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Comparative analysis of seasonal air quality around an industrial area: A case study using air dispersion modelling and pollution index assessment

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ABSTRACT
Background: Manufacturing activities can release combustion gases and fine particles whose ambient distribution varies with meteorology and source characteristics. Integrating source oriented dispersion modelling with Indonesia's air pollutant standard index/*indeks standar pencemar udara* (ISPU) can provide complementary spatial and regulatory interpretations. **Methods:** This secondary-data case study combined facility monitoring records with archived 24 hour AERMOD outputs for rainy and dry season scenarios in Banten, Indonesia. Carbon monoxide (CO), nitrogen oxides/nitrogen dioxide (NO_x/NO_2), fine particulate matter ($PM_{2.5}$), and sulfur dioxide (SO_2) were assessed. Model output consistency, units, seasonal differences, and ISPU calculation were independently cross checked. Because complete AERMOD input files, receptor level time series, and co-located monitoring series were unavailable, independent calibration and statistical model observation validation were not performed. **Findings:** Dry-season maximum concentrations were higher for all modelled pollutants: CO increased from 42.745 to 51.226 μg/m^3, NOx from 467.8 to 561 μg/m^3, $PM_{2.5}$ from 274 to 329 μg/m^3, and SO_2 from 483.9 to 580 μg/m^3. The relative increase was approximately 20% for each pollutant. ISPU values were good for CO (39.36), NO_2 (22.64), and SO_2 (36.65), while $PM_{2.5}$ reached 68.68 and was classified as moderate. **Conclusion:** The combined assessment identifies the dry season as the higher-concentration scenario and $PM_{2.5}$ as the principal ambient-air management priority. Facilities should strengthen dry-season surveillance, fugitive-dust control, filtration maintenance, and combustion-efficiency checks. The results are screening-level and comparative because the study relied on secondary model outputs and one monitoring dataset. **Novelty/Originality of this article:** The article demonstrates how seasonal AERMOD outputs and pollutant specific ISPU values can be used together to prioritize industrial air quality controls while explicitly distinguishing modelled maxima from measured ambient concentrations.

KEYWORDS: AERMOD; industrial emissions; ISPU; $PM_{2.5}$; seasonal variation.

1. Introduction

Since the Industrial Revolution, industrial activities have intensified pressure on the environment through energy consumption, combustion, material processing, and the release of airborne pollutants (Katarzyna et al., 2020). The manufacturing sector is one of the major contributors to these environmental impacts, as its production activities rely heavily on electricity, diesel fuel, and other fossil fuels. The use of these energy sources and fuels may generate fugitive particulates, combustion gases, and other airborne contaminants during production processes. Each stage of manufacturing can contribute

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differently to ambient air quality because emissions interact with meteorogical conditions, topography, plant layout, and receptors surrounding industrial areas. Therefore, industrial impacts are not only limited to carbon emissions but also include deterioration of local air quality, which may affect environmental conditions around industrial zones (Araujo-Morera et al., 2021; Dong et al., 2021).

The increase in emissions from industrial activities is also closely associated with the global climate crisis, which can trigger serious impacts and pose major challenges to environmental stability, sustainable development, and the continuity of human life (Bolan et al., 2024). Air pollution is also influenced by other anthropogenic sources, including motor vehicle use, which is recognized as an important contributor to CO_2 emissions and air pollution (Xia & Li, 2022). However, this study focuses specifically on manufacturing activities because environmental impacts arise throughout production stages, including energy consumption, raw-material processing, combustion, and the release of pollutants into the environment (Dong et al., 2021). These industrial activities can generate combustion gases and particulate matter that may affect ambient air quality around industrial facilities, depending on emission characteristics, meteorological conditions, and the location of surrounding receptors.

Rubber-based manufacturing industries have increasingly been examined from the perspectives of sustainable manufacturing, cleaner production, and the circular economy. Previous studies have shown that material substitution, life cycle assessment, green productivity, and improved energy performance are important aspects in reducing environmental impacts, particularly the deterioration of air quality in manufacturing industries (Dewi et al., 2023; Katarzyna et al., 2020; Marimin et al., 2018; Shanbag & Manjare, 2020). The stages of rubber manufacturing in the automotive industry also contribute substantially to carbon emissions, with estimates ranging from approximately 550 kg CO_2 eq to 840 kg CO_2 eq (Dong et al., 2021). In this manufacturing industry, environmental challenges are not limited to the impacts of air emissions but also include environmental degradation, risks to human health and ecosystems, habitat damage, and biodiversity loss (Dong et al., 2021).

Air pollution is associated with respiratory and cardiovascular health burdens, as well as broader environmental health risks. Previous reviews have shown that particulate matter, nitrogen oxides, sulfur dioxide, ozone, and carbon monoxide affect human health through different toxicological pathways and exposure durations (Manisalidis et al., 2020; Rovira et al., 2020). Evidence from Indonesia also shows that air pollution causes disease and economic losses through increased measurable health-related costs in major urban areas, reinforcing the need for local air quality management in manufacturing zones (Syuhada et al., 2023). Cleaner production studies emphasize that process optimization, energy efficiency, and air pollution prevention should be managed proactively rather than treated merely as end-of-pipe compliance activities (Fan et al., 2020; Giannetti et al., 2020). In industrial manufacturing processes, improving energy efficiency is particularly relevant because on-site combustion activities can contribute directly to airborne pollutant emissions, while electricity consumption may contribute indirectly to the overall environmental and greenhouse-gas footprint (Chen et al., 2024; Farghali et al., 2023). In manufacturing processes, energy performance indicators can help identify potential opportunities for improvement in steam generation systems, compressed air systems, heating processes, and production control activities (Piccioni et al., 2024).

Air dispersion analysis using the American Meteorological Society/Environmental Protection Agency Regulatory Model (AERMOD) is widely applied in air quality studies to estimate the dispersion of pollutants originating from industrial sources, transportation, combustion processes, and emission stacks (Bayraktar & Mutlu, 2024; Sarwono et al., 2022). The model integrates emission-source characteristics, meteorological data, atmospheric stability, terrain, and receptor locations to describe spatial concentration patterns in ambient air (Bayraktar & Mutlu, 2024; Naess & Isakov, 2026). In this study, AERMOD is used as a technical instrument to compare pollutant dispersion patterns during the rainy and dry seasons because seasonal meteorological variations can influence maximum concentration levels, plume direction, dispersion direction, and the potential accumulation of pollutants around emission source (Firdaus et al., 2025; Sarwono et al., 2022). The use of AERMOD is relevant for evaluating air quality parameters such as SO_2, NO_x, CO, and $PM_{2.5}$, particularly in industrial facilities that have stationary emission sources and combustion-based production processes (Bayraktar & Mutlu, 2024; Nugraha, 2023; Sarwono et al., 2022).

Air dispersion modeling using AERMOD is a steady-state Gaussian plume model designed for near field regulatory applications. Its theoretical structure represents the planetary boundary layer using surface and profile meteorological parameters, treats vertical and horizontal dispersion differently under stable and convective conditions, and account for terrain effects through receptor elevations (Cimorelli et al., 2005). In practical applications, source parameters with meteorological and terrain data to estimate concentrations at defined receptors. Consequently, model outputs are conditional estimates rather than direct ambient measurement. Their interpretation depends on the completeness of the emission inventory, the representativeness of meteorological inputs, receptor density, averaging period, and quality-assurance procedures. This distinction is important in the present study because the AERMOD results compare seasonal scenarios, whereas Air Pollutant Standard Index, or *Indeks Standar Pencemar Udara* (ISPU)values are derived from measured ambient concentrations. The two datasets therefore answer complementary questions and should not be treated as interchangeable observations.

Air-dispersion modelling should be complemented by index-based calculations so that concentration results are not interpreted only as technical outputs but are also translated into communicable air-quality categories. The Air Pollutant Standard Index converts measured ambient concentrations into standardized categories for public communication and regulatory interpretation (Fahim et al., 2024; Irjayana et al., 2025), ISPU covers parameters including $PM_{2.5}$, PM_{10}, SO_2, CO, O_3, NO_2, and hydrocarbons. The index helps stakeholders identify the pollutant that determines the overall category and select appropriate management priorities. However, ISPU does not explain the spatial relationship between emission sources and receptors because it classifies measured concentrations rather than simulating atmospheric transport. AERMOD and ISPU therefore address different analytical needs: the former provides source-oriented spatial estimates, while the latter provides a standardized interpretation of ambient measurements (Shihab, 2023; Ravindra et al., 2024).

The relevance of this combined approach increases in industrial areas characterized by variable emissions, meteorological conditions, and community exposure. Therefore, air quality studies show that meteorological variations can influence pollutant concentrations, particularly for particulate matter and combustion-related gases (Cimorelli et al., 2005; Sarwono et al., 2022). Manufacturing processes involving thermal systems, combustion activities, material handling, and electricity consumption have the potential to generate combustion gases, particulate matter, and indirect emissions that require appropriate control measures, these emission may vary according to production intensity, equipment performance, fuel characteristics, and the effectiveness of ventilation or pollution control system (Ma et al., 2024; Piccioni et al., 2024). Consequently, air quality control requires an approach that can identify differences both in seasonal dispersion and pollutant-specific air quality categories (Bayraktar & Mutlu, 2024).

This combined calculation is also relevant to green-industry implementation because it links technical assessment with cleaner production, energy efficiency, and control of emission-related impacts. Sustainable-manufacturing studies indicate that environmental performance should be assessed together with economic and social performance rather than treated as administrative compliance alone (Ahmad et al., 2023; Karuppiah et al., 2024; Nogueira et al., 2023). Research on cleaner production and Industry 4.0 further emphasize that energy efficiency, smart technologies, production process optimization, and green innovation can support the control and reduction of air emissions, this approaches are relevant for manufacturing facilities because they can improve operational efficiency while reducing pollutant generation form energy use, combustion activities, and production processes, it can also help the industries identify emission sources mor accurately and implement corrective actions more quickly (Ma et al., 2024; Piccioni et al., 2024). In rubber manufacturing, sustainability assessment is particularly important because energy use, material handling, and production processes contribute to environmental burdens throughout the product life cycle (Dewi et al., 2023; Dong et al., 2021).

Based on these conditions, a research gap exists at the intersection between air dispersion analysis in industrial areas and the calculated values of ambient air quality indices. Previous studies have examined dispersion modelling, air quality monitoring, ISPU classification, cleaner production, energy efficiency, and sustainable manufacturing. However, the integration of AERMOD-based seasonal dispersion analysis with ISPU-based ambient air quality classification for identifying pollutant-specific management priorities at the facility level remains limited (Bayraktar & Mutlu, 2024; Fahim et al., 2024; Ma et al., 2024; Salsabila & Utami, 2025). This study assumes that seasonal meteorological differences can generate variations in maximum pollutant concentrations and uses AERMOD and ISPU as complementary approaches to identify seasonal and pollutant-specific air quality management priorities (Nugraha, 2023), in this context, the objective of this article is to compare air dispersion patterns during the rainy and dry seasons and to calculate ISPU values for the main pollutants around the manufacturing industrial area (Ahmad et al., 2023; Dewi et al., 2023; Ren & Mia, 2025).

Accordingly, this study addresses thress research question: (1) how do the 24-hour modelled maximum concentrations of CO, NO_x, $PM_{2.5}$, and SO_2 differ between rainy and dry season scenarios; (2) what air quality categories are obtained when the available ambient measurements are converted to ISPU values; and (3) how can the two forms of evidence be combined to identify seasonal and pollutant specific priorities for industrial air quality management. The objective is not to demonstrate direct statistical equivalence between modelled maxima and measured concentrations, bu to use them as the complementary evidence within the limits of the available secondary data.

2. Methods

2.1 Data sources and study variable

This study used ambient-air monitoring results and archived modelling outputs previously processed using AERMOD. The modelled parameters were carbon monoxide (CO), nitrogen oxides (NOx), fine particulate matter ($PM_{2.5}$), and sulfur dioxide (SO_2). These parameters are relevant to combustion, thermal processing, material handling, and air-quality interpretation in industrial areas. CO is associated with incomplete combustion; NOx reflects high-temperature combustion; SO_2 is associated with sulfur-containing fuels or process emissions; and $PM_{2.5}$ represents fine inhalable particles generated by combustion and material-related activities (Jalali & Tourani, 2025; Sarwono et al., 2022).

The study consisted of pollutant types, seasonal scenarios, modeled maximum concentrations, measured ambient concentrations, ISPU values, and index categories. In the AERMOD interpretation, the seasonal scenarios included the rainy season and the dry season, because changes in meteorological conditions can influence wind direction, atmospheric stability, dilution, and pollutant accumulation (Bayraktar & Mutlu, 2024). In the ISPU interpretation, ambient concentrations were obtained from air monitoring results for carbon monoxide (CO), nitrogen dioxide (NO_2), fine particulate matter ($PM_{2.5}$), and sulfur dioxide (SO_2).

The main materials used in this study consisted of data including emission source information, ambient air monitoring results, and air dispersion modeling results. Emission source information was used to describe manufacturing activities, combustion processes, and energy consumption. Emission source data are important because industrial air quality modeling requires information on source types, emission characteristics, and other conditions that can influence pollutant concentrations (Buttigieg et al., 2016; Kumar et al., 2021). Meteorological data were used as input in air dispersion modeling because wind speed, wind direction, temperature, humidity, rainfall, and atmospheric conditions can influence pollutant movement, dilution, and accumulation (Istiana et al., 2023). Ambient air monitoring data were used to calculate ISPU, which was applied to the measured concentrations of CO, NO_2, $PM_{2.5}$, and SO_2 to determine air quality categories and the most dominant parameters influencing ambient air status around the facility. This approach was used because pollutant concentrations need to be translated into values or categories that are easier to understand for risk communication and environmental decision-making (Ravindra et al., 2024; Shihab, 2023).

The study adopted a descriptive comparative secondary-data design. Three evidence groups were used; (1) archived facility-level information describing relevant production, combustion, energy-use, and material-handling activities; (2) archived 24-hour AERMOD concentration maps and maximum values for rainy- and dry-season scenarios; and (3) one ambient monitoring dataset used for regulatory comparison and ISPU calculation. The AERMOD outputs and ambient measurements were analysed in parallel rather than merged into a single statistical series. Modelled values represent scenario-specific maximum receptor concentrations, whereas monitoring values represent concentrations observed at the sampling location and time. This distinction prevents the ambient measurements from being interpreted as direct validation points for the model.

Methodological transparency was constrained by the form in which the secondary data were available. The archived package did not contain the complete emission-inventory worksheet, source-by-source mass emission rates, stack dimensions, exhaust temperature and velocity, receptor coordinates and spacing, complete meteorological time series, or native AERMOD input and output files. Accordingly, the original model run could not be reconstructed and calibration choices could not be independently confirmed. The analysis was limited to outputs documented in the facility records. Internal quality assurance consisted of cross-checking pollutant names, units, averaging periods, seasonal labels, maximum values, arithmetic differences, relative changes, and ISPU calculations against the available tables and maps.

2.2 Data processing

Air-dispersion modelling was used to compare archived 24-hour maximum concentrations under rainy- and dry-season scenarios for CO, NOx, $PM_{2.5}$, and SO_2 (Sarwono et al., 2022). For each pollutant, the absolute seasonal difference was calculated by subtracting the rainy-season maximum from the dry-season maximum. The relative seasonal change was calculated as [(dry-season maximum - rainy-season maximum) / rainy-season maximum] x 100%. These descriptive calculations were used to determine the direction and proportional magnitude of seasonal variation. A 24-hour averaging period was retained because this was the averaging period available in the archived output and it allowed a consistent comparison across the four pollutants.

Because receptor-level time series and co-located, time-matched monitoring observations were unavailable, conventional model-performance indicators such as mean bias, normalized mean bias, root-mean-square error, fractional bias, index of agreement, and the fraction of predictions within a factor of two could not be calculated. No inferential test was applied to the four seasonal maxima because these values are pollutant-specific outputs rather than repeated independent observations. The analysis therefore used absolute differences and relative percentage changes as descriptive indicators. The absence of statistical model-observation validation is treated as a limitation, and the results are interpreted as a screening-level seasonal comparison rather than a definitive exposure or compliance model.

Ambient concentrations of CO, NO_2, $PM_{2.5}$, and SO_2 were then converted into ISPU values using the linear interpolation formula stipulated in Regulation of the Minister of Environment and Forestry of the Republic of Indonesia No. 14 of 2020 concerning the Air Pollutant Standard Index. The procedure involved identifying the concentration breakpoints surrounding each measured value, matching them to the corresponding index breakpoints, calculating the interpolated The ambient-air measurements were compared with the applicable ambient air quality standards stipulated in Government Regulation of the Republic of Indonesia No. 22 of 2021, while the corresponding ISPU categories were assigned based on the 0–500 scale. All concentration units were standardized to μg/m^3, and decimal points were used consistently in the English-language manuscript., as follows Equation 1. In the ISPU calculation, I represents the calculated ISPU value, Ia represents the upper ISPU breakpoint, and Ib represents the lower ISPU breakpoint. Xa represents the upper ambient concentration breakpoint (μg/m^3), Xb represents the lower ambient concentration breakpoint (μg/m^3), and Xx represents the actual measured ambient concentration (μg/m^3).

$$\mathrm{I} = \frac{(\mathrm{Ia}-\mathrm{Ib})}{(\mathrm{Xa}-\mathrm{Xb})}\,\mathrm{c}\,(\mathrm{Xx}-\mathrm{Xb}) + \mathrm{Ib} \quad \text{(Eq.1)}$$

The ISPU values obtained from the interpolation results were then classified into air quality categories according to the index ranges stipulated in Regulation of the Minister of Environment and Forestry of the Republic of Indonesia No. 14 of 2020. This classification translate numeric results not only indicate numerical values but also describe air quality status that can be understood by decision-makers, industrial managers, and the public. In this study, the ISPU categories were used to determine the pollutant parameters that contributed most dominantly to the air quality status around the manufacturing facility. The pollutant with the highest ISPU value was used as the principal indicator of ambient-air quality during the monitoring period because it most strongly determined the reported category. Quality assurance for the ISPU analysis consisted of verifying the pollutant-specific breakpoint interval, independently recalculating each interpolation, checking unit consistency, and confirming the category assignment. The highest pollutant-specific ISPU value was then used to represent the overall ambient-air category for the monitoring period in accordance with the national index procedure.

Table 1. Category ranges of the air pollutant standard index (ISPU)

ISPU Range	Category	Interpretation
1-50	Good	Air quality is very good and does not have negative impacts on humans, animals, plants, or the aesthetic value of the environment
51-100	Moderate	Air quality remains acceptable for the health of humans, animals, and plants
101-200	Unhealthy	Air quality is harmful to humans, animals, and plants
201-300	Very Unhealthy	Air quality can increase health risks among exposed community groups
>300	Hazardous	Air quality can cause serious health problems and requires immediate handling

(KLHK, 2020)

The highest index value among pollutant parameters was used as the main indicator of the ambient air quality category. This approach is consistent with the principle of air quality indices, which convert pollutant concentrations into values or categories that can be used to communicate air quality status more simply to the public and decision makers (Ravindra et al., 2024; Shihab, 2023). This approach allows the study to compare two complementary forms of evidence, namely the spatial dispersion patterns from AERMOD and the index based air quality status from ISPU. The two evidence streams were integrated interpretively by comparing the pollutants showing the largest seasonal increases in AERMOD-modelled concentrations with those exhibiting the highest measured ISPU values. This comparison was used to identify pollutants of greater management priority, without treating modelled and measured concentrations as directly equivalent (Bayraktar & Mutlu, 2024; Ren & Mia, 2025).

2.3 Research sites

This study was conducted at a location situated around the manufacturing industrial area in Tangerang City, Banten. The location was selected because it represents an urban industrial area characterized by production activities, energy use, combustion processes, material handling, road transpsortation, and interaction with residential areas. Industrial areas with production and combustion activities require location-based air quality assessment because pollutant concentrations can be influenced by emission source characteristics, meteorological conditions, and the positions of surrounding receptors (Bayraktar & Mutlu, 2024; Kumar et al., 2021). These characteristics make the study location relevant for examining air pollutant dispersion patterns and index-based interpretation of ambient air quality.

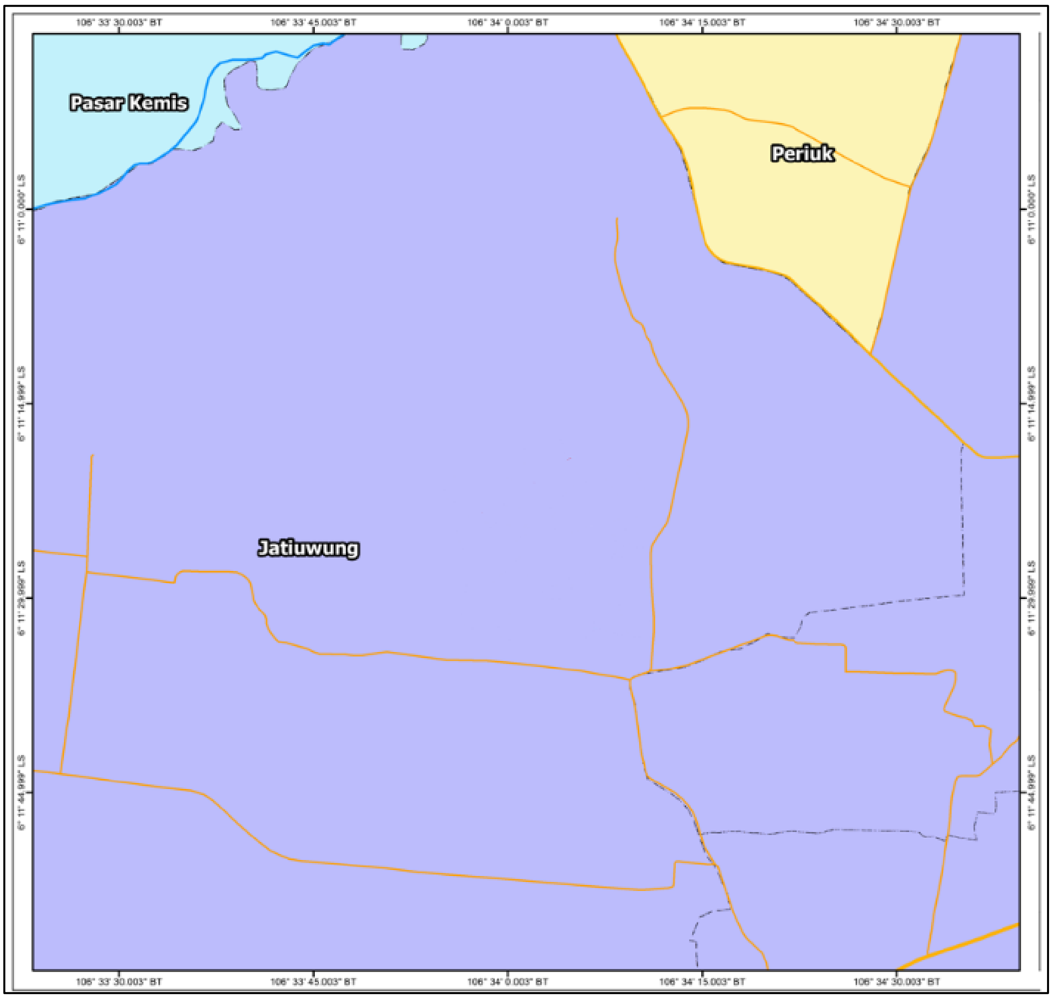

Fig. 1. Study Location

3. Results and Discussion

3.1 Seasonal dispersion pattern of air pollutants

Air dispersion analysis was conducted to determine the distribution pattern, range, and maximum concentration of pollutants originating from emission sources at the manufacturing facility. The modelling was performed using AERMOD with 24-hour output under two seasonal scenarios, namely the rainy season and the dry season. The parameters analyzed included carbon monoxide (CO), nitrogen oxides (NO_X), fine particulate matter ($PM_{2.5}$), and sulfur dioxide (SO_2). These four parameters were selected because they are related to combustion processes, thermal processing, material handling, and industrial operational activities. The 24-hour averaging period was retained because it was consistently available in the archived outputs, allowing comparison of modelled maximum concentrations across pollutants and seasonal scenarios. The results were therefore used to characterize 24-hour modelled ambient concentration patterns and identify locations with relatively higher concentrations around the facility.

The modelling results showed that the CO parameter had differences in maximum concentration between the rainy season and the dry season. During the rainy season, the maximum CO concentration was recorded at 42.745 μg/m^3, whereas during the dry season it increased to 51.226 μg/m^3. The difference between the two seasons reached 8.481 μg/m^3. This value indicates that the maximum CO concentration was higher during the dry season. The higher maximum concentration in the dry-season scenario may reflect differences in meteorological conditions, including reduced rainfall, atmospheric stability, and dispersion conditions. However, because the complete meteorological inputs were unavailable, the contribution of individual meteorological factors to the observed seasonal differences could not be independently evaluated. During the rainy-season scenario, rainfall may also influence pollutant concentrations through wet deposition; however, this mechanism could not be directly assessed based on the available modelling data. In contrast, during the dry season, drier air and lower rainfall can cause pollutants to remain longer in the atmosphere. In the context of manufacturing facilities, CO needs to be considered because this parameter is related to incomplete combustion from fuel-based sources, such as boilers, generators, or other thermal equipment (Fig. 2).

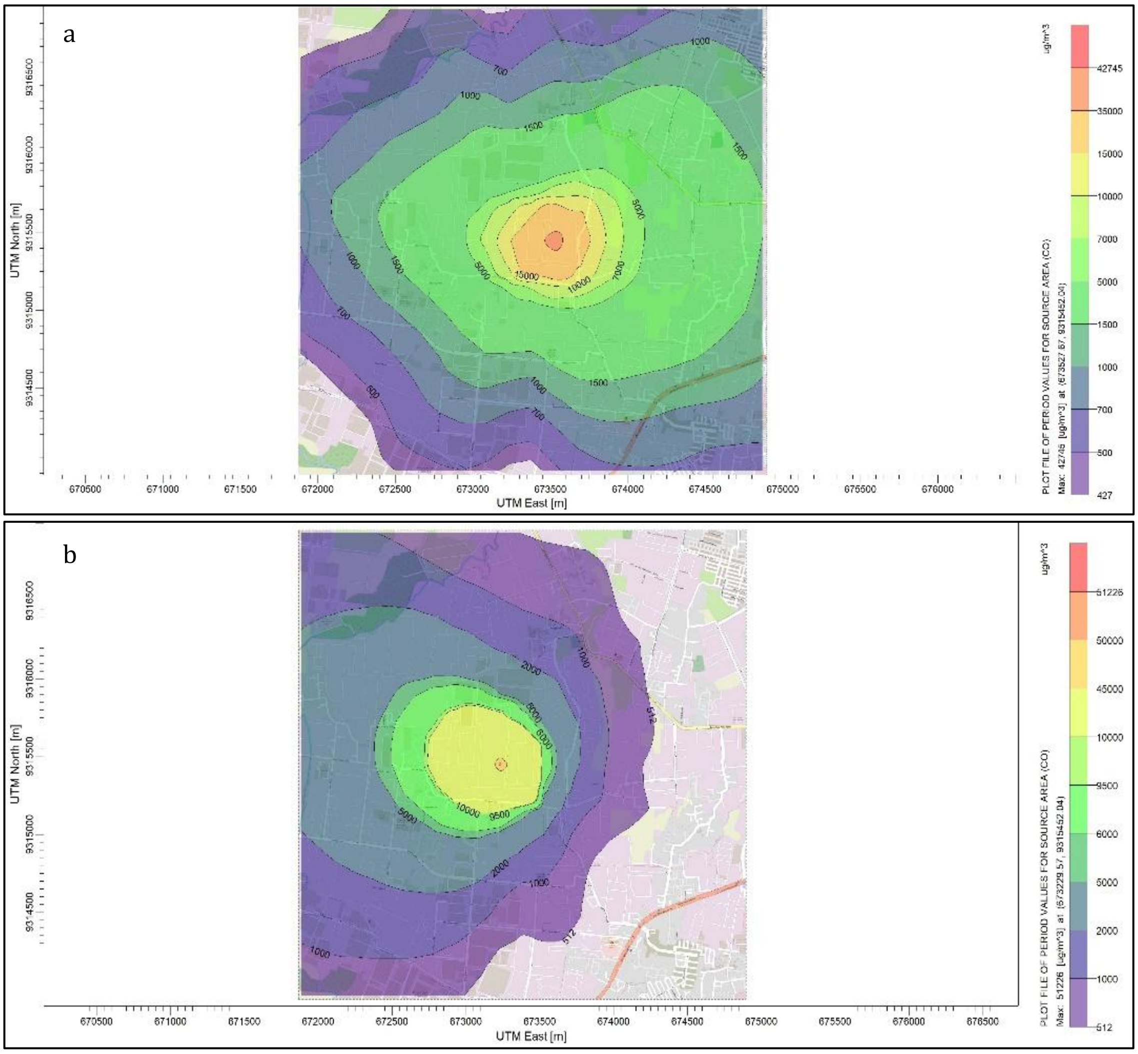

Fig. 2. (a) Analysis of CO parameter during the rainy season; (b) Analysis of CO parameter during the dry season

In addition, dry-season conditions may be associated with more stable atmospheric layers, reduced wet removal, and lower dispersion capacity, depending on local meteorological conditions. These factors can limit vertical and horizontal transport, making CO concentrations more dependent on emission rates, stack characteristics, wind direction, wind speed, and surrounding terrain. The seasonal increase therefore emphasizes the importance of combustion-efficiency control during dry periods. Regular maintenance of combustion equipment, verification of fuel quality, and continuous air-quality monitoring are needed to minimize CO emissions and reduce potential exposure for workers and nearby communities.

The NOx parameter also showed an increasing pattern during the dry season. During the rainy season, the maximum NO_x concentration was recorded at 467.8 μg/m^3. During the dry season, this value increased to 561 μg/m^3. The concentration difference of 93.2 μg/m^3 indicates that the dry period had a greater potential for NOx exposure than the rainy season. This increase needs to be considered because NOx is related to high-temperature combustion processes and the formation of reactive nitrogen compounds. In industrial activities, NOx sources can originate from combustion systems, heating processes, and fuel use in operational equipment. The higher concentration pattern during the dry season indicates that NOx control needs to be linked to the evaluation of combustion efficiency, the regulation of air to fuel ratios, and periodic inspection of stacks and stationary emission sources (Fig. 3).

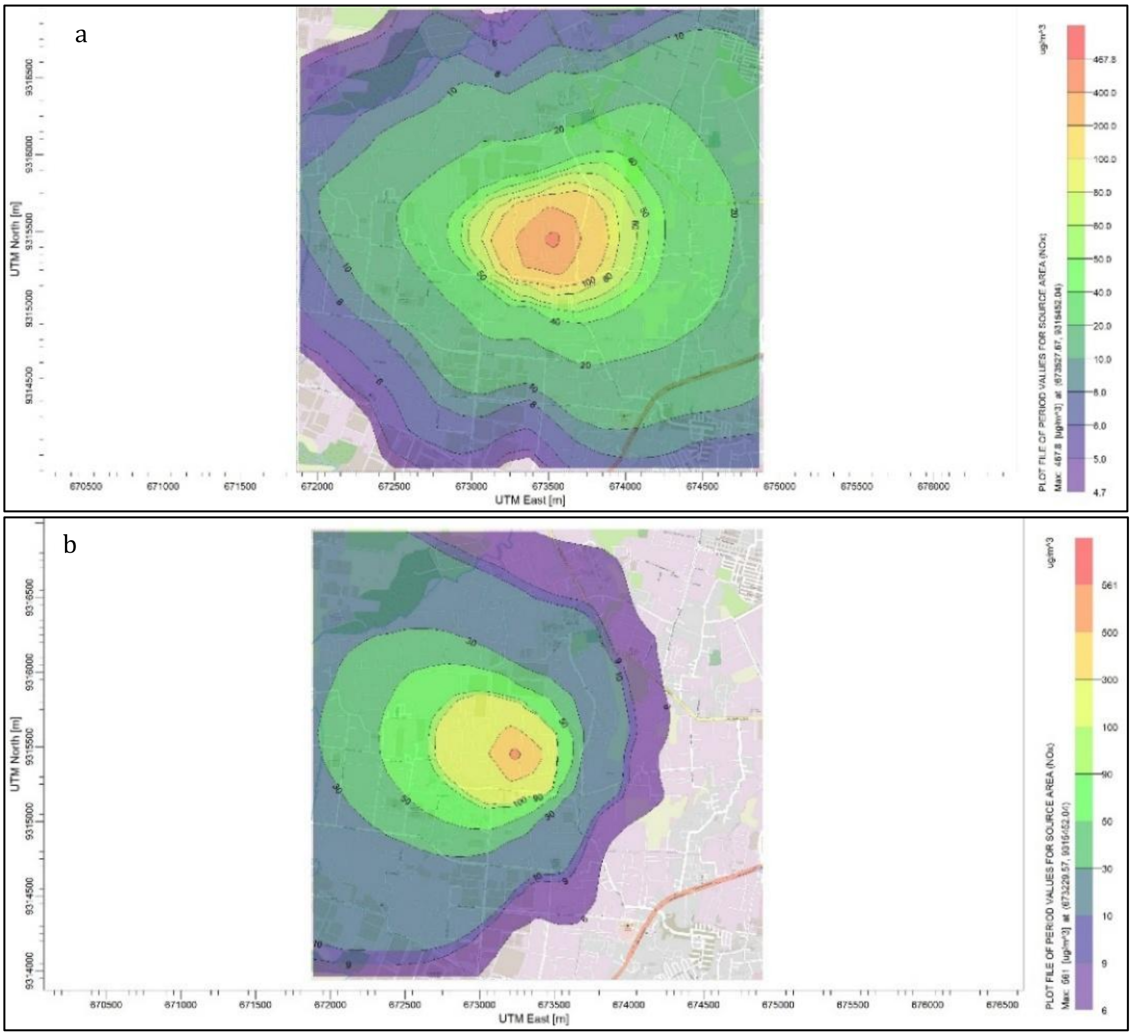

Fig. 3 (a) Analysis of NO_x parameter during the rainy season; (b) Analysis of NO_x parameter during the dry season

The dispersion maps show that the highest NOx concentrations were centred near the emission source and decreased toward surrounding receptors. This spatial pattern is consistent with the influence of source location, wind direction, and atmospheric dispersion. Lower rainfall during the dry season may reduce atmospheric removal and allow nitrogen oxides to persist for longer periods. The result supports periodic evaluation of combustion conditions, stack performance, and ambient monitoring during the dry season. It should not, however, be interpreted as a direct model-validation result because receptor-level monitoring data were unavailable.

Regarding the $PM_{2.5}$ parameter, the modelling results also showed an increase in maximum concentration during the dry season. The maximum $PM_{2.5}$ concentration during the rainy season was recorded at 274 μg/m^3, whereas during the dry season it increased to 329 μg/m^3. The concentration difference of 55 μg/m^3 indicates that fine particulate matter has a greater potential to accumulate during the dry period. This finding is important because $PM_{2.5}$ has a small particle size, allowing it to remain longer in the air and potentially enter the lower respiratory tract. In manufacturing facilities, $PM_{2.5}$ can originate from combustion processes, material handling activities, dust from production areas, internal vehicle movement, and particle resuspension from road surfaces or work floors. The increase in $PM_{2.5}$ during the dry season indicates that particulate control needs to receive particular attention, especially through improved housekeeping, dust control, filtration system inspection, and management of material areas that have the potential to generate fine particles (Fig. 4).

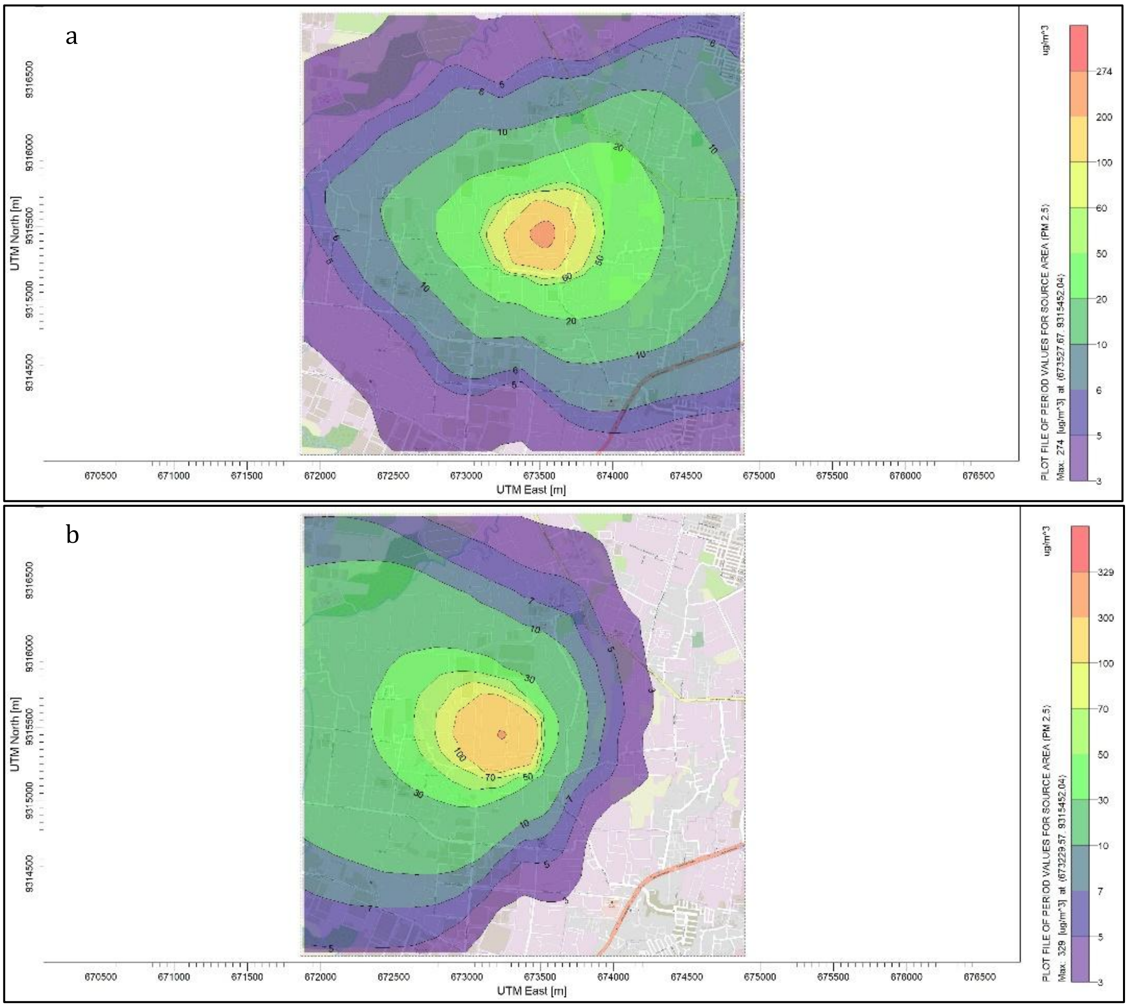

Fig. 4. (a) Analysis of $PM_{2.5}$ parameter during the rainy season; (b) Analysis of $PM_{2.5}$ parameter during the dry season

The spatial distribution shown in the modelling maps also indicates that the highest $PM_{2.5}$ concentration was concentrated near the emission source and gradually decreased toward the surrounding area. This pattern suggests that particulate dispersion was influenced by source location, wind movement, dry surface conditions, and reduced atmospheric removal during the dry season. Lower rainfall can reduce the wet deposition, while dry surfaces can increase particle resuspension caused by vehicle movement and production activities. Therefore, $PM_{2.5}$ management should address both stack emissions and fugitive dust sources. Periodic road cleaning, controlled water spraying in dusty areas, enclosure of material storage, and maintenance of dust-collector systems are relevant measures for reducing fine-particle accumulation during dry periods.

The SO_2 parameter showed the same tendency as the other parameters. During the rainy season, the maximum SO_2 concentration was recorded at 483.9 μg/m^3. During the dry season, the maximum concentration increased to 580 μg/m^3. The concentration difference of 96.1 μg/m^3 indicates that the potential exposure to SO_2 was higher during the dry season. SO_2 is generally associated with the combustion of sulfur-containing fuels or certain industrial processes that produce sulfur compounds. Therefore, the increase in SO_2 concentration during the dry period can serve as a signal for the need to monitor fuel quality, combustion system performance, and the effectiveness of emission control at stationary sources. Although the modelled values need to be interpreted as scenario-based results, this increasing pattern remains important because it indicates a period that requires greater operational attention (Fig. 5).

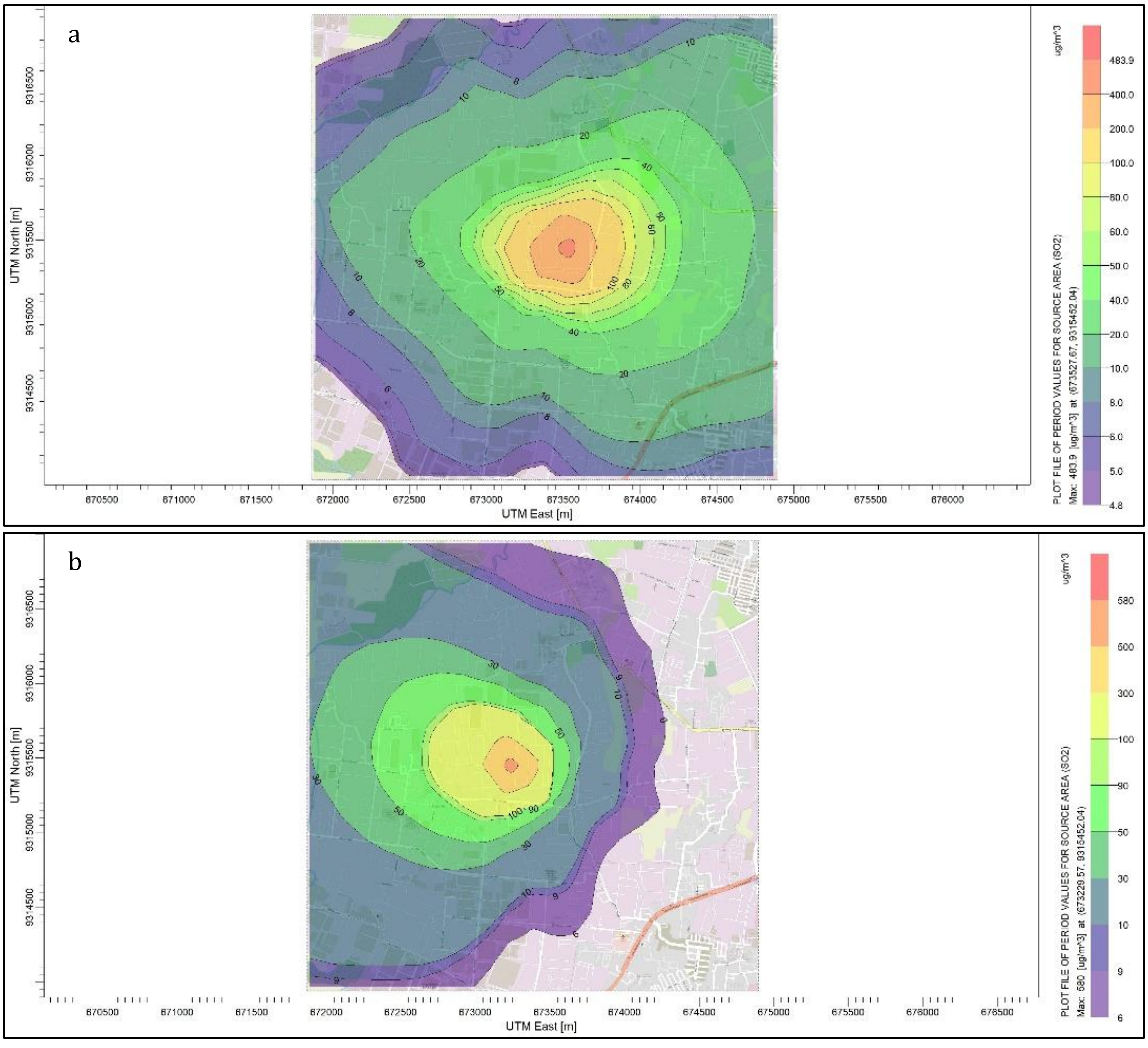

Fig. 5. (a) Analysis of SO_2 parameter during the rainy season; (b) Analysis of SO_2 parameter during the dry season

The dispersion maps shows that the highest SO_2 concentration occured near the emission source and decreased gradually toward the surrounding area. This pattern reflects the influence of stack location, emission strength, wind direction, and atmospheric stability. During the dry season, lower rainfall can reduce removal through wet deposition, allowing sulfur compounds to remain in the air for longer periods. Preventive control is therefore important for facilities that use sulfur-containing fuels or operate combustion equipment continuously. SO_2 management should include routine fuel-specification checks, stack-emission monitoring, combustion-system maintenance, and evaluation of control devices. These measures can reduce emission intensity and support more consistent air-quality protection during dry periods.

Taken together, the AERMOD results show that all four pollutants had higher maximum concentrations in the dry-season scenario. CO increased by 8.481 μg/m^3, NOx by 93.2 μg/m^3, $PM_{2,5}$ by 55 μg/m^3, and SO_2 by 96.1 μg/m^3. Although these pollutants have different sources, formation mechanisms, and environmental implications, the common direction of change indicates that seasonal conditions are relevant to facility-level air-quality management. Reduced rainfall can limit wet removal, while atmospheric stability and dry-surface resuspension may increase persistence or near-source accumulation. The rainy season, by contrast, may reduce some concentrations through rainfall and greater atmospheric removal.

Table 2. Comparison of maximum pollutant concentrations during the rainy and dry seasons

Parameter	Rainy Season	Dry Season	Difference	Relative change and interpretation
CO	42.745 μg/m^3	51,226 μg/m^3	8,481 μg/m^3	19.84%; higher in the dry season
NO_x	467.8 μg/m^3	561 μg/m^3	93.2 μg/m^3	19.92%; higher in the dry season
$PM_{2.5}$	274 μg/m^3	329 μg/m^3	55 μg/m^3	20.07%; higher in the dry season
SO_2	483.9 μg/m^3	580 μg/m^3	96.1 μg/m^3	19.86%; higher in the dry season

These results demonstrate the value of seasonal evaluation for identifying periods with higher potential concentrations. Emission control should not focus only on annual compliance but should also account for seasonal operational risk. More intensive dry-season monitoring can support early detection, timely maintenance, and preventive action before concentration increases become more significant around the facility. Because the analysis used archived maximum values rather than repeated receptor-level observations, the results describe a directional seasonal pattern and do not establish statistical significance.

The relative increases were 19.84% for CO, 19.92% for NOx, 20.07% for $PM_{2,5}$, and 19.86% for SO_2. Their close clustering around 20% suggests a common seasonal scaling pattern in the archived scenarios, although the available data are insufficient to determine whether this similarity arose from meteorological conditions, emission assumptions, or model configuration. The percentages should therefore not be interpreted as evidence that the pollutants have identical atmospheric behaviour. Previous industrial applications show that source characteristics and meteorological inputs can substantially alter concentration magnitude and plume direction (Kumar et al., 2021; Bayraktar & Mutlu, 2024). The near-source pattern visible in the maps is also consistent with AERMOD studies of boilers, diesel generators, and furnace stacks (Sarwono et al., 2022; Nugraha, 2023; Jalali & Tourani, 2025). Direct numerical comparison among studies remains inappropriate because emission rates, stack parameters, terrain, meteorology, receptor networks, and averaging periods differ. In the present case, the consistent seasonal direction is more defensible than the precise magnitude of change.

3.2 Ambient air quality and ISPU-based interpretation

Ambient-air quality assessment was conducted to complement the dispersion-modelling results. Whereas AERMOD provides spatially resolved scenario estimates, ISPU translates measured ambient concentrations into communicable air-quality categories. The analysis used 2025 monitoring results for CO, NO_2, $PM_{2,5}$, and SO_2. The monitoring values were analysed independently from the modelled maxima because the available datasets were not co-located and time-matched.

The measured concentrations were compared with the applicable ambient-air quality standards specified in Government Regulation of the Republic of Indonesia No. 22 of 2021 concerning the Implementation of Environmental Protection and Management (Government of the Republic of Indonesia, 2021). CO was measured at 3,149 μg/m^3 compared with a standard of 10,000 μg/m^3. NO_2 was 36.23 μg/m^3 compared with 200 μg/m^3; $PM_{2.5}$ was 30.41 μg/m^3 compared with 55 μg/m^3; and SO_2 was 38.12 μg/m^3 compared with 150 μg/m^3. These results indicate that the measured ambient conditions were within the referenced concentration limits. Nevertheless, interpretation should also consider each pollutant's relative contribution to the ISPU category because a parameter can remain below its concentration standard while still becoming the dominant index pollutant.

Table 3. Ambient air concentrations at the study location

Parameter	Quality Standard	Measurement Result
CO	10,000 μg/m^3	3,149 μg/m^3
NO_2	200 μg/m^3	36.23 μg/m^3
$PM_{2.5}$	55 μg/m^3	30.41 μg/m^3
SO_2	150 μg/m^3	38.12 μg/m^3

(Government of the Republic of Indonesia, 2021)

The ISPU calculation converted each measured concentration into the corresponding pollutant-specific index range. CO obtained an ISPU value of 39.36 and was classified as good. NO_2 obtained 22.64 and SO_2 obtained 36.65, both in the good category. $PM_{2.5}$ produced the highest value, 68.68, and was classified as moderate. $PM_{2.5}$ was therefore the pollutant that most strongly influenced the reported ambient-air category. The moderate category does not indicate severe pollution, however, $PM_{2.5}$ had the highest ISPU value and determined the overall air-quality category during the monitoring period. ISPU is thus useful not only for classifying air quality but also for identifying priority parameters. In this case, $PM_{2.5}$ control should be strengthened through fugitive-dust management, monitoring of combustion sources, maintenance of filtration systems, and regular ambient-air evaluation.

Table 4. ISPU calculation results at the research location

Parameter	Measurement Result	ISPU Value	Category
CO	3,149 μg	39.36	Good
NO_2	36.23 μg	22.64	Good
$PM_{2.5}$	30.41 μg	68.68	Moderate
SO_2	38.12 μg	36.65	Good

Based on these results, $PM_{2.5}$ had the highest ISPU value. Although the measured $PM_{2.5}$ concentration remained below the applicable ambient-air quality standard for the stated averaging period, its ISPU value was classified as moderate. This finding demonstrates that compliance-oriented concentration comparison and index-based communication provide different, complementary information. $PM_{2.5}$ requires priority attention because fine particles can remain airborne for extended periods and penetrate into the lower respiratory tract. Management around industrial facilities should therefore address both direct emissions and secondary resuspension pathways.

The ISPU values of CO, NO_2, and SO_2, which were classified in the good category, indicate that these three parameters were not the main determinants of ambient air quality status during the monitoring period. However, this result does not mean that control of combustion gases can be ignored. CO remains associated with incomplete combustion, NO_2 is associated with high-temperature combustion processes, and SO_2 is associated with fuels or processes containing sulfur. Therefore, management of these three parameters still needs to be carried out through combustion equipment maintenance, emission source inspection, fuel quality monitoring, and regular air monitoring.

Compared with the AERMOD results, the ISPU analysis provides a different layer of interpretation. AERMOD showed that the maximum concentrations of CO, NOx, $PM_{2.5}$, and SO_2 were higher in the dry-season scenario, whereas ISPU identified $PM_{2.5}$ as the dominant pollutant in the measured ambient-air category. The combined findings indicate two management priorities: strengthening seasonal emission control during dry periods and prioritizing fine-particulate management throughout routine operations.

This finding has direct implications for industrial environmental management. Emission control should extend beyond pass-fail comparison with quality standards and aim to prevent concentration increases that could change the air-quality category. $PM_{2.5}$ controls should address production dust, material handling, internal vehicle movement, road-surface resuspension, and combustion sources. These measures can be supported by filtration maintenance, improved housekeeping, enclosure of raw-material areas, energy-efficiency measures, and repeated ambient monitoring. Taken together, the ISPU results show that the ambient-air category was good for CO, NO_2, and SO_2 and moderate for $PM_{2.5}$. Fine particulate matter is therefore the priority parameter for control in the available monitoring dataset.

The combined interpretation provides three practical advantages. First, AERMOD identifies where and under which seasonal scenario concentrations may be elevated, while ISPU identifies which measured pollutant most strongly determines the communicable air-quality category. Second, the approach avoids equating regulatory compliance with the absence of management concern: $PM_{2.5}$ remained below the referenced concentration standard but produced a moderate ISPU value. Third, the combined evidence supports a tiered control plan. During the dry season, the facility should increase inspection frequency for dust collectors and filters, improve enclosure and housekeeping in material-handling areas, control vehicle speed and road dust, and verify that combustion systems operate at appropriate air-to-fuel ratios. CO management should emphasize combustion completeness and preventive maintenance; NOx management should focus on combustion temperature, burner condition, and air-fuel control; SO_2 management should include fuel-sulfur verification and stationary-source monitoring; and $PM_{2.5}$ management should integrate stack and fugitive-source controls.

These implications are consistent with the broader literature. Industrial AERMOD studies emphasize that dispersion models are useful for source-receptor analysis and control planning but remain sensitive to emission inventories, meteorological inputs, receptor selection, and validation procedures (Kumar et al., 2021; Bayraktar & Mutlu, 2024; Jalali & Tourani, 2025). Air-quality indices are effective communication tools, but they cannot attribute an observed concentration to a particular source (Shihab, 2023; Ravindra et al., 2024). Used together, the two approaches can inform management without overstating certainty: modelled maxima guide spatial and seasonal attention, while monitored ISPU values guide pollutant prioritization and risk communication. A seasonal monitoring plan should therefore define trigger levels, responsible personnel, corrective actions, and follow-up verification so that modelling and monitoring results are connected to operational decisions.

Operationalization of the combined framework can be organized into three management phases. During the baseline phase, the facility should maintain a verified inventory of stationary and fugitive sources, document operating hours and fuel use, and establish routine ambient and stack-monitoring schedules. During the intensified dry-season phase, inspection frequency should be increased for boilers, generators, burners, bag filters, dust collectors, material-transfer points, internal roads, and storage areas. Corrective actions should be linked to observable indicators such as unusual smoke, pressure-drop changes across filters, increased dust deposition, fuel-specification deviations, or rising ambient $PM_{2.5}$ values. During the evaluation phase, monitoring results should be reviewed together with production and meteorological records to determine whether controls reduced concentration patterns and whether additional modelling is required. This management cycle would convert the study findings into an auditable environmental programme rather than a one-time assessment. It would also provide the documentation needed for future model validation, because emission rates, operating conditions, receptor observations, and meteorological data could be aligned by date and location. In this way, the current screening-level analysis can serve as a foundation for a progressively more reproducible and evidence-based air-quality management system.

4. Conclusions

This study demonstrates that combining air-dispersion modelling with ISPU calculation provides complementary information for assessing air quality around industrial manufacturing facilities, where AERMOD provides information on seasonal and spatial patterns of modelled pollutant concentrations while ISPU provides a categorical interpretation of measured ambient air quality. AERMOD provides information on seasonal and spatial patterns of modelled pollutant concentrations, whereas ISPU provides a categorical interpretation of measured ambient air quality. The two approaches should be treated as complementary rather than directly comparable because modelled maxima and monitoring values represent different locations, times, and analytical purposes. Their integration nevertheless supports environmental control, pollutant prioritization, and risk communication.

The principal findings show that the dry-season scenario produced higher modelled maxima for all pollutants and that $PM_{2.5}$ was the priority pollutant in the available monitoring dataset because it had the highest pollutant-specific ISPU value and determined the overall ambient-air category. The article's contribution lies in connecting seasonal dispersion evidence, measured air-quality status, and facility-level green-industry priorities while explicitly distinguishing modelled from measured concentrations. The findings support targeted dry-season monitoring, enhanced particulate-source control, continued attention to combustion-system performance, and the integration of air-quality assessment into cleaner-production and sustainable-management programmes.

In practical terms, industrial air-quality management should be responsive to seasonal variation. Control measures should not be limited to routine compliance activities but should be intensified during periods with greater accumulation potential. During the dry season, facilities should increase inspection of emission sources, maintain combustion and filtration equipment, control fugitive dust from production and transport activities, verify fuel specifications, and document corrective actions through a seasonal monitoring plan.

Integrated assessment tools can support more evidence-based pollution control. AERMOD helps identify potential spatial concentration patterns around emission sources, while ISPU simplifies the interpretation of measured air quality for managers, regulators, workers, and surrounding communities. The combined approach can guide the selection of priority pollutants, critical seasons, and control strategies without overstating the certainty of secondary data.

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Author Contribution

Conceptualization, P.I.N.K., W.B., and H.A.; Methodology, P.I.N.K. and H.A.; Software, P.I.N.K.; Validation, W.B. and H.A.; Formal Analysis, P.I.N.K.; Investigation, P.I.N.K.; Resources, P.I.N.K.; Data Curation, P.I.N.K.; Writing – Original Draft Preparation, P.I.N.K.; Writing – Review & Editing, W.B. and H.A.; Visualization, P.I.N.K.; Supervision, W.B. and H.A.; Project Administration, P.I.N.K.; and Funding Acquisition, P.I.N.K.

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Ethical Review Board Statement

Ethical review and approval were waived for this study because the manuscript analyzes facility-level secondary environmental monitoring and modeling data and does not involve biomedical intervention, animal subjects, or identifiable personal health data. If required by the target journal or institution, the authors should replace this statement with the official ethics approval number before submission.

Informed Consent Statement

Not available for the air-dispersion and ambient-index analysis because the manuscript does not report identifiable human-participant data.

Data Availability Statement

The data supporting the reported results are derived from the thesis dataset and facility monitoring records. Access to raw facility data is restricted due to confidentiality. The processed tables used in this article are available in the manuscript.

Conflicts of Interest

The authors declare no conflict of interest. The authors also declare that there are no personal circumstances or interests that could be perceived as influencing the representation or interpretation of the reported research results. Since this research received no external funding, no funder had any role in the design of the study, the collection, analysis, or interpretation of data, the writing of the manuscript, or the decision to publish the results.

Declaration of Generative AI Use

During the preparation of this work, the authors used ChatGPT by OpenAI to assist in improving language clarity, academic structure, grammar, and manuscript formatting. The tool was used only to support manuscript preparation and did not replace the authors' scientific judgment, data analysis, interpretation, or conclusions. After using this tool, the authors reviewed, verified, and edited the content as needed and took full responsibility for the content of the publication.

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References

Ahmad, S., Wong, K. Y., & Butt, S. I. (2023). Status of sustainable manufacturing practices: literature review and trends of triple bottom-line-based sustainability assessment methodologies. *Environmental Science and Pollution Research*, *30*(15), 43068–43095. https://doi.org/10.1007/s11356-022-22172-z

Araujo-Morera, J., Verdejo, R., López-Manchado, M. A., & Hernández Santana, M. (2021). Sustainable mobility: The route of tires through the circular economy model. *Waste Management*, *126*, 309–322. https://doi.org/10.1016/j.wasman.2021.03.025

Bayraktar, O. M., & Mutlu, A. (2024). Analyses of industrial air pollution and long-term health risk using different dispersion models and WRF physics parameters. *Air Quality, Atmosphere and Health*, *17*(10), 2277–2305. https://doi.org/10.1007/s11869-024-01573-8

Bolan, S., Padhye, L. P., Jasemizad, T., Govarthanan, M., Karmegam, N., Wijesekara, H., Amarasiri, D., Hou, D., Zhou, P., Biswal, B. K., Balasubramanian, R., Wang, H., Siddique, K. H. M., Rinklebe, J., Kirkham, M. B., & Bolan, N. (2024). Impacts of climate change on the fate of contaminants through extreme weather events. *Science of the Total Environment*, *909*(August 2023). https://doi.org/10.1016/j.scitotenv.2023.168388

Buttigieg, S. C., Dey, P. K., & Cassar, M. R. (2016). Combined quality function deployment and logical framework analysis to improve quality of emergency care in Malta. *International Journal of Health Care Quality Assurance*, *29*(2), 123–140. https://doi.org/10.1108/IJHCQA-04-2014-0040

Chen, W., Alharthi, M., Zhang, J., & Khan, I. (2024). The need for energy efficiency and economic prosperity in a sustainable environment. *Gondwana Research*, *127*, 22–35. https://doi.org/10.1016/j.gr.2023.03.025

Cimorelli, A. J., Perry, S. G., Venkatram, A., Weil, J. C., Paine, R. J., Wilson, R. B., Lee, R. F., Peters, W. D., & Brode, R. W. (2005). AERMOD: A dispersion model for industrial source applications. Part I: General model formulation and boundary layer characterization. *Journal of Applied Meteorology*, *44*(5), 682–693. https://doi.org/10.1175/JAM2227.1

Dewi, S. K., Febrianti, R., & Utama, D. M. (2023). An integrated method for manufacturing sustainability assessment in tire industry: a case study in Indonesian. *International Journal of Sustainable Engineering*, *16*(1), 1–12. https://doi.org/10.1080/19397038.2023.2276936

Dong, Y., Zhao, Y., Hossain, M. U., He, Y., & Liu, P. (2021). Life cycle assessment of vehicle tires: A systematic review. *Cleaner Environmental Systems*, *2*, 100033. https://doi.org/10.1016/j.cesys.2021.100033

Fahim, K., Sholichah, S. A., Hanafi, L., Surjanto, S. D., Herisman, I., & Doctorina, W. F. (2024). prediksi indeks standar pencemar udara (ISPU) di Kota Surabaya menggunakan rantai markov waktu diskrit. *Jurnal Ilmiah Soulmath : Jurnal Edukasi Pendidikan Matematika*, *12*(2), 121–134. https://doi.org/10.25139/smj.v12i2.8684

Fan, Y. V., Chin, H. H., Klemeš, J. J., Varbanov, P. S., & Liu, X. (2020). Optimisation and process design tools for cleaner production. *Journal of Cleaner Production*, *247*, 119181. https://doi.org/10.1016/j.jclepro.2019.119181

Farghali, M., Osman, A. I., Mohamed, I. M., Chen, Z., Chen, L., Ihara, I., ... & Rooney, D. W. (2023). Strategies to save energy in the context of the energy crisis: a review. *Environmental Chemistry Letters*, *21*(4), 2003-2039. https://doi.org/10.1007/s10311-023-01591-5

Firdaus, A., Al Khalidi, S. M., Adhitya, R. F., & Hadna, A. H. (2025). Uncovering Jakarta air pollution problem using classification analysis of public policy. *Jurnal Borneo Administrator*, *21*(2), 105-124. https://doi.org/10.24258/jba.v21i2.1595

Giannetti, B. F., Agostinho, F., Eras, J. C., Yang, Z., & Almeida, C. M. V. B. (2020). Cleaner production for achieving the sustainable development goals. *Journal of Cleaner*

Production, *271*, 122127. https://doi.org/10.1016/j.jclepro.2020.122127
Government of the Republic of Indonesia. (2021). *Peraturan Pemerintah Republik Indonesia Nomor 22 Tahun 2021 tentang Penyelenggaraan Perlindungan dan Pengelolaan Lingkungan Hidup*. Lembaran Negara Republik Indonesia Tahun 2021 Nomor 32, Tambahan Lembaran Negara Republik Indonesia Nomor 6634. Pemerintah Republik Indonesia. https://peraturan.bpk.go.id/Details/161852/pp-no-22-tahun-2021
Irjayana, R. C., Fadlil, A., & Umar, R. (2025). Pengaruh seleksi fitur terhadap klasifikasi indeks standar pencemar udara menggunakan naïve bayes. *Insect (Informatics and Security): Jurnal Teknik Informatika*, *11*(1), 67–78. https://doi.org/10.33506/insect.v11i1.4303
Istiana, T., Kurniawan, B., Soekirno, S., Nahas, A., Wihono, A., Nuryanto, D. E., Adi, S. P., & Hakim, M. L. (2023). Causality analysis of air quality and meteorological parameters for $PM_{2.5}$ characteristics determination: evidence from Jakarta. *Aerosol and Air Quality Research*, *23*(9), 1–18. https://doi.org/10.4209/aaqr.230014
Jalali, I., & Tourani, S. (2025). Dispersion modeling of NOx from stacks of cracking furnaces of OLEFIN unit using AERMOD. *Results in Chemistry*, *13*(August 2024), 102051. https://doi.org/10.1016/j.rechem.2025.102051
Karuppiah, K., Sankaranarayanan, B., & Lo, H. W. (2024). A systematic literature review on the evolution of sustainable manufacturing practices: Key findings and implications. *Cleaner Engineering and Technology*, *22*(August), 100798. https://doi.org/10.1016/j.clet.2024.100798
Katarzyna, P., Izabela, P., Patrycja, B. W., Weronika, K., & Andrzej, T. (2020). Lca as a tool for the environmental management of car tire manufacturing. *Applied Sciences (Switzerland)*, *10*(20), 1–25. https://doi.org/10.3390/app10207015
KLHK. (2020). *Peraturan Menteri Lingkungan Hidup dan Kehutanan Republik Indonesia Nomor P.14/MENLHK/SETJEN/KUM.1/7/2020 tentang Indeks Standar Pencemar Udara*. Berita Negara Republik Indonesia Tahun 2020 Nomor 774. Kementerian Lingkungan Hidup dan Kehutanan Republik Indonesia. https://peraturan.bpk.go.id/Details/163466/permen-lhk-no-14-tahun-2020
Kumar, A., Dikshit, A. K., & Patil, R. S. (2021). Use of simulated and observed meteorology for air quality modeling and source ranking for an industrial region. *Sustainability (Switzerland)*, *13*(8), 14–20. https://doi.org/10.3390/su13084276
Ma, S., Ding, W., Liu, Y., Zhang, Y., Ren, S., Kong, X., & Leng, J. (2024). Industry 4.0 and cleaner production: A comprehensive review of sustainable and intelligent manufacturing for energy-intensive manufacturing industries. *Journal of Cleaner Production*, *467*, 142879. https://doi.org/10.1016/j.jclepro.2024.142879
Manisalidis, I., Stavropoulou, E., Stavropoulos, A., & Bezirtzoglou, E. (2020). Environmental and health impacts of air pollution: a review. *Frontiers in public health*, *8*, 14. https://doi.org/10.3389/fpubh.2020.00014
Marimin, Darmawan, M. A., Widhiarti, R. P., & Teniwut, Y. K. (2018). Green productivity improvement and sustainability assessment of the motorcycle tire production process: A case study. *Journal of Cleaner Production*, *191*, 273–282. https://doi.org/10.1016/j.jclepro.2018.04.228
Naess, B., Isakov, V., & Teyssier, M. (2026). Dispersion modeling to characterize air pollution exposure from sargassum in martinique. *Air*, *4*(1), 4. https://doi.org/10.3390/air4010004
Nogueira, E., Gomes, S., & Lopes, J. M. (2023). Triple bottom line, sustainability, and economic development: What binds them together? a bibliometric approach. In *Sustainability (Switzerland)* (Vol. 15, Issue 8). MDPI. https://doi.org/10.3390/su15086706
Nugraha, P. S. (2023). AERMOD modeling analysis of CO And NOx parameters from diesel generator emission sources in the coal mining industry. *Sriwijaya Journal of Environment*, *8*(2), 92–97. https://doi.org/10.22135/sje.2023.8.2.92-97
Piccioni, M., Martini, F., Martini, C., & Toro, C. (2024). Evaluation of energy performance indicators and energy saving opportunities for the Italian rubber manufacturing

industry. *Energies*, *17*(7). https://doi.org/10.3390/en17071584

Ravindra, K., Singh, V., & Mor, S. (2024). Why we should have a universal air quality index? *Environment International*, *187*(April), 108698. https://doi.org/10.1016/j.envint.2024.108698

Ren, X., & Mia, M. A. (2025). The determinants of green innovations in manufacturing industries: a systematic literature review. *Future Business Journal*, *11*(1), 42. https://doi.org/10.1186/s43093-025-00461-6

Rovira, J., Domingo, J. L., & Schuhmacher, M. (2020). Air quality, health impacts and burden of disease due to air pollution (PM_{10}, $PM_{2.5}$, NO_2 and O_3): Application of AirQ+ model to the Camp de Tarragona County (Catalonia, Spain). *Science of the Total Environment*, *703*, 135538. https://doi.org/10.1016/j.scitotenv.2019.135538

Salsabila, D., & Utami, N. F. (2025). Klasifikasi dan pemetaan spasial kualitas udara berbasis ispu menggunakan support vector machine dengan data multisumber: Indonesia. *Jurnal Sains & Teknologi Lingkungan*, *17*(2), 167-187. https://doi.org/10.20885/jstl.vol17.iss2.art6

Sarwono, E., Wijayanto, E., Huda, H., Harrits, R. F., & Zain, I. F. (2022). Dispersion of SO_2 and NO_2 emitted by auxiliary boiler of pt kmi methanol industrial using the gaussian plum model aermod in Bontang City East Kalimantan Indonesia. *Jurnal Chemurgy*, *6*(2), 109. https://doi.org/10.30872/cmg.v6i2.9560

Shanbag, A., & Manjare, S. (2020). Life cycle assessment of tyre manufacturing process. *Journal of Sustainable Development of Energy, Water and Environment Systems*, *8*(1), 22–34. https://doi.org/10.13044/j.sdewes.d7.0260

Shihab, A. S. (2023). Assessment of air quality through multiple air quality index models – a comparative study. *Journal of Ecological Engineering*, *24*(4), 110–116. https://doi.org/10.12911/22998993/159398

Syuhada, G., Akbar, A., Hardiawan, D., Pun, V., Darmawan, A., Heryati, S. H. A., Siregar, A. Y. M., Kusuma, R. R., Driejana, R., Ingole, V., Kass, D., & Mehta, S. (2023). Impacts of air pollution on health and cost of illness in Jakarta, Indonesia. *International Journal of Environmental Research and Public Health*, *20*(4). https://doi.org/10.3390/ijerph20042916

Xia, X., & Li, P. (2022). A review of the life cycle assessment of electric vehicles: Considering the influence of batteries. *Science of the Total Environment*, *814*, 152870. https://doi.org/10.1016/j.scitotenv.2021.152870

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