NO₂ and CO in Brazilian cities and to predict pollution levels within industrial areas using multiple data sources (Bodah et al., 2022; Nakhjiri and Kakroodi, 2024). Its applications have also expanded to more specific pollution events and point sources, including refinery-related NO₂ monitoring in Vietnam and wildfire impact assessment using combinations of optical and atmospheric observations (Trinh et al., 2026; Yilgan et al., 2025). In Indonesia, an integrated assessment using ground observations, TROPOMI data, and atmospheric trajectory modelling in the Jabodetabek metropolitan region demonstrated the ability of satellite observations to identify pollution hotspots outside the existing monitoring network while also revealing the contribution of regional pollutant transport (Saputra et al., 2025). Furthermore, remote sensing studies incorporating air quality variables into composite environmental indices have shown that pollutant distributions can influence interpretations of urban ecological conditions beyond those based solely on vegetation and surface temperature (Wang et al., 2022).

Urban atmospheric conditions are also strongly influenced by the physical and ecological characteristics of the urban environment. This indicates that air pollution should be examined within a broader urban environmental framework rather than being interpreted exclusively in terms of emission sources. Land cover and land use affect surface energy exchange and boundary-layer processes, which subsequently influence land surface temperature and local precipitation patterns (Suharyanto et al., 2023). Satellite-based thermal observations have consequently been used to examine the relationship between urban expansion, increasing built-up areas, and thermal conditions across cities with different geological and coastal characteristics (Al-Rjoub et al., 2025). In Indonesia, a spatiotemporal assessment of land surface temperature and biomass in the new capital city of Nusantara found that open areas and dryland agriculture were associated with stronger thermal intensification, whereas forest and plantation areas exhibited relatively stable

thermal conditions. These findings highlight vegetation cover as an important factor controlling the physical urban climate (Rushayati et al., 2025). Urban expansion itself can also be modelled, allowing future development trajectories to be anticipated and potentially incorporated into planning strategies (Sidiq et al., 2024).

Vegetation has an additional and complex role in urban environmental conditions. Spectral vegetation indices have been shown to provide useful proxies for estimating carbon stocks and sequestration potential in urban environments (Andita and Hidayati, 2025; Sunaryo et al., 2026). Studies in rapidly urbanizing regions of Indonesia have also quantified the contribution of urban green spaces to pollution removal and carbon-related ecosystem services (Dewi et al., 2026). However, recent evidence suggests that the pollutant-removal capacity of vegetation may frequently be overestimated because its effectiveness depends strongly on species composition, canopy structure, and local atmospheric ventilation (Venter et al., 2024). The integration of diverse environmental datasets through accessible monitoring and analytical platforms has therefore been proposed as an important foundation for evidence-based environmental management (Bernatska et al., 2023). Consequently, spatial variations in pollutant concentrations should be interpreted in relation to the coupled physical and ecological characteristics of urban areas rather than being attributed solely to emission intensity.

Malang City represents an important but relatively underexplored case for this type of analysis. As the second-largest city in East Java, Malang has a long historical development associated with the Kanjuruhan Kingdom and has subsequently developed into an important national centre for higher education and tourism. These functions have contributed to continued residential development, expansion of commercial and service activities, and a substantial student population whose presence varies seasonally. Together, these characteristics increase transportation demand within a geographically constrained highland basin. Such physical conditions may promote pollutant accumulation during periods of atmospheric stability, potentially reinforcing pollution patterns generated by local emissions. Despite these characteristics, continuous reference monitoring within the city remains limited. Air quality is generally assessed using the national Air Pollution Standard Index framework, but the relatively sparse observations make it difficult to identify

variations at the neighbourhood scale (Ministry of Environment and Forestry of the Republic of Indonesia, 2020). Malang therefore represents a broader category of rapidly developing medium-sized tropical cities where urban growth is substantial, monitoring infrastructure remains limited, and spatially detailed evidence for targeted environmental policies is still insufficient.

MATERIAL AND METHODS

Study area

This study was conducted in Malang City, East Java Province, Indonesia, a highland urban area located at approximately 440–667 m above sea level. The city is situated at approximately 112.55°–112.67° E and 7.92°–8.03° S and comprises five administrative districts and 57 urban villages. Malang City is characterized by predominantly undulating and hilly terrain and is surrounded by Singosari and Karangploso to the north, Pakis and Tumpang to the east, Tajinan and Pakisaji to the south, and Wagir and Dau to the west.

The interaction between urban development, transportation activity, land-use change, and the surrounding peri-urban area makes Malang City a relevant case for examining atmospheric pollutant distributions. However, because this study does not incorporate an emission inventory, atmospheric dispersion modelling, or inverse modelling, spatial pollutant patterns were interpreted as spatial associations rather than direct evidence of specific emission sources. The study area is shown in Figure 1.

Data sources and Sentinel-5P/TROPOMI processing

This study integrated Sentinel-5P/TROPOMI observations, administrative spatial data, ground-based observations from the Ministry of Environment and Forestry of Indonesia (KLHK), and Copernicus Atmosphere Monitoring Service (CAMS) data. TROPOMI observations of nitrogen dioxide (NO₂), sulfur dioxide (SO₂), and carbon monoxide (CO) were used as the primary spatial dataset. KLHK observations were used as the principal ground-based reference, whereas CAMS data were analysed separately as a model/reanalysis reference. The Sentinel-5P/TROPOMI

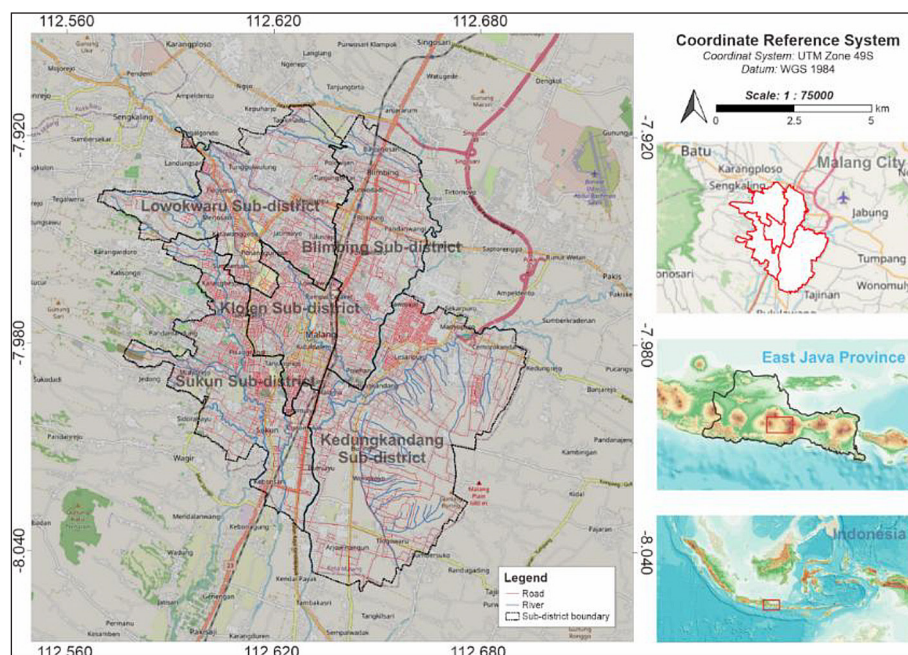


Figure 1. Study area: Malang City, East Java, Indonesia

observations were obtained through Google Earth Engine (GEE) using the Offline (OFFL) Level-3 collections. The pollutant datasets and bands used are summarized in Table 1. The analysis covered observations on 1 January, 9 June, and 18 August 2021, and 8 January, 11 March, 5 June, and 2 July 2025. The two years were therefore not sampled in the same calendar months, and January and June are the only months common to both. This asymmetry is treated as a first-order confounder of any between-period comparison and is quantified in the sensitivity analysis. The Level-3 products have a nominal GEE grid spacing of approximately 1.1 km, whereas the effective TROPOMI observation footprint is substantially coarser. Therefore, TROPOMI observations were treated as spatially integrated atmospheric information rather than point-scale measurements.

The GEE preprocessing consisted of pollutant-specific band selection, masking of invalid or missing observations, clipping to the Malang City administrative boundary obtained from Ina-Geoportal, and temporal aggregation. Quality screening is applied upstream rather than by the present

workflow. The Earth Engine OFFL Level-3 collections are generated from the ESA Level-2 products with harpconvert using a validity filter (tropospheric_NO2_column_number_density_validity > 50, SO2_column_number_density_validity > 50, CO_column_number_density_validity > 50), corresponding to a qa_value threshold of 0.75 for the tropospheric NO₂ band and 0.50 for SO₂ and CO. The gridded Level-3 images consequently do not carry a per-pixel qa_value band, and no additional user-side masking is applied or possible. Our earlier description of applying these thresholds within the processing chain is corrected here: the screening is a property of the product, not of our script.

Additional product-level validity criteria were respected rather than replacing them with arbitrary zero-value substitution. In particular, negative SO₂ column values were retained when they met the product validity criteria, whereas values below $-0.001 \text{ mol m}^{-2}$ were excluded as invalid or anomalous retrievals. The OFFL SO₂ Level-3 product also incorporates screening related to cloud fraction, solar zenith angle, snow/ice, and

Table 1. Sentinel-5P/TROPOMI datasets and bands used in GEE

Pollutant	GEE Dataset ID	Band used	Unit
NO ₂	COPERNICUS/S5P/OFFL/L3_NO2	tropospheric_NO2_column_number_density	mol/m ²
SO ₂	COPERNICUS/S5P/OFFL/L3_SO2	SO2_column_number_density	mol/m ²
CO	COPERNICUS/S5P/OFFL/L3_CO	CO_column_number_density	mol/m ²

the sulfur dioxide air-mass-factor conditions during product generation. For each analysis period, the valid observations were aggregated using the arithmetic temporal mean:

$$\bar{C}_t(x, y) = \frac{1}{n_t(x, y)} \sum_{i=1}^{n_t(x, y)} C_i(x, y) \quad (1)$$

where: $\bar{C}_t(x, y)$ – the mean pollutant value at location (x, y) , $C_i(x, y)$ – an individual valid observation, $n_t(x, y)$ – the number of valid observations contributing to the mean.

The number of valid observations was retained as a quality indicator.

Column density to concentration conversion

TROPOMI provides vertically integrated atmospheric column quantities rather than direct near-surface concentrations. Therefore, the retrieved values in mol/m² cannot be directly compared with ground-level concentrations in µg/m³. To facilitate spatial screening and comparison with the Indonesian air pollution standard index (ISPU), the column number density was converted to an estimated concentration using an effective atmospheric mixing height. The conversion was performed as:

$$C = \frac{C_s \times M \times 10^6}{H} \quad (2)$$

where: C – the final concentration (µg/m³),
 C_s – satellite column value (mol/m²),
 M – molecular mass of gas (g/mol),
 H – atmospheric mixing height (m).

The molecular masses used were 46.0055 g/mol for NO₂, 64.0638 g/mol for SO₂, and 28.0101 g/mol for CO. The effective atmospheric depth used for the column-to-volume conversion was set to 164 m for NO₂, 13 km for SO₂, and 6 km for CO. The value of 164 m for NO₂ was adopted from published literature (Yang et al., 2023; Grzybowski et al., 2023) as a representative planetary boundary layer height. It was not extracted from the ERA5 reanalysis for Malang City; no ERA5 retrieval was performed for this study, and our previous wording, which implied a local extraction, is corrected here. Because the value originates from studies conducted elsewhere and is shallow for a 13:30 local-time overpass in the tropics, it is treated as an adopted convention rather than a measured local quantity. Of

the three, only the NO₂ depth has a physical rationale: tropospheric NO₂ has a lifetime of hours and is genuinely confined to the boundary layer, so a PBLH-scaled depth is a coherent, if crude, surface estimate. The 13 km used for SO₂ derives from the volcanic-plume profile assumptions of the Sentinel-5P SO₂ retrieval, and the 6 km used for CO from the reported lower bound of the upper-troposphere CO distribution. Neither was derived for an urban anthropogenic column over a city such as Malang, and we no longer present them as physically justified depths. They are retained as explicit scaling conventions so that the values remain comparable with the earlier version of this analysis, and the consequences of that choice are quantified in the sensitivity analysis rather than assumed to be small. For CO in particular, the retrieved quantity is a total column whose weeks-to-months lifetime means most of it reflects regional and hemispheric background rather than local emissions; dividing it by any single depth yields a layer-averaged quantity and not a surface concentration. These pollutant-specific effective heights were applied consistently to the 2021 and 2025 observations. For carbon monoxide the full transformation chain is stated explicitly to remove any ambiguity. The conversion factor is $F = (M_{CO} \times 10^6)/H = (28.0101 \times 10^6)/6000 = 4668.35 \text{ µg m}^{-3} \text{ per mol m}^{-2}$, and a worked example is: $X = 0.0257 \text{ mol m}^{-2} \rightarrow M = 28.0101 \text{ g mol}^{-1} \rightarrow H = 6000 \text{ m} \rightarrow F = 4668.35 \rightarrow C \approx 120 \text{ µg m}^{-3}$. Two points follow that we state plainly rather than leave to inference. First, adopting $H = 6000 \text{ m}$ does not reconcile the satellite estimate with the reanalysis: at this depth the ratio of mean TROPOMI-derived to mean CAMS CO is approximately 0.28, not unity. The ratio of about 10 arises at $H = 164 \text{ m}$, not at 6000 m, and no depth makes the two quantities equivalent. Second, and more importantly, the quantity obtained at $H = 6000 \text{ m}$ is not a surface concentration. It is a column-averaged CO concentration over an assumed 6 km atmospheric layer, and it is referred to as such throughout this paper.

The conversion assumes that the retrieved pollutant column is distributed within the corresponding effective atmospheric layer. Accordingly, the resulting values represent estimated column-to-volume-equivalent concentrations rather than direct measurements of near-surface ambient concentrations. They were therefore used for spatial screening and ISPU-based classification,

while ground-based KLHK measurements were retained as the reference observations.

A sensitivity analysis was conducted by varying the effective atmospheric depth around the baseline values of 164 m for NO₂, 13 km for SO₂, and 6 km for CO to quantify the influence of the assumed vertical distribution on the estimated concentrations and resulting ISPU classifications. Eight depths were tested per pollutant, spanning boundary-layer to free-tropospheric scales, and the full propagated effect on concentrations, spatial gradients, regression statistics, error metrics and index categories is reported in Table 19. A separate diagnostic examined the depth that would be required to reconcile the satellite estimates with each reference dataset. It should also be noted that the ERA5 PBLH value of 164 m is shallow for a 13:30 local-time overpass in the tropics, where the convective boundary layer typically reaches several hundred metres or more; the extraction rule for this value is documented in the supplementary provenance table, and all NO₂ concentrations scale inversely with it.

ISPU calculation and classification

The Indonesian Air Pollution Standard Index (Indeks Standar Pencemar Udara; ISPU) was calculated separately for NO₂, SO₂, and CO using the estimated concentrations. The calculation followed Regulation of the Minister of Environment and Forestry of the Republic of Indonesia No. 14 of 2020. For a pollutant concentration (X_x) located between two consecutive concentration breakpoints, the ISPU was calculated using linear interpolation:

$$I = \frac{(I_a - I_b)}{(X_a - X_b)} \cdot (X_x - X_b) + I_b \quad (3)$$

where: I – air pollution standard index (ISPU), X_x – observed pollutant concentration ($\mu\text{g}/\text{m}^3$), X_a , X_b – upper and lower concentration breakpoints, I_a , I_b – corresponding upper and lower index values.

The interpolation was implemented using raster calculations in GIS. The resulting ISPU values were classified into five categories according to the national regulation, as summarized in Table 2.

Because the ISPU input concentrations were derived from satellite column observations using a mixing-height assumption, the resulting ISPU maps were interpreted as spatial screening

Table 2. Indonesian air pollution standard index categories

Category	Color status	ISPU range
Good	Green	1–50
Moderate	Blue	51–100
Unhealthy	Yellow	101–200
Very Unhealthy	Red	201–300
Hazardous	Black	≥ 301

products rather than direct regulatory measurements of ground-level air quality.

Ground-based and CAMS validation

Ground-based NO₂, SO₂, and CO measurements obtained from the Ministry of Environment and Forestry (KLHK) were used as the primary reference for evaluating the satellite-derived estimates. The validation dataset contained the pollutant species, measured concentration, observation date and time, geographic coordinates, measurement unit, measurement method or instrument, and available QA/QC information. CAMS data were evaluated separately as atmospheric model/reanalysis reference data and were not treated as independent ground truth. This distinction is particularly important for CO because the available CAMS observations represented a limited number of dates and were therefore not considered independent spatial observations. A provenance limitation must be recorded for the CAMS comparison. The originating documentation identifies the provider as CAMS but does not record which CAMS product was used, the variable name and vertical level, the native unit prior to conversion, the extraction hour, or the download date. These fields could not be recovered, and we decline to supply values that a reader could not verify against the Atmosphere Data Store. The satellite–CAMS comparison for CO is therefore reported as not independently reproducible, and is presented as an indication of scale rather than as validation. No conclusion in this paper rests upon it.

Temporal matching between Sentinel-5P/TROPOMI and KLHK observations was performed at the level of the calendar date. Matching to the closest valid TROPOMI overpass within ± 3 h was the intended procedure, but the ground-based records available to this study did not retain the clock time of each measurement, so the time difference between each ground observation and

the corresponding overpass cannot be computed or verified. The ± 3 h criterion is therefore reported as a recommendation for future work rather than as a procedure applied to the present dataset, and the resulting temporal mismatch is carried through as a source of uncertainty. Spatial matching accounted for the substantially larger spatial footprint of TROPOMI relative to individual ground-based monitoring sites. The primary satellite-derived value was extracted from the TROPOMI pixel containing the geographic coordinates of the corresponding KLHK monitoring location, while the mean value of a 3×3 pixel window centered on the monitoring location was additionally evaluated to assess the effect of spatial representativeness. Because the effective footprint is approximately 5.5×3.5 km, several monitoring locations fall within the same TROPOMI pixel, so the number of spatially independent satellite values is smaller than the number of sites.

The matched satellite and ground-based observations were subsequently compared using statistical performance metrics, including the coefficient of determination (R^2), Pearson correlation coefficient (r), root mean square error (RMSE), mean absolute error (MAE), and mean bias error (MBE). These metrics were calculated separately for NO_2 , SO_2 , and CO to evaluate the consistency between satellite-derived estimates and ground-based measurements. CAMS-derived values were analyzed separately to provide an additional model-based reference and were not combined with the KLHK observations in the primary validation statistics.

Statistical, uncertainty, and sensitivity analysis

Agreement between satellite-derived estimates and reference observations was evaluated using ordinary least squares regression, coefficient of determination (R^2), Pearson correlation coefficient (r), root mean square error (RMSE), mean absolute error (MAE), and mean signed difference (MSD). The coefficient of determination was calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (4)$$

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (5)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (6)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \quad (7)$$

$$\text{MSD} = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i) \quad (8)$$

where: x_i represents the satellite-derived values, y_i represents the reference observations, $\hat{y}_i$ represents the corresponding fitted values from the regression, $\bar{x}$ and $\bar{y}$ represent their respective means. RMSE and MAE were reported jointly because RMSE is more sensitive to large residuals, whereas MAE assigns equal weight to individual absolute residuals. MSD was used to identify systematic overestimation or underestimation.

The number of matched records was distinguished from the number of statistically independent observations. When multiple monitoring locations shared the same date-level reference value, such observations were not treated as independent evidence. Validation was therefore evaluated at both point and date levels where applicable. For CO, particular emphasis was placed on date-level analysis because the CAMS reference dataset consisted of a limited number of independent dates. Direct inspection of the reference data confirmed that the CAMS CO field takes a single value at all sampling locations on each date, so the effective number of independent CO observations is three in 2021 and four in 2025 rather than nine and twenty-three. Confidence intervals were computed for all reported metrics: Fisher z-transformation intervals for the correlation coefficient, and bias-corrected bootstrap intervals with 5 000 resamples for RMSE and MAE. Statistical significance is reported alongside each correlation so that weak relationships are not described as detected effects. Uncertainty was assessed by considering satellite retrieval variability, effective atmospheric depth assumptions, spatial representativeness, temporal mismatch, and meteorological variability. Sensitivity analyses evaluated the influence of the assumed effective atmospheric depths of 164 m for NO_2 , 13 km for SO_2 , and 6 km for CO, together with alternative temporal matching windows, spatial extraction methods, and minimum valid-observation criteria.

Meteorological considerations and spatial interpretation

Meteorological conditions were considered when interpreting differences between the 2021 and 2025 observation periods because pollutant

concentrations are influenced by atmospheric transport, dispersion, and vertical mixing. Precipitation, wind speed and direction, air temperature, and atmospheric mixing conditions were examined for the corresponding observation dates. The effective atmospheric depths used in the column-to-volume conversion were 164 m for NO₂, 13 km for SO₂, and 6 km for CO. These parameters were considered when interpreting differences in the estimated pollutant concentrations between the two analysed periods.

Because the analysis covered only selected months or observation periods rather than a continuous multi-year record, differences between 2021 and 2025 were interpreted as differences between the analysed periods rather than as evidence of an established long-term decline or trend. The potential influence of meteorological variability was assessed by comparing pollutant differences with variations in precipitation, wind conditions, air temperature, and atmospheric mixing. Sensitivity analyses were used to determine whether the direction and magnitude of the observed differences were substantially affected by alternative temporal aggregation, spatial extraction, and atmospheric-depth assumptions. Therefore, the observed inter-period differences were interpreted cautiously and were not attributed solely to changes in anthropogenic emissions.

The spatial distributions of NO₂, SO₂, and CO were examined jointly to identify recurring spatial patterns and areas of relatively elevated or reduced pollutant concentrations. Elevated pollutant areas were interpreted as spatial patterns consistent with potential influences from transportation, urban activities, industrial activity, biomass burning, or regional atmospheric transport,

rather than as direct evidence of individual emission sources. No specific emission source was considered demonstrated because the study did not incorporate an emission inventory, traffic-volume data, industrial emission measurements, fire-hotspot analysis, chemical transport modelling, or inverse modelling. Independent spatial datasets, where available, were used only as supporting evidence for spatial consistency. Independent spatial datasets, where available, were used only as supporting evidence for spatial consistency.

RESULT AND DISCUSSION

Nitrogen dioxide (NO₂) analysis and spatial distribution

Nitrogen dioxide was analysed first because its short atmospheric lifetime makes it a relatively short atmospheric lifetime of near-field combustion and its retrieval algorithm has undergone extensive validation (van Geffen et al., 2022). Sentinel-5P concentrations were classified using the national index and mapped for each observation month in both years.

In January 2021, concentrations ranged from 0.872–6.451 $\mu\text{g m}^{-3}$, with higher values in the northern and western sectors and lower values in the east and south. Concentrations increased in June (5.540–9.854 $\mu\text{g m}^{-3}$), with the northern and western dominance becoming more pronounced, before declining in August (3.466–6.033 $\mu\text{g m}^{-3}$), while elevated values persisted in western and central areas. The recurring northwestern maximum corresponds to the Blimbing and Lokowaru arterial corridors and areas with dense

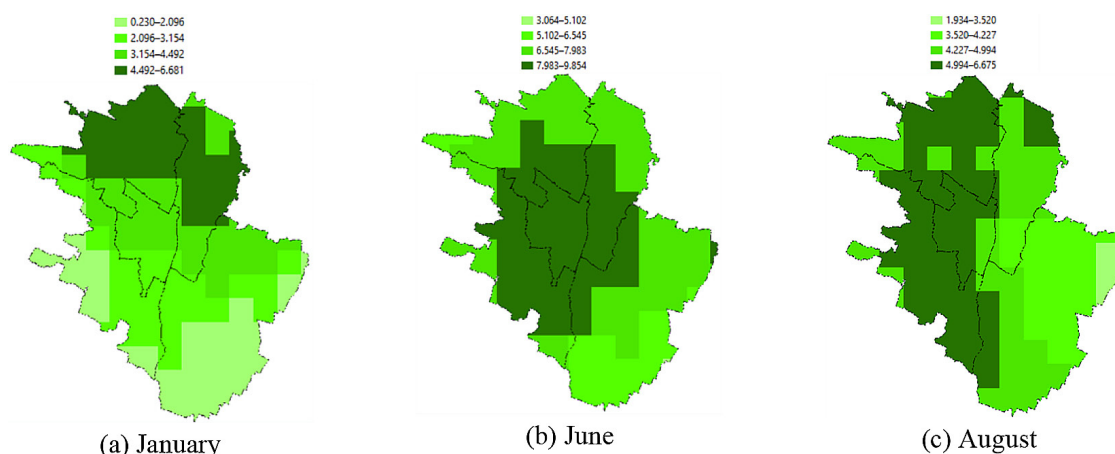


Figure 2. Classified distribution of nitrogen dioxide over Malang City in 2021

educational institutions and student housing. This spatial alignment with major transport axes is consistent with the short atmospheric lifetime of NO₂, which limits substantial redistribution from emission sources (Bodah et al., 2022). Figure 2 shows classified distribution of nitrogen dioxide over Malang City in 2021.

The corresponding 2025 distributions are shown in Figure 3. January concentrations ranged from 1.991–5.442 $\mu\text{g m}^{-3}$, with maxima in the central and eastern sectors. In March, values ranged from 2.605–6.092 $\mu\text{g m}^{-3}$, with a return to northern and western dominance, while June concentrations of 4.377–6.489 $\mu\text{g m}^{-3}$ were concentrated in western and central areas. July recorded the widest range (2.519–7.357 $\mu\text{g m}^{-3}$), with elevated values extending from the north into the centre. Compared with 2021, the 2025 fields were lower overall and showed greater spatial variability in their maxima, indicating a more diffuse and mobile source pattern rather than fixed emission points.

Table 3 summarizes the area within each concentration interval. In January 2021, the largest area (28.40 km²) occurred within 3.154–4.492 $\mu\text{g m}^{-3}$, while in June the modal interval shifted to 7.983–9.854 $\mu\text{g m}^{-3}$, covering 49.93 km². A similar seasonal shift occurred in 2025 but at lower concentrations, with the June modal interval of 5.035–6.489 $\mu\text{g m}^{-3}$ covering 84.22 km², approximately three-quarters of the city. This concentration of a large area within a narrow interval indicates greater spatial homogeneity in June 2025, providing an important diagnostic feature. Table 4 compares monthly and annual means. The city-wide mean decreased from 5.36 $\mu\text{g m}^{-3}$ in 2021 to 4.60 $\mu\text{g m}^{-3}$ in 2025, a reduction of 0.76 $\mu\text{g m}^{-3}$. This corresponds to –14.2% as sampled, but because the two years cover different months the figure is not a stable property of the city: recomputing it across every possible month subset gives an envelope of –24.9% to –3.5%, and a wet-season-only comparison reverses the sign (Table 20).

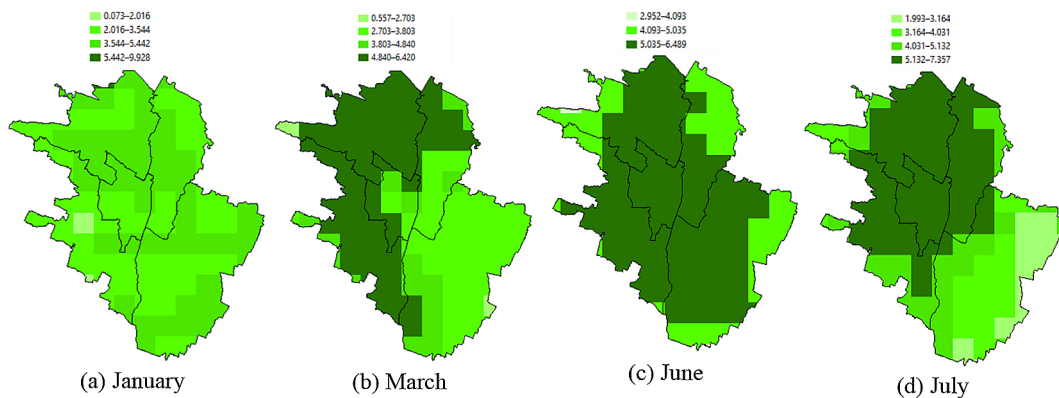


Figure 3. Classified distribution of nitrogen dioxide over Malang City in 2025

Table 3. Area of Malang City occupied by each nitrogen dioxide concentration interval

Year	Period	Concentration intervals in $\mu\text{g m}^{-3}$, with the corresponding area in km ² in parentheses
2021	January	0.230–2.096 (26.70); 2.096–3.154 (28.20); 3.154–4.492 (28.40); 4.492–6.681 (27.78)
	June	3.064–5.102 (0.04); 5.102–6.545 (14.51); 6.545–7.983 (46.60); 7.983–9.854 (49.93)
	August	1.934–3.520 (2.76); 3.520–4.227 (21.55); 4.227–4.994 (35.30); 4.994–6.675 (51.47)
2025	January	0.073–2.016 (1.43); 2.016–3.544 (53.16); 3.544–5.442 (56.28); 5.442–9.928 (0.20)
	March	0.557–2.703 (1.22); 2.703–3.803 (38.53); 3.803–4.840 (14.62); 4.840–6.420 (56.70)
	June	2.952–4.093 (0.31); 4.093–5.035 (26.55); 5.035–6.489 (84.22)
	July	1.993–3.164 (9.79); 3.164–4.031 (18.60); 4.031–5.132 (22.96); 5.132–7.357 (59.73)

Table 4. Monthly and annual mean nitrogen dioxide concentrations derived from Sentinel-5P

Year	January	March	June	July	August	Annual mean	Index category
2021	3.66	–	7.70	–	4.75	5.36	Good (1–50)
2025	3.72	4.35	5.43	4.94	–	4.60	Good (1–50)

The direction of the difference is therefore robust while its magnitude is not, and the specific value is not carried into the interpretation. The seasonal pattern persisted, with June maxima of 7.70 and 5.43 $\mu\text{g m}^{-3}$ and January minima of 3.66 and 3.72 $\mu\text{g m}^{-3}$, while seasonal amplitude contracted from 4.04 to 1.71 $\mu\text{g m}^{-3}$. The persistent mid-year maximum is consistent with the regional dry season, when reduced wet deposition, lower cloud cover, and open burning favour higher retrieved concentrations. The low January 2021 value also coincided with large-scale social restrictions in Java, providing a suppressed baseline against which the June increase should be interpreted (Bauwens et al., 2020; Liu et al., 2020).

The reference network in Figure 4 and Table 5 comprised one ministry monitoring station and four sampling points in 2021, yielding nine paired observations. In 2025, it expanded to twelve sampling points across residential, commercial, industrial, civic, and transport-terminal environments, producing twenty-three paired observations. Five sites were common to both years, enabling limited site-level comparison. Paired concentrations for nitrogen dioxide are given in Table 6.

In 2021, satellite estimates were lower than ground measurements at eight of nine locations, with differences of 2–13 $\mu\text{g m}^{-3}$ and a mean signed difference of $-6.80 \mu\text{g m}^{-3}$. In 2025, the bias decreased to $-2.33 \mu\text{g m}^{-3}$, although satellite

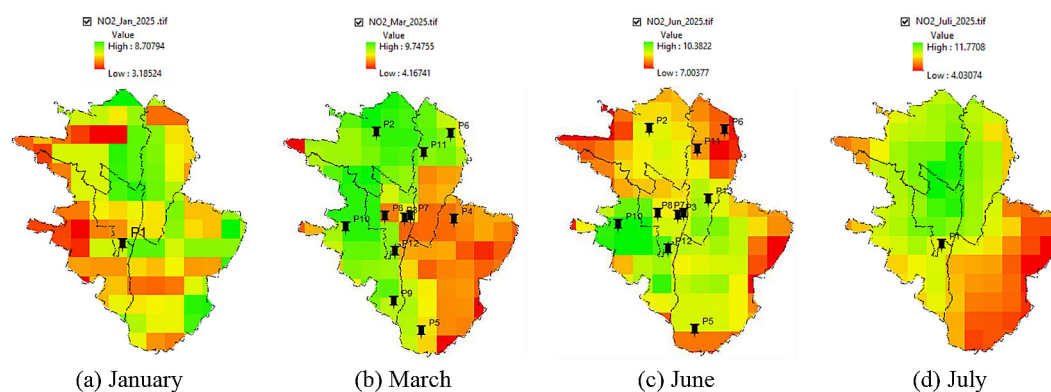


Figure 4. Configuration of the NO₂ reference sampling network across Malang City in 2025

Table 5. Register of reference sampling sites

Site	Location	Longitude (°)	Latitude (°)	Setting	Code 2021	Code 2025
P1	Ministry monitoring station, Jalan Halmahera, Ciptomulyo, Sukun	112.6286	-7.9926	Roadside, mixed residential	P1	P1
P2	Malang City Hall, Jalan Tugu No. 1	112.6342	-7.9774	Urban core, civic	P2	–
P3	Sampoerna, Jalan Industri Barat, Blimbing	112.6428	-7.9442	Industrial	P3	P11
P4	Araya, Polowijen, Blimbing	112.6545	-7.9351	Residential, industrial edge	P4	P6
P5	Integrated Block Office, Arjowinangun, Kedungkandang	112.6421	-8.0353	Civic, peri-urban	P5	P5
P6	Permata Jingga estate, Tunggulwulung, Lowokwaru	112.6186	-7.9329	Residential	–	P2
P7	Mini Block Office, Jalan Majapahit, Klojen	112.6336	-7.9785	Commercial, civic	–	P3
P8	Sawojajar estate, Jalan Danau Toba, Kedungkandang	112.6597	-7.9793	Residential	–	P4
P9	East of City Hall, Jalan Kertanegara	112.6367	-7.9776	Urban core	–	P7
P10	Malang Olympic Garden, Jalan Kawi, Klojen	112.6232	-7.9775	Commercial	–	P8
P11	Gadang terminal junction, Jalan Kolonel Sugiono, Sukun	112.6278	-8.0227	Transport terminal	–	P9
P12	Gandum industrial site, Jalan Raya Bandulan, Sukun	112.6025	-7.9833	Industrial	–	P10
P13	Leather and tobacco industrial area, Jalan Susanto	112.6283	-7.9961	Industrial	–	P12
P14	Jalan Mayjen Wiyono	112.6495	-7.9699	Arterial road	–	P13

estimates exceeded ground measurements at seven locations. This discrepancy likely reflects three factors. First, Sentinel-5P overpasses the study area at approximately 13:30 local solar time, after the morning traffic peak, when photochemical loss and boundary-layer mixing have reduced near-surface NO₂. Second, ground instruments measure point concentrations at breathing height, whereas satellite retrievals represent tropospheric column concentrations rescaled to surface values; therefore, the two measurements are not directly equivalent (Douros et al., 2023). Third, the coarse spatial resolution ($\sim 5.5 \times 3.5$ km) averages heterogeneous urban environments within each pixel, creating a scale mismatch between localized ground measurements and satellite estimates (Zhalehdooost and Taleai, 2025). This spatial mismatch can substantially affect satellite–ground agreement.

Regression relationships and error metrics are summarized in Table 7 and Figure 5. Ground and satellite NO₂ values showed weak positive relationships, with R² increasing from 0.061 in 2021 to 0.128 in 2025. Neither relationship is statistically significant ($p = 0.52$ and $p = 0.09$), and the 95% confidence intervals on r span zero in both years (-0.50 to 0.78 and -0.06 to 0.67 ; Table 21). The correct reading is therefore that no significant association between the satellite estimates and the

in situ measurements was detected, rather than that a weak association was measured. Regression slopes of 0.155 and 0.240 indicate substantial dynamic-range compression, consistent with spatial averaging over satellite footprints larger than roadside concentration gradients. Thus, Sentinel-5P NO₂ is better interpreted as a district-scale indicator than a substitute for point measurements.

Error metrics decreased between the two periods, with RMSE falling from 8.31 to 4.64 $\mu\text{g m}^{-3}$ and MAE from 7.14 to 3.87 $\mu\text{g m}^{-3}$. These reductions are not statistically distinguishable: the bootstrap 95% intervals overlap substantially for both metrics (RMSE 5.73–10.40 against 3.44–5.75; MAE 4.42–9.89 against 2.88–4.94; Table 21). They are also confounded by the change in reference network, which expanded from five to thirteen locations between the two years, so the 2021 and 2025 error statistics are not computed over comparable samples. The apparent improvement is therefore not interpreted as evidence of better retrieval performance. The stable RMSE/MAE ratio (1.16–1.20) indicates that the change was not driven by removal of extreme outliers but by a reduced systematic offset (Hodson, 2022). The mean signed difference relative to MAE also fell from 82% to 60% between the analysed periods, indicating less one-sided residuals as the

Table 6. Paired in situ and Sentinel-5P nitrogen dioxide concentrations by site and observation date

Site	1 Jan 2021	9 Jun 2021	18 Aug 2021	8 Jan 2025	11 Mar 2025	5 Jun 2025	2 Jul 2025
P1	18.07 / 5.10	–	–	18.30 / 11.10	–	–	17.20 / 6.87
P2	–	20.57 / 12.30	19.00 / 7.34	–	–	–	–
P3	–	15.65 / 10.00	16.24 / 5.69	–	7.63 / 9.60	12.42 / 8.49	–
P4	–	14.51 / 12.30	15.50 / 5.69	–	11.13 / 9.60	10.24 / 9.46	–
P5	–	7.77 / 9.33	6.08 / 4.47	–	8.29 / 5.60	4.12 / 3.07	–
P6	–	–	–	–	7.08 / 9.80	4.14 / 8.55	–
P7	–	–	–	–	8.08 / 6.50	7.25 / 10.78	–
P8	–	–	–	–	6.84 / 3.70	–	–
P9	–	–	–	–	13.45 / 6.50	13.42 / 10.78	–
P10	–	–	–	–	7.40 / 0.60	7.06 / 10.78	–
P11	–	–	–	–	15.96 / 7.30	–	–
P12	–	–	–	–	14.52 / 9.50	15.08 / 10.78	–
P13	–	–	–	–	6.48 / 7.90	14.28 / 10.12	–
P14	–	–	–	–	–	10.52 / 10.03	–

Table 7. Regression relationships and error metrics for nitrogen dioxide

Year	n	Regression equation	R ²	r	RMSE ($\mu\text{g m}^{-3}$)	MAE ($\mu\text{g m}^{-3}$)	Mean bias ($\mu\text{g m}^{-3}$)
2021	9	$y = 0.1549x + 5.7293$	0.0611	0.247	8.31	7.14	–6.80
2025	23	$y = 0.2399x + 5.6356$	0.1281	0.358	4.64	3.87	–2.33

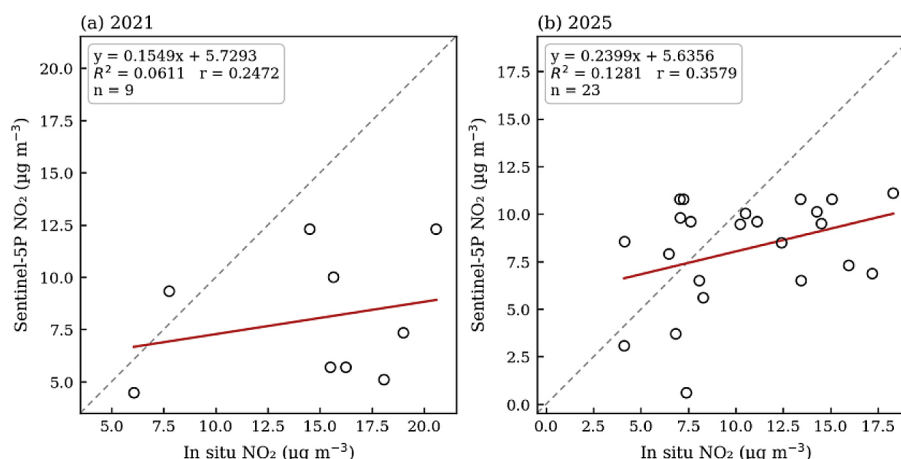


Figure 5. Relationship between in situ and Sentinel-5P nitrogen dioxide concentrations

network expanded. These results suggest that reference-network density and representativeness were important limitations in the comparison.

A further constraint on the spatial interpretation is visible in Table 6. On 5 June 2025, sites P7, P9, P10 and P12 all returned an identical satellite value of $10.78 \mu\text{g m}^{-3}$ despite being separated by 3–6 km, and on 11 March 2025 sites P7 and P9 both returned $6.50 \mu\text{g m}^{-3}$. Identical values at distinct locations indicate that these sites fall within the same TROPOMI pixel. The thirteen-site network of 2025 therefore does not deliver thirteen spatially independent satellite observations, and part of the apparent within-city gradient reflects pixel geometry rather than atmospheric structure. The number of distinct pixels sampled, rather than the number of sites, is the relevant measure of spatial sample size in this comparison. Two independent lines of evidence now quantify this. First, counting distinct extracted values per pollutant and date places a lower bound on the number of independent satellite values: on 5 June 2025, ten NO_2 site observations yielded only seven distinct values and ten SO_2 observations only six. Second, the site geometry confirms that these coincidences are genuine co-location rather than chance: the sites returning identical values are separated by 0.36 to 2.37 km, well inside a single 5.5 km extraction cell. Tiling the network with a regular grid of the extraction cell size over 2000 randomised grid origins gives 4 to 7 distinct cells (median 5) for the thirteen-site 2025 network, and 2 to 5 cells (median 3) for the five-site 2021 network, against network extents of $6.3 \times 11.7 \text{ km}$ and $2.5 \times 10.7 \text{ km}$ respectively. Approximately five independent satellite values, not thirteen, are therefore available in 2025. The exact pixel

identifiers are exported by the analysis script and will replace these bounds with counts.

Sulfur dioxide (SO_2) analysis and spatial distribution

Sulfur dioxide provides a contrasting diagnostic because urban concentrations are more strongly influenced by discrete sources than by distributed mobile emissions, while its retrieval has lower sensitivity to weak emitters (Fioletov et al., 2023).

Figure 6 shows the classified SO_2 distributions for 2021. Concentrations ranged from $0.291\text{--}2.167 \mu\text{g m}^{-3}$ in January, with maxima in the north and west; increased to $1.885\text{--}5.189 \mu\text{g m}^{-3}$ in June, with maxima shifting to the east and south; and reached $0.975\text{--}5.597 \mu\text{g m}^{-3}$ in August, with elevated values concentrated in the east and north. The seasonal relocation of the maximum, particularly between January and June, suggests that SO_2 variability was influenced by changing transport conditions and episodic industrial activity rather than stable point sources alone.

The 2025 distributions are shown in Figure 7. January and March concentrations remained low at $0.265\text{--}1.730$ and $0.363\text{--}1.946 \mu\text{g m}^{-3}$, respectively, with maxima in the east and north. Concentrations increased sharply in June ($2.818\text{--}5.485 \mu\text{g m}^{-3}$), with maxima in the south and east, while July values ($1.615\text{--}4.437 \mu\text{g m}^{-3}$) retained an eastern maximum. The eastern sector was the only area appearing as a maximum in six of seven observation months across both years, providing the strongest evidence of a persistent point-source contribution to the urban SO_2 burden. Table 8 shows area of Malang City occupied by each sulfur dioxide concentration interval.

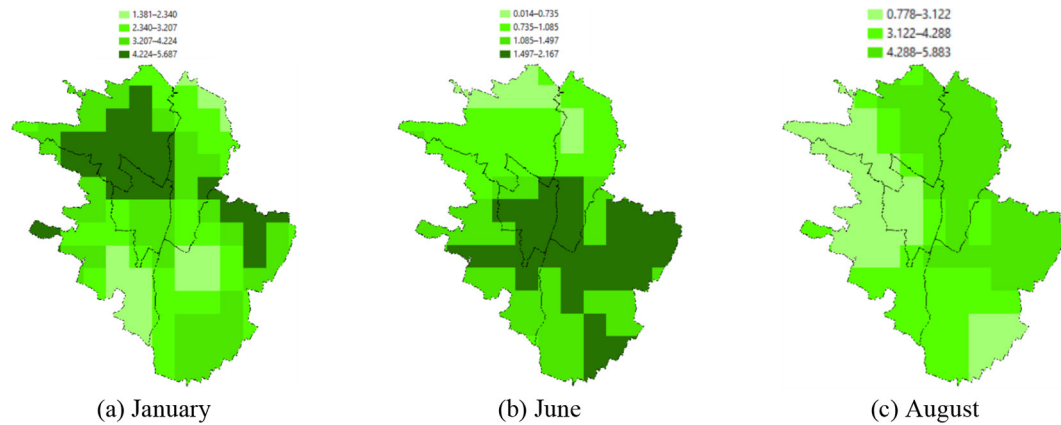


Figure 6. Classified distribution of sulfur dioxide over Malang City in 2021

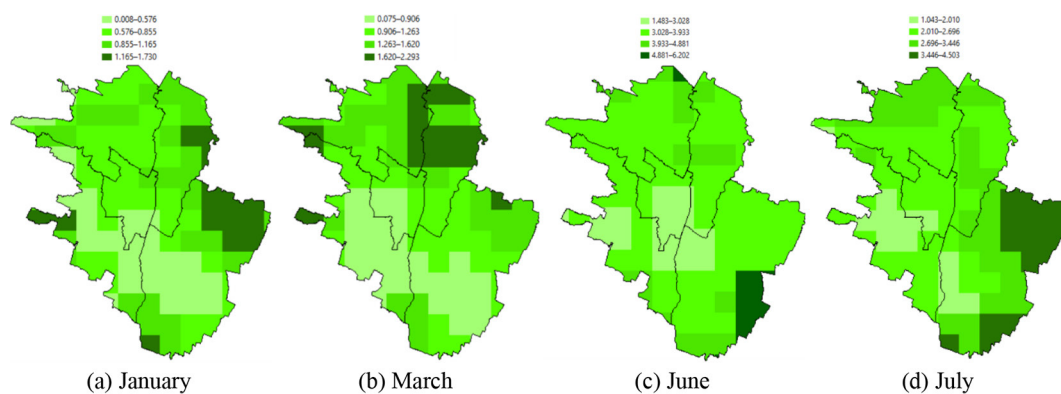


Figure 7. Classified distribution of sulfur dioxide over Malang City in 2025

Table 9 compares mean concentrations. The city-wide SO_2 mean was $2.684 \mu\text{g m}^{-3}$ across the 2021 observations and $2.332 \mu\text{g m}^{-3}$ across those of 2025. As sampled this is a reduction of $0.352 \mu\text{g m}^{-3}$ (13.1%), but the difference does not survive the unequal month coverage of the two years. Restricting the comparison to January and June, the only months observed in both years, reverses it into an increase of 8.0%, and the envelope across all possible month subsets runs from –60% to +34% (Table 20). No SO_2 difference between the two periods is therefore reported,

and the earlier statement of a 13.1% decrease is withdrawn. Unlike NO_2 , seasonal amplitude increased from 2.31 to $3.15 \mu\text{g m}^{-3}$, with the June 2025 mean of $4.15 \mu\text{g m}^{-3}$ exceeding all monthly values in 2021. This combination of stronger seasonal peaks without a demonstrable change in the mean is consistent with episodic rather than continuous emissions, such as intermittent industrial activity and dry-season open burning.

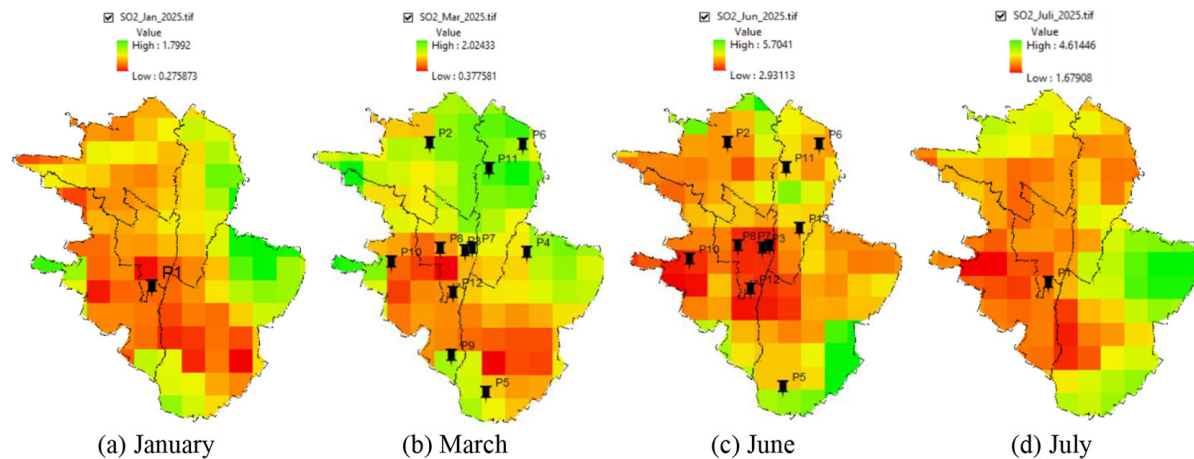
Figure 8 and Table 10 shows the 2025 SO_2 reference network, comprising one ministry monitoring station and four sampling points. Paired

Table 8. Area of Malang City occupied by each sulfur dioxide concentration interval

Year	Period	Concentration intervals in $\mu\text{g m}^{-3}$, with the corresponding area in km^2 in parentheses
2021	January	1.381–2.340 (13.69); 2.340–3.207 (31.41); 3.207–4.224 (39.72); 4.224–5.687 (26.26)
	June	0.014–0.735 (8.32); 0.735–1.085 (30.43); 1.085–1.497 (32.04); 1.497–2.167 (40.29)
	August	0.778–3.122 (31.74); 3.122–4.288 (35.39); 4.288–5.883 (43.95)
2025	January	0.008–0.576 (27.58); 0.576–0.855 (40.55); 0.855–1.165 (29.55); 1.165–1.730 (13.40)
	March	0.075–0.906 (29.82); 0.906–1.263 (34.04); 1.263–1.620 (31.15); 1.620–2.293 (16.06)
	June	1.483–3.028 (16.35); 3.028–3.933 (74.84); 3.933–4.881 (14.88); 4.881–6.202 (5.02)
	July	1.043–2.010 (13.30); 2.010–2.696 (47.19); 2.696–3.446 (35.37); 3.446–4.503 (15.23)

Table 9. Monthly and annual mean sulfur dioxide concentrations derived from Sentinel-5P

Year	January	March	June	July	August	Annual mean	Index category
2021	1.23	–	3.54	–	3.29	2.684	Good (1–50)
2025	1.00	1.15	4.15	3.03	–	2.332	Good (1–50)

**Figure 8.** Configuration of the SO₂ reference sampling network across Malang City in 2025

concentrations for sulfur dioxide are given in Table 11.

Paired concentrations from the reference sites are presented in Table 9. Satellite estimates were lower than ground measurements at all sites in 2025 and at seven of nine sites in 2021, with mean signed differences of -5.98 and $-3.76 \mu\text{g m}^{-3}$, respectively. This bias may reflect two processes. First, SO₂ undergoes oxidation to sulfate within hours, reducing the SO₂ signal before the early-afternoon satellite overpass. Second, planetary boundary-layer growth dilutes near-surface SO₂ within a deeper mixed layer, lowering the retrieved column relative to point-based ground measurements. Given the low urban SO₂ signal, short atmospheric lifetime, and retrieval characteristics optimized for stronger emission sources, the product is more appropriate for identifying persistent SO₂ sources than for estimating ambient concentrations quantitatively in a city of this scale.

Table 12 and Figure 9 summarize the comparison. The relationship between satellite and in situ SO₂ was effectively absent in both years, with R^2 values of 0.0066 and 0.0052 and correlation coefficients of -0.082 and 0.072 in 2021 and 2025, respectively. Neither is statistically significant ($p = 0.84$ and $p = 0.74$) and both confidence intervals on r are wide and centred near zero (-0.71 to 0.62 and -0.35 to 0.47 ; Table 21), so the sign of the correlation carries no interpretable information

in either year. The near-zero slopes (-0.020 and 0.031) indicate that the satellite retrieval captured neither the magnitude nor the spatial ranking of ground observations.

Unlike NO₂, where improved errors accompanied a persistent physical relationship, SO₂ showed lower RMSE (7.94 to $4.70 \mu\text{g m}^{-3}$) and MAE (6.12 to $3.83 \mu\text{g m}^{-3}$) without improved correlation. The mean signed difference accounted for 98% of MAE in both years, indicating that the apparent error reduction mainly reflected a smaller systematic offset rather than improved spatial representation. Thus, error metrics alone would overstate the 2025 improvement; joint interpretation of bias, correlation, and error provides a more reliable assessment (Hodson, 2022).

Carbon monoxide (CO) analysis and spatial distribution

Carbon monoxide completes the diagnostic triad. Its weeks-to-months atmospheric lifetime means that Sentinel-5P total-column CO is dominated by regional and hemispheric background, with local urban emissions contributing only a small enhancement (Landgraf et al., 2016). A smooth field with low relative variability is therefore expected, unlike the sharper NO₂ gradients. Figures 10 and 11 show the classified CO distributions. In 2021, concentrations ranged from

Table 10. Register of reference sampling sites

Site	Location	Longitude (°)	Latitude (°)	Setting	Code 2021	Code 2025
P1	AQMS KLHK Malang, Halmahera Street, Ciptomulyo, Sukun District, Malang City	112.629	−7.9916	Urban monitoring station	P1	P1
P2	Malang City Hall, Tugu Street No. 1, Malang City	112.634	−7.9774	Urban–administrative	P2	—
P3	PT. HM Sampoerna, Industri Barat Street, Malang City	112.642	−7.9444	Industrial	P3	P11
P4	Araya Residential Area, in front of the Marketing Office, Malang City	112.651	−7.9365	Residential	P4	P6
P5	Integrated Government Office Complex, Malang City	112.642	−8.0323	Administrative	P5	—
P6	Permata Jingga Residential Area, Puncak Borobudur Street, Tunggulwulung, Lowokwaru District, Malang City	112.619	−7.9329	Residential	—	P2
P7	Mini Block Office, Majapahit Street, RW 3, Kiduldalem, Klojen District, Malang City	112.634	−7.9785	Urban–administrative	—	P3
P8	Sawojajar Residential Area, Danau Toba Street, Sawojajar, Kedungkandang District, Malang City	112.660	−7.9793	Residential	—	P4
P9	Integrated Government Office Complex, Mayjen Sungkono Street, Arjowinangun, Kedungkandang District, Malang City	112.642	−8.0383	Administrative	—	P5
P10	Araya, Blimbing Indah Megah Street, Polowijen, Blimbing District, Malang City	112.658	−7.9338	Residential	—	P6
P11	East of City Hall, Kertanegara Street, Malang City	112.637	−7.9776	Urban–traffic	—	P7
P12	MOG (Malang Olympic Garden), Kawi Street No. 24, Kauman, Klojen District, Malang City	112.623	−7.9775	Commercial–urban	—	P8
P13	Gadang Terminal Intersection, Kolonel Sugiono Street, Gadang, Sukun District, Malang City	112.628	−8.0227	Traffic–urban	—	P9
P14	PT. Gandum Industrial Area, Raya Bandulan Street, Mulyorejo, Sukun District, Malang City	112.602	−7.9833	Industrial	—	P10
P15	Pabrik sekitar Industri Kulit/Rokok, Jl. Susanto, Kota Malang	112.628	−7.9961	Industrial	—	P12
P16	Jl. Mayjen Wiyono, Kota Malang	112.650	−7.9699	Urban–traffic	—	P13

Table 11. Paired in situ and Sentinel-5P sulfur dioxide concentrations by site and observation date

Site	1 Jan 2021	9 Jun 2021	18 Aug 2021	8 Jan 2025	11 Mar 2025	5 Jun 2025	2 Jul 2025
P1	9.38 / 1.00	—	—	4.67 / 0.50	—	—	7.00 / 2.30
P2	—	5.45 / 2.76	5.24 / 4.28	—	—	—	—
P3	—	4.50 / 4.69	4.32 / 4.75	—	3.49 / 1.90	6.87 / 4.00	—
P4	—	11.50 / 2.26	10.89 / 4.69	—	11.56 / 1.50	10.03 / 3.70	—
P5	—	17.73 / 3.80	17.37 / 4.31	—	4.44 / 1.10	3.58 / 3.90	—
P6	—	—	—	—	5.34 / 1.50	7.00 / 3.60	—
P7	—	—	—	—	3.22 / 1.30	2.57 / 3.00	—
P8	—	—	—	—	5.34 / 1.20	—	—
P9	—	—	—	—	4.74 / 1.30	3.81 / 3.00	—
P10	—	—	—	—	8.47 / 0.90	12.50 / 3.00	—
P11	—	—	—	—	3.35 / 1.50	—	—
P12	—	—	—	—	9.02 / 0.70	5.85 / 3.00	—
P13	—	—	—	—	4.27 / 0.80	5.30 / 3.10	—
P14	—	—	—	—	—	4.55 / 3.60	—

Table 12. Regression relationships and error metrics for sulfur dioxide

Year	n	Regression equation	R ²	r	RMSE (µg m ⁻³)	MAE (µg m ⁻³)	Mean bias (µg m ⁻³)
2021	9	$y = -0.0204x + 3.8117$	0.0066	-0.082	7.94	6.12	-5.98
2025	23	$y = 0.0309x + 2.0071$	0.0052	0.072	4.70	3.83	-3.76

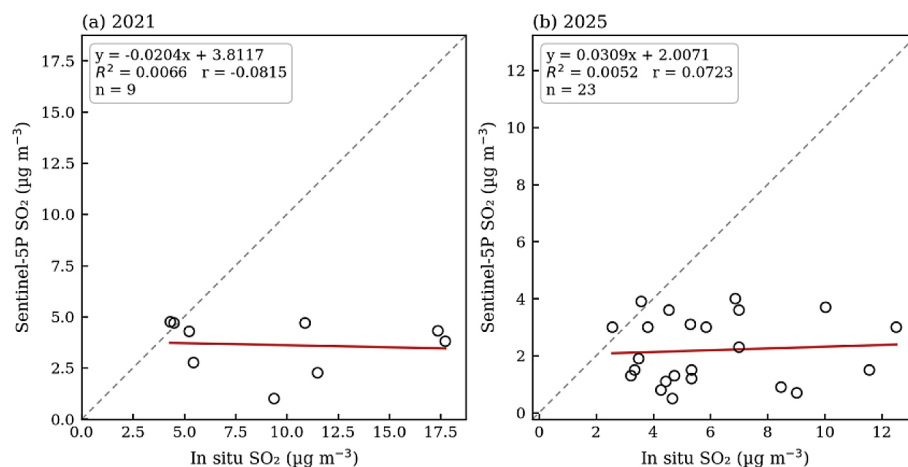


Figure 9. Relationship between in situ and Sentinel-5P sulfur dioxide concentrations

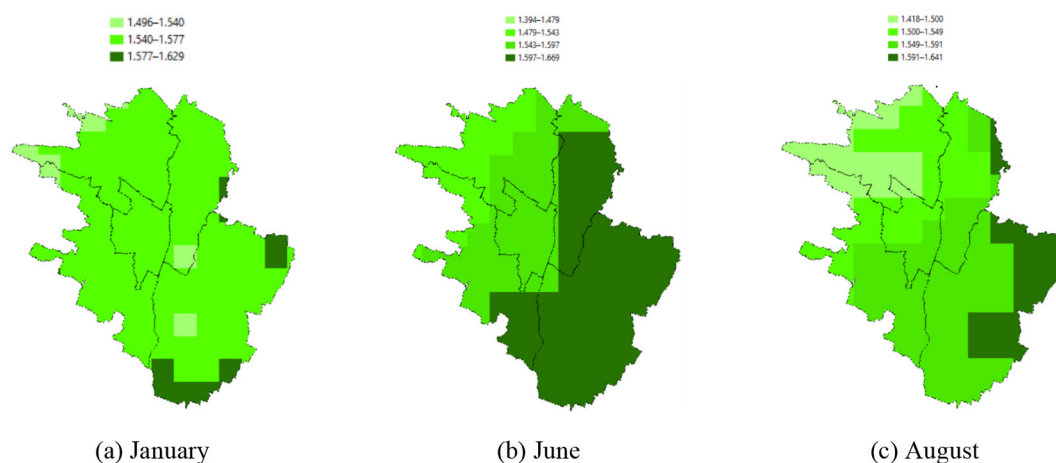


Figure 10. Classified distribution of carbon monoxide over Malang City in 2021

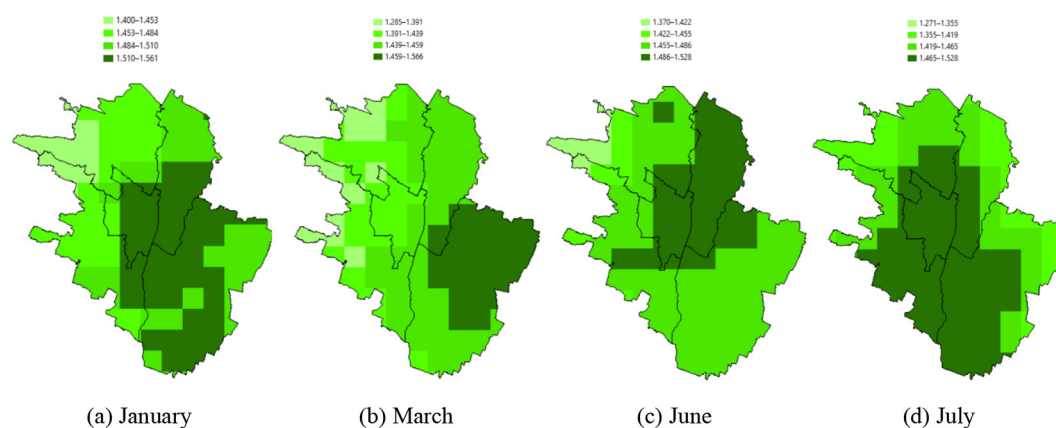


Figure 11. Classified distribution of carbon monoxide over Malang City in 2025

1.539–1.617 $\mu\text{g m}^{-3}$ in January, 1.503–1.657 $\mu\text{g m}^{-3}$ in June, and 1.482–1.627 $\mu\text{g m}^{-3}$ in August. In 2025, ranges were 1.428–1.539, 1.344–1.547, 1.413–1.528, and 1.391–1.528 $\mu\text{g m}^{-3}$ for January, March, June, and July, respectively. Across all seven months, the within-month range remained below 0.21 $\mu\text{g m}^{-3}$ and the coefficient of variation below 2%, contrasting with over 25% for NO_2 in June 2021. This low spatial variability is consistent with the long atmospheric lifetime and total-column nature of CO retrievals, indicating expected background dominance rather than poor sensitivity. Table 13 shows area of Malang City occupied by each carbon monoxide concentration interval.

Table 14 shows conditional dependence of the derived CO concentration on the assumed effective atmospheric depth and Table 15 shows that the city-wide mean CO concentration decreased from 1.571 $\mu\text{g m}^{-3}$ in 2021 to 1.465 $\mu\text{g m}^{-3}$ in 2025, a reduction of 0.106 $\mu\text{g m}^{-3}$ (6.7%). Of the three pollutants this is the only difference that proved robust to the unequal month sampling: recomputed across every possible month subset it varies only between –7.3% and –6.1% (Table 20), and it is retained as a quantitative result. This decline was smaller than that observed for the other pollutants, consistent with CO's longer atmospheric lifetime and stronger regional background influence. Thus,

a given reduction in local emissions would produce a smaller change in the total CO column than in shorter-lived pollutants dominated by local sources.

The absolute CO concentration is therefore conditional on the assumed depth across more than two orders of magnitude, while the ratio to the reanalysis never approaches unity at any physically motivated depth. This is the clearest available demonstration that the two quantities are not the same physical variable: TROPOMI measures the total atmospheric CO column, whereas the reanalysis field is near-surface CO.

Because coincident ground-based CO measurements were unavailable, satellite estimates were compared with Copernicus Atmosphere Monitoring Service (CAMS) reanalysis data at matching coordinates and dates in Table 16. This comparison represents an observation–model assessment rather than direct measurement validation. Moreover, CAMS assimilates satellite CO observations, limiting the independence between the two datasets (Borsdorff et al., 2023). As set out in the Methods and in Supplementary S3, the specific CAMS product underlying these reference values is not documented, so this comparison cannot be independently reproduced. It is retained for transparency and as a diagnostic of the reference structure, not as evidence of retrieval quality.

Table 13. Area of Malang City occupied by each carbon monoxide concentration interval

Year	Period	Concentration intervals in $\mu\text{g m}^{-3}$, with the corresponding area in km^2 in parentheses
2021	January	1.496–1.540 (5.83); 1.540–1.577 (97.99); 1.577–1.629 (72.51)
	June	1.394–1.479 (3.36); 1.479–1.543 (16.72); 1.543–1.597 (35.87); 1.597–1.669 (58.45)
	August	1.418–1.500 (16.00); 1.500–1.549 (29.46); 1.549–1.591 (47.60); 1.591–1.641 (15.86)
2025	January	1.400–1.453 (90.68); 1.453–1.484 (26.99); 1.484–1.510 (28.79); 1.510–1.561 (46.22)
	March	1.285–1.391 (13.79); 1.391–1.439 (24.90); 1.439–1.459 (46.17); 1.459–1.566 (26.21)
	June	1.370–1.422 (4.27); 1.422–1.455 (6.49); 1.455–1.486 (62.50); 1.486–1.528 (37.82)
	July	1.271–1.355 (18.82); 1.355–1.419 (18.48); 1.419–1.465 (32.07); 1.465–1.528 (60.50)

Table 14. Conditional dependence of the derived CO concentration on the assumed effective atmospheric depth

H	Conversion factor ($\mu\text{g m}^{-3}$ per mol m^{-2})	Mean TROPOMI-derived CO ($\mu\text{g m}^{-3}$)	Mean CAMS surface CO ($\mu\text{g m}^{-3}$)	TROPOMI / CAMS ratio
56 m (obsolete script version)	500,180	12,879	434.3	29.65
164 m	170,793	4,398	434.3	10.13
1 km	28,010	721	434.3	1.66
6 km (adopted here)	4,668	120	434.3	0.28
12 km	2,334	60	434.3	0.14

Table 15. Monthly and annual mean carbon monoxide concentrations derived from Sentinel-5P

Year	January	March	June	July	August	Annual mean	Index category
2021	1.58	–	1.58	–	1.55	1.571	Good (1–50)
2025	1.48	1.45	1.47	1.46	–	1.465	Good (1–50)

Table 16. Date-level comparison between Sentinel-5P and reanalysis carbon monoxide

Year	Date	Sites	Reanalysis ($\mu\text{g m}^{-3}$)	Sentinel-5P mean ($\mu\text{g m}^{-3}$)	Sentinel-5P range ($\mu\text{g m}^{-3}$)	Mean difference ($\mu\text{g m}^{-3}$)	Difference (%)
2021	1 Jan 2021	1	220.77	125.30	–	–95.47	–43.2
	9 Jun 2021	4	312.39	128.04	126.65–128.89	–184.35	–59.0
	18 Aug 2021	4	138.14	124.14	121.64–125.93	–14.00	–10.1
2025	8 Jan 2025	1	360.80	123.16	–	–237.64	–65.9
	11 Mar 2025	11	587.30	115.95	111.24–120.28	–471.35	–80.3
	5 Jun 2025	10	466.50	119.31	117.73–120.94	–347.19	–74.4
	2 Jul 2025	1	389.31	120.82	–	–268.49	–69.0

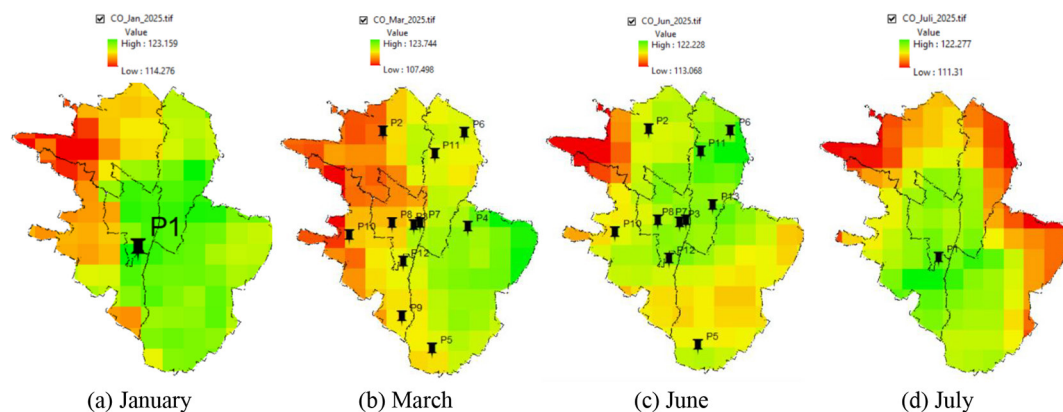
**Figure 12.** Configuration of the CO reference sampling network across Malang City in 2025

Figure 12 and Table 17 shows the 2025 CO reference network, comprising one ministry monitoring station and four sampling points

Table 18 and Figure 13 summarize the comparison. Although R^2 values of 0.698 in 2021 and 0.609 in 2025 suggest strong agreement, this interpretation is misleading because the reanalysis assigns a single value to all sampling locations on each date, leaving only three distinct reference values in 2021 and four in 2025. The apparent correlation therefore reflects date-level covariation rather than spatial agreement. In 2025, the regression slope was -0.0283 , consistent with an inverse relationship and correcting the original correlation sign from $+0.780$ to -0.780 . The consequence for the effective sample size is severe and is now stated explicitly: because the within-date variance of the reference is exactly zero, the CO comparison rests on three independent observations in 2021 and four in 2025, not nine and

twenty-three. Evaluated at the date level, the 2021 association is not significant ($p = 0.13$), while the 2025 association is significant but negative ($r = -0.98$, $p = 0.02$). The strongest-looking validation statistic in this study is therefore its least informative, and no claim of satellite–reanalysis agreement for CO is made. Combined with the undocumented provenance of the reference product, this means the CO comparison supports no statement about agreement in either direction, and the CO findings reported in this study rest on the Sentinel-5P observations alone.

Error statistics further indicate systematic disagreement: RMSE increased from 127.30 to $405.28 \mu\text{g m}^{-3}$ and MAE from 98.77 to $398.38 \mu\text{g m}^{-3}$. The identical MAE and absolute mean signed difference indicate residuals with the same sign, with satellite values consistently lower than reanalysis by 44% in 2021 and 74% in 2025. Meanwhile, mean satellite concentrations changed little

Table 17. Register of reference sampling sites

Site	Location	Longitude (°)	Latitude (°)	Setting	Code 2021	Code 2025
P1	AQMS KLHK Malang, Halmahera Street, Ciptomulyo, Sukun District, Malang City	112.629	-7.9916	Urban monitoring station	P1	P1
P2	Malang City Hall, Tugu Street No. 1, Malang City	112.634	-7.9774	Urban-administrative	P2	—
P3	PT. HM Sampoerna, Industri Barat Street, Malang City	112.642	-7.9444	Industrial	P3	P11
P4	Araya Residential Area, in front of the Marketing Office, Malang City	112.651	-7.9365	Residential	P4	P6
P5	Integrated Government Office Complex, Malang City	112.642	-8.0323	Administrative	P5	—
P6	Permata Jingga Residential Area, Puncak Borobudur Street, Tunggulwulung, Lowokwaru District, Malang City	112.619	-7.9329	Residential	—	P2
P7	Mini Block Office, Majapahit Street, RW 3, Kiduldalem, Klojen District, Malang City	112.634	-7.9785	Urban-administrative	—	P3
P8	Sawojajar Residential Area, Danau Toba Street, Sawojajar, Kedungkandang District, Malang City	112.660	-7.9793	Residential	—	P4
P9	Integrated Government Office Complex, Mayjen Sungkono Street, Arjowinangun, Kedungkandang District, Malang City	112.642	-8.0383	Administrative	—	P5
P10	Araya, Blimbing Indah Megah Street, Polowijen, Blimbing District, Malang City	112.658	-7.9338	Residential	—	P6
P11	East of City Hall, Kertanegara Street, Malang City	112.637	-7.9776	Urban-traffic	—	P7
P12	MOG (Malang Olympic Garden), Kawi Street No. 24, Kauman, Klojen District, Malang City	112.623	-7.9775	Commercial-urban	—	P8
P13	Gadang Terminal Intersection, Kolonel Sugiono Street, Gadang, Sukun District, Malang City	112.628	-8.0227	Traffic-urban	—	P9
P14	PT. Gandum Industrial Area, Raya Bandulan Street, Mulyorejo, Sukun District, Malang City	112.602	-7.9833	Industrial	—	P10
P15	Leather/Cigarette Industrial Area, Susanto Street, Malang City	112.6283	-7.9961	Industrial	—	P12
P16	Mayjen Wiyono Street, Malang City	112.6495	-7.9699	Urban-traffic	—	P13

Table 18. Comparison statistics between Sentinel-5P and reanalysis carbon monoxide

Year	n	Distinct reference values	Regression equation	R ²	r	RMSE (μg m ⁻³)	MAE (μg m ⁻³)	Mean bias (μg m ⁻³)
2021	9	3	$y = 0.0224x + 120.957$	0.6975	0.835	127.30	98.77	-98.77
2025	23	4	$y = -0.0283x + 132.552$	0.6092	-0.781	405.28	398.38	-398.38

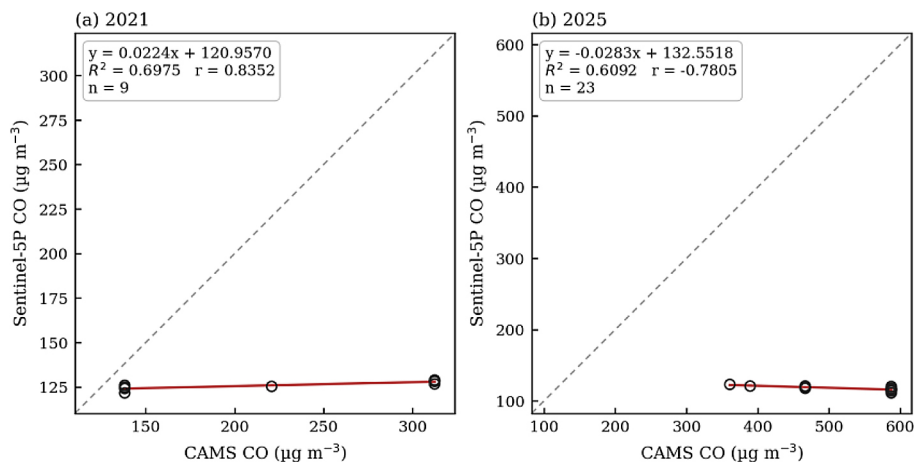


Figure 13. TROPOMI CO column converted to a column-averaged concentration assuming an effective atmospheric depth of 6 km, compared with CAMS CO surface concentration, for 2021 and 2025. The two quantities are not directly equivalent: TROPOMI represents the total atmospheric CO column, whereas CAMS represents near-surface CO. The comparison indicates scale only and is not a validation.

(125.99 to 117.86 $\mu\text{g m}^{-3}$), whereas reanalysis values increased from 224.76 to 516.24 $\mu\text{g m}^{-3}$. Thus, the increased error reflects divergence in the reference product rather than retrieval degradation, demonstrating why correlation must be interpreted jointly with bias and error (Hodson, 2022).

Atmospheric fingerprints of urbanization

The three species are best interpreted jointly because their contrasting spatial and temporal patterns provide a multi-pollutant characterization of Malang City's atmospheric environment. Figure 14 compares their monthly trajectories, while Table 19 summarizes the principal diagnostic contrasts. Rather than representing direct source identification, these combined patterns are interpreted as an atmospheric fingerprint that describes the spatial and temporal heterogeneity of NO_2 , SO_2 , and CO across the city.

First, mean concentrations were lower in the analysed 2025 period than in 2021 for nitrogen dioxide and carbon monoxide, but the three pollutants do not support equally strong statements.

The carbon monoxide difference of 6.7% is robust to the unequal month sampling of the two years and is reported as a quantitative result. The nitrogen dioxide difference is robust in direction only, its magnitude spanning -24.9% to -3.5% depending on which months are compared. The sulfur dioxide difference reverses sign under the most conservative comparison available and is not reported. Although the ordering of the two retained differences is compatible with differences in atmospheric lifetime and the relative influence of local and regional processes, it should not be interpreted as evidence of a locally driven emission reduction. The analyzed periods cover only three or four months in each year, and meteorological variability, boundary-layer conditions, and regional transport were not normalized. The observed differences therefore represent contrasts between the analyzed periods rather than an established long-term trend.

Second, the pollutants exhibited distinct spatial distributions. NO_2 maxima were concentrated mainly in the northern and western sectors, where built-up areas, arterial corridors, and

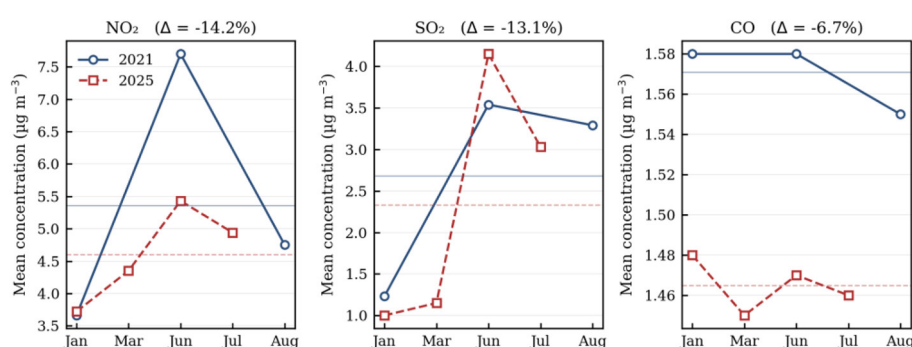


Figure 14. Monthly mean concentrations of the three pollutants in 2021 and 2025

Table 19. Multi-pollutant synthesis of the atmospheric fingerprint of Malang City

Attribute	Nitrogen dioxide	Sulfur dioxide	Carbon monoxide
Annual mean 2021 ($\mu\text{g m}^{-3}$)	5.36	2.684	1.571
Annual mean 2025 ($\mu\text{g m}^{-3}$)	4.60	2.332	1.465
Difference between analysed periods (%)	Direction robust; magnitude not (-24.9 to -3.5)	Not robust; sign reverses (-60 to $+34$) — withdrawn	-6.7 (robust, -7.3 to -6.1)
Seasonal amplitude 2021 ($\mu\text{g m}^{-3}$)	4.04	2.31	0.03
Seasonal amplitude 2025 ($\mu\text{g m}^{-3}$)	1.71	3.15	0.03
Dominant sector	North and west	East and south	East and south
Within-month spatial contrast	High	Moderate	Very low
Spatial pattern consistent with	Built-up and traffic-influenced areas	Industrial/peripheral activity	Regional/background influence
Agreement with reference data	Weak, not significant	Absent, not significant	Between-date only (independent $n = 3$ and 4)
Diagnostic value at city scale	High	Moderate (screening)	Low (background)

dense educational and commercial activities are present. SO₂ showed relatively higher values in the eastern and southern peripheral sectors, while CO displayed a comparatively homogeneous distribution with only weak spatial contrast. These patterns are spatially consistent with differences in urban activity and potential emission influences, but they do not constitute direct evidence of specific mobile, stationary, or regional sources because independent traffic, industrial-emission, transport, and emissions-inventory data were not used for formal source attribution. The contrasting distributions nevertheless demonstrate the value of examining multiple pollutants jointly rather than interpreting a single pollutant in isolation.

Third, the seasonal amplitudes differed substantially among pollutants. The NO₂ seasonal amplitude decreased from 4.04 to 1.71 $\mu\text{g m}^{-3}$ (approximately 58%), whereas the SO₂ amplitude increased from 2.31 to 3.15 $\mu\text{g m}^{-3}$ (approximately 36%). CO remained nearly invariant at 0.03 $\mu\text{g m}^{-3}$ in both periods. These differences indicate that the temporal variability of the three pollutants was not uniform. However, attributing the reduced NO₂ variability or increased SO₂ episodicity specifically to changes in mobile or stationary activity would require concurrent meteorological and activity data. The patterns are therefore interpreted as differences in temporal variability rather than definitive evidence of changes in source behavior.

These atmospheric patterns can also be considered in relation to urban land-cover characteristics. The higher NO₂ values in northern and western areas spatially coincide with more intensively built-up environments and areas undergoing urban development. Such land-cover changes can influence surface energy balance, boundary-layer development, and pollutant dispersion (Suharyanto et al., 2023). Urban vegetation may also contribute to pollutant removal, although its effectiveness depends on vegetation characteristics, atmospheric conditions, and local ventilation (Venter et al., 2024; Dewi et al., 2026). These relationships provide useful spatial context for interpreting the observed atmospheric patterns, but they should not be regarded as causal relationships without independent measurements of meteorology, emissions, and urban activity. Overall, the multi-pollutant perspective provides a more informative description of Malang City's atmospheric heterogeneity than any individual pollutant alone. The principal contribution is therefore the identification and characterization

of contrasting NO₂, SO₂, and CO spatial-temporal patterns in a tropical highland city with limited ground-based monitoring, while recognizing that source attribution and long-term trends require additional independent observations.

Sensitivity and uncertainty analysis

Because Equation 2 is a multiplication by a positive constant with zero intercept, the assumed effective atmospheric depth rescales the concentration field without altering its relative structure. Recomputing the entire analysis across eight depths per pollutant confirmed this exactly. The Pearson correlation coefficient and the coefficient of determination were invariant to four decimal places at every depth tested, for all three pollutants and both years, as were the spatial coefficients of variation and the percentage differences between periods. Absolute concentrations, regression slopes, bias, RMSE, MAE and the resulting index values instead scale inversely with the assumed depth. The correlation-based conclusions of this study are therefore insensitive to the conversion assumption, whereas every absolute value is conditional on it. Table 20 reports the propagated effect.

Two consequences follow. First, the index category is not robust. Sulfur dioxide moves from Good to Unhealthy between the adopted 13 km depth and a boundary-layer depth of 164 m in both years, and carbon monoxide does the same between 6 km and 56 m. The finding that all pollutants fall within the national Good category is thus a direct consequence of adopting free-tropospheric depths for SO₂ and CO, and is reported here as conditional rather than as an observed air-quality state. Second, the depth that would reconcile the satellite estimates with the reference data differs systematically from the adopted values: 89 m and 128 m for NO₂ in 2021 and 2025, 4 897 m and 4 784 m for SO₂, and 3 364 m and 1 371 m for CO. The stability of the SO₂ figure across years contrasts with a factor-2.5 swing for CO, which indicates that for CO the depth is absorbing model–satellite representation error rather than describing a physical layer.

The unequal month coverage of the two observation years was examined separately, because it affects the between-period differences directly. Each difference was recomputed under four sampling schemes and across every possible subset of the 2025 months, holding the 2021 months

Table 20. Sensitivity of the derived quantities to the assumed effective atmospheric depth

Pollutant	Year	H (m)	Mean conc. ($\mu\text{g m}^{-3}$)	Spatial range ($\mu\text{g m}^{-3}$)	r	R ²	RMSE ($\mu\text{g m}^{-3}$)	Mean index	Index category
NO ₂	2021	100	13.16	12.84	0.247	0.061	5.96	8.2	Good
NO ₂	2021	164 (baseline)	8.02	7.83	0.247	0.061	8.31	5.0	Good
NO ₂	2021	500	2.63	2.57	0.247	0.061	12.98	1.7	Good
NO ₂	2021	1000	1.32	1.28	0.247	0.061	14.24	0.8	Good
SO ₂	2021	164	286.60	297.26	−0.082	0.007	294.25	149.5	Unhealthy
SO ₂	2021	1000	47.00	48.75	−0.082	0.007	41.22	43.5	Good
SO ₂	2021	5000	9.40	9.75	−0.082	0.007	6.15	9.0	Good
SO ₂	2021	13000 (baseline)	3.62	3.75	−0.082	0.007	7.94	3.5	Good
SO ₂	2025	164	173.70	277.44	0.072	0.005	190.44	100.3	Unhealthy
SO ₂	2025	13000 (baseline)	2.19	3.50	0.072	0.005	4.70	2.1	Good
CO	2021	56	13499.76	776.79	0.835	0.698	13276.13	178.8	Unhealthy
CO	2021	1000	755.99	43.50	0.835	0.698	536.01	9.5	Good
CO	2021	6000 (baseline)	126.00	7.25	0.835	0.698	127.30	1.6	Good
CO	2021	12000	63.00	3.63	0.835	0.698	181.02	0.8	Good

fixed. The results are given in Table 21. The carbon monoxide difference is robust to within 0.6 percentage points across every subset and is retained. The nitrogen dioxide difference is robust in direction but its magnitude varies sevenfold, so only the direction is reported. The sulfur dioxide difference is not robust at all: its sign reverses under the most conservative available comparison, and the earlier figure of −13.1% is therefore withdrawn from the Results, the synthesis, and the Conclusion. This test controls for month composition only. Precipitation, wind, temperature and mixing-height differences between the two periods were not normalized, and with three and four scenes per year a formal meteorological adjustment is not statistically feasible; the remaining differences are consequently reported as raw and meteorologically unadjusted.

Meteorological confounding. The 2021 and 2025 observation periods differed in their meteorological conditions. To evaluate whether the observed inter-period differences could be explained by meteorological variability, total precipitation, 10 m wind speed and direction, 2 m air

temperature and boundary-layer height were compiled for each observation period; the corresponding period means and ranges are reported in Table 22. Wind direction is summarised as a circular mean with circular dispersion rather than an arithmetic mean. Because only three observation dates were available in 2021 and four in 2025, we did not perform formal meteorological normalization or multivariable regression, as the number of independent temporal observations is insufficient for a reliable adjustment. The 2021–2025 differences are therefore interpreted as differences between the sampled periods rather than as meteorologically adjusted long-term changes. The common-month sensitivity analysis reported above gives −19.5% for NO₂, +8.0% for SO₂ and −6.7% for CO; the previously reported 13.1% decrease in SO₂ is accordingly not robust to sampling-period composition and is no longer interpreted as evidence of a decrease between the two periods.

The first four variables are extracted by the analysis script, which exports them per observation period. Boundary-layer height is not available through Earth Engine, whose ERA5 collections

Table 21. Sensitivity of the 2021–2025 differences to month-sampling composition (%)

Pollutant	As published (all months)	Common months (Jan + Jun)	Wet-season months	Dry-season months	Envelope over all 2025 month subsets
NO ₂	−14.2	−19.5	+10.3	−16.7	−24.9 to −3.5
SO ₂	−13.1	+8.0	−12.6	+5.1	−60.0 to +33.6
CO	−6.7	−6.7	−7.3	−6.4	−7.3 to −6.1

Table 22. Meteorological comparability of the 2021 and 2025 observation periods

Variable	Unit	2021 mean	2025 mean	Absolute difference	% difference	2021 range	2025 range	Source
Total precipitation	mm per period	—	—	—	—	—	—	ERA5-Land, GEE
10 m wind speed	m s ⁻¹	—	—	—	—	—	—	ERA5-Land, GEE
10 m wind direction (circular mean; dispersion)	deg	—	—	n/a	n/a	—	—	ERA5-Land, GEE
2 m air temperature	deg C	—	—	—	—	—	—	ERA5-Land, GEE
Boundary-layer height	m	—	—	—	—	—	—	ERA5 single levels, CDS (not available in GEE)

expose only nine surface variables, and must be retrieved separately from the Copernicus Climate Data Store. The cells are left empty rather than populated with a proxy variable, and no conclusion in this paper is conditioned on them: the differences are reported as unadjusted throughout.

Table 23 summarizes the validation statistics with their associated uncertainty. Distinguishing matched records from independent observations changes the interpretation for CO in particular, where the reanalysis reference is constant within each date.

No NO₂ or SO₂ correlation is significant at the 5% level and every corresponding interval on *r* spans zero. The CO correlations are significant at the point level but rest on three and four independent observations. Taken together, the validation exercise establishes the magnitude of the satellite–reference discrepancy with reasonable precision while establishing no reliable association between the two, which supports the use of these products for spatial screening rather than concentration estimation.

Limitations of the study

Several limitations should be considered when interpreting the results. First, ground-based measurements were matched to satellite overpasses by calendar date rather than by sampling hour, because the clock time and averaging period of each ground measurement were not retained in the records available to this study. The ± 3 h matching window described as the intended procedure could therefore not be verified against the data actually used, and the resulting temporal mismatch introduces variability associated with boundary-layer dynamics and photochemical conditions. Future validation should record exact sampling times and averaging periods. Second, validation involved only nine paired observations in 2021 and twenty-three in 2025, while the monitoring network expanded between the two periods. For carbon monoxide the effective number of independent observations is smaller still, at three and four, because the reanalysis reference is constant within each date. Consequently, validation

Table 23. Validation statistics with significance levels and confidence intervals

Pollutant	Year	Matched n	Independent n	<i>r</i>	<i>p</i>	95% CI on <i>r</i>	RMSE [95% CI]	MAE [95% CI]
NO ₂	2021	9	9	0.247	0.52	−0.50 to 0.78	8.31 [5.73, 10.40]	7.14 [4.42, 9.89]
NO ₂	2025	23	23	0.358	0.09	−0.06 to 0.67	4.64 [3.44, 5.75]	3.87 [2.88, 4.94]
SO ₂	2021	9	9	−0.082	0.84	−0.71 to 0.62	7.94 [4.64, 10.63]	6.12 [3.03, 9.48]
SO ₂	2025	23	23	0.072	0.74	−0.35 to 0.47	4.70 [3.40, 5.87]	3.83 [2.75, 4.97]
CO	2021	9	3	0.835	0.005	0.38 to 0.96	127.30 [76.92, 165.11]	98.77 [50.91, 154.93]
CO	2025	23	4	−0.781	<0.001	−0.90 to −0.54	405.28 [374.95, 433.52]	398.38 [367.50, 428.51]

performance and interannual differences may partly reflect changes in network coverage and sampling representativeness. Third, the effective TROPOMI footprint (approximately 5.5×3.5 km) is relatively coarse compared with the spatial scale of Malang City, limiting the number of independent observations and the detection of fine-scale urban variability. This is directly observable in the data: several monitoring sites separated by 3–6 km returned identical satellite values, confirming that they occupy the same pixel and that the site count overstates the spatial sample size. Spatial matching and averaging therefore remain important sources of uncertainty. Fourth, the carbon monoxide scaling discrepancy identified in the previous review has been traced to its source. An earlier version of the processing script applied a conversion multiplier equivalent to an effective depth of approximately 56 m, whereas the depth reported in the Methods and used to generate the published values is 6 km; the ratio between the two conversion factors is 107, that is, two orders of magnitude. The published values correspond to the 6 km depth, and the script has been corrected and released in full. Beyond this bookkeeping error, a more fundamental limitation remains: the TROPOMI carbon monoxide product is a total column dominated by regional and hemispheric background, whereas the reanalysis field is a near-surface quantity, so the two describe different parts of the atmosphere and no single effective depth reconciles them. The depth required to force agreement differs by a factor of 2.5 between the two years, which indicates that it absorbs representation error rather than describing a physical layer. CAMS is therefore treated as a model reference rather than independent ground truth, and no claim of satellite–reanalysis agreement for carbon monoxide is made. Fifth, the analyzed periods covered only three or four months in each year, and not the same months in both. The observed differences between 2021 and 2025 therefore cannot be interpreted as an established long-term trend: month-composition sensitivity accounts for a substantial part of their magnitude, and meteorological variability including precipitation, wind, temperature, and mixing height was not normalized. Sixth, the effective atmospheric depths used to convert columns to concentrations are scaling conventions rather than measured quantities. All absolute concentrations, error metrics, and index categories scale inversely with them, and the classification of sulfur dioxide and

carbon monoxide as Good would change to Unhealthy under boundary-layer depths. The ERA5 boundary-layer height of 164 m adopted for nitrogen dioxide is also shallow for an early-afternoon tropical overpass and warrants re-derivation at the overpass hour. Finally, the attribution of spatial maxima to particular emission sources remains inferential because independent traffic, industrial-emission, fire, or emissions-inventory data were not incorporated. The observed patterns should consequently be interpreted as spatial patterns consistent with potential source influences rather than direct evidence of specific emission sources. Longer continuous observations, improved temporal and spatial matching, meteorological normalization, and independent source datasets are required to strengthen future inference. A seventh limitation concerns provenance itself. The CAMS product used for the carbon monoxide comparison is not documented to the level required for independent reproduction, and the effective depth of 164 m applied to NO₂ was adopted from published literature rather than extracted for the study area. Both are stated explicitly in Supplementary S3, and the conclusions that would have depended on them have been withdrawn rather than retained with a caveat.

CONCLUSIONS

Sentinel-5P observations provided a multi-pollutant characterization of atmospheric spatial patterns over Malang City, a medium-sized tropical highland city with relatively limited ground-based monitoring. During the analyzed periods, city-wide mean concentrations were lower in 2025 than in 2021 for NO₂ (5.36 to 4.60 $\mu\text{g}/\text{m}^3$) and CO (1.571 to 1.465 $\mu\text{g}/\text{m}^3$). Because the two years were not sampled in the same months, each difference was tested against every possible month subset. Only the CO difference of 6.7% was robust; the NO₂ difference was robust in direction but varied between –24.9% and –3.5% in magnitude; and the apparent SO₂ decrease reversed to an increase under the most conservative comparison and is not reported. These differences should be interpreted as changes between the analyzed periods rather than evidence of an established long-term decline, because the observation window was limited and meteorological variability was not normalized. The three pollutants exhibited contrasting spatial patterns. NO₂ maxima were

concentrated along northern and western built-up corridors, SO₂ showed higher values near the eastern and southern industrial periphery, whereas CO displayed a relatively homogeneous distribution, with within-month coefficients of variation below 2%. These contrasting patterns constitute the principal empirical contribution of the study and provide a multi-pollutant spatial characterization of Malang's atmospheric environment. However, the spatial patterns are considered consistent with potential differences in urban activity and emission influences rather than direct evidence of specific mobile or stationary sources.

Agreement with reference observations varied among pollutants. Neither the weak NO₂ correspondence nor the effectively absent SO₂ relationship reached statistical significance, and every confidence interval on the correlation coefficient spanned zero. The apparent strong CO relationship reflected between-date variability across only three and four independent reference values, and its 2025 sign is in fact negative. Accordingly, the satellite-derived concentrations are more appropriately used for spatial screening and comparative assessment than as direct substitutes for ground-level measurements.

All analyzed pollutant estimates remained within the national good air-quality category under the effective atmospheric depths adopted here. This classification is, however, conditional on those depths rather than robust to them. The sensitivity analysis showed that correlation-based results are entirely invariant to the assumed depth, whereas absolute concentrations, error metrics and index categories scale inversely with it: under boundary-layer depths the SO₂ and CO classifications would move from Good to Unhealthy. The categorical index therefore carries less diagnostic information than the spatial distribution of the estimated concentrations, and should not be read as an independent statement about compliance. Overall, the study demonstrates the value of multi-pollutant satellite observations for complementing sparse ground-based monitoring and characterizing urban atmospheric patterns in data-limited tropical cities.

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