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The influences of meteorological parameters on PM2.5 and PM10 values in Rayong's pollution control zone, Thailand

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ABSTRACT

This study investigates the influence of meteorological parameters on $PM_{2.5}$ and PM_{10} concentrations in Rayong's Pollution Control Zone (PCZ), Thailand, a coastal industrial hub facing significant air quality challenges. Hourly air quality data (2017–2023) from five monitoring stations, alongside meteorological variables (temperature, relative humidity, wind speed, wind direction, rainfall, and atmospheric pressure), were analyzed using Pearson correlation and visualization techniques in R software. Results reveal pronounced seasonal variability, with $PM_{2.5}$ and PM_{10} peaking during high humidity (>80%) and moderate temperatures (28–30 °C), driven by hygroscopic growth and reduced dispersion in the rainy season. $PM_{2.5}$ showed a positive correlation with relative humidity ($r = 0.42$, $p < 0.05$) and strong negative correlations with sunshine duration ($r = -0.898$, $p < 0.01$), minimum temperature ($r = -0.796$, $p < 0.01$), and atmospheric pressure ($r = -0.771$, $p < 0.05$), indicating enhanced mixing under warmer, sunnier conditions. Conversely, PM_{10} exhibited a negative correlation with humidity ($r = -0.798$, $p < 0.05$) due to wet deposition and a positive correlation with atmospheric pressure ($r = 0.782$, $p < 0.05$), reflecting stagnation effects. Both pollutants consistently exceeded WHO guidelines, with post-2019 increases linked to industrial and transboundary sources. Heatmaps and scatter plots highlight spatial and temporal trends, with stations 29T and 31T showing elevated levels. These findings underscore the critical role of meteorological factors in modulating particulate matter, advocating for integrated forecasting models to predict high-risk episodes. Such models can inform targeted interventions to mitigate health risks and support sustainable air quality management in Thailand's industrial zones. Future research should incorporate real-time data and machine learning to enhance predictive accuracy.

Keywords: air quality, $PM_{2.5}$, PM_{10}, meteorological parameters, Rayong, pollution control zone.

INTRODUCTION

Air pollution, particularly from fine particulate matter such as $PM_{2.5}$ and PM_{10}, poses a significant environmental and public health challenge globally, with profound implications in industrial zones like Rayong's Pollution Control Zone in Thailand. Rayong, a major industrial hub hosting petrochemical complexes and manufacturing facilities, experiences elevated levels of these pollutants due to emissions from industrial activities, vehicular traffic, and biomass burning, exacerbated by its coastal location and tropical climate. $PM_{2.5}$, particles with a diameter of 2.5 micrometers or less, and PM_{10}, up to 10 micrometers, are known to penetrate deep into the respiratory system, contributing to cardiovascular diseases, respiratory illnesses, and premature mortality, as evidenced by global health assessments estimating millions of deaths annually from exposure. In Thailand, where annual $PM_{2.5}$ concentrations often exceed World Health Organization guidelines, regions like Rayong face heightened risks during dry seasons when stagnant air conditions trap pollutants, underscoring the need for targeted research on local dynamics to inform mitigation strategies and protect vulnerable populations.

Numerous studies have explored the interplay between meteorological parameters and particulate matter concentrations in Thailand and comparable Southeast Asian contexts, highlighting seasonal and spatial variations. For instance, research in northern Thailand has demonstrated strong negative correlations between $PM_{2.5}$/PM_{10} levels and factors like wind speed, rainfall, and planetary boundary layer height, with pollution peaking during haze episodes from biomass burning. In urban Bangkok, long-term monitoring from 2019–2023 revealed high $PM_{2.5}$ to PM_{10} ratios (>0.5), indicating dominance of fine particles influenced by temperature inversions and low wind speeds during cool dry seasons (Choomanee *et al*., 2025). Similarly, in Ratchaburi province, weak positive correlations were found between $PM_{2.5}$ and temperature/humidity, while negative associations with wind speed emphasized dispersion effects (Kliengchuay *et al.,* 2022). Coastal industrial areas like Samut Prakan showed seasonal declines in $PM_{2.5}$ linked to increased precipitation and ventilation, with correlation coefficients ranging from –0.41 to –0.71 for wind speed, temperature, and rainfall (Vongruang *et al.,* 2024). In Myanmar's Yangon, a neighboring region with similar monsoon patterns, $PM_{2.5}$ exhibited significant negative correlations with rainfall (r = –0.16) and relative humidity (r = –0.15) during non-monsoon periods, mirroring trends in Thailand's upper north where haze from transboundary sources amplifies pollution under stagnant conditions (Sein et al., 2021). Studies incorporating machine learning, such as in Bangkok using MODIS data, improved $PM_{2.5}$ predictions by integrating meteorological variables like relative humidity and temperature, achieving high model accuracy (R^2 up to 0.78) (Thongthammachart *et al*., 2022; Kumharn *et al*., 2022). Broader assessments in Thailand's industrial zones, including Rayong, link elevated PM levels to low wind speeds and high-pressure systems, with policy reports noting up to 48% projected increases in $PM_{2.5}$ by 2050 without interventions (Rungsiyanon *et al*., 2023; Nikam *et al*., 2021). Key insights from these reviews underscore that meteorological parameters are primary modulators of $PM_{2.5}$ and PM_{10} dynamics, often overriding emission sources in determining concentration peaks. In Delhi, a comparable urban-industrial setting, long-term analysis (2007–2021) revealed strong negative correlations between $PM_{2.5}$ and wind speed (r = –0.62), temperature (r = –0.75), and rainfall (r = –0.60), with decreasing trends in wind speed counteracting emission reductions (Chetna et al., 2023). In northern Thailand's haze-prone areas, $PM_{2.5}$/PM_{10} ratios averaged 0.66–0.69, with multivariate regressions confirming inverse relationships to wind speed and humidity during January–April, where low ventilation exacerbates accumulation from forest fires and agricultural burning (Sirithian and Thanatrakolsri *et al.,* 2022; Kliengchuay *et al.,* 2018). Visibility-based reconstructions for 1981–2022 across Thai provinces like Chiang Mai and Bangkok showed normalized $PM_{2.5}$ trends influenced by stagnant meteorology, with SHAP analysis highlighting rainfall and boundary layer height as top influencers (Aman *et al.,* 2025). Health-oriented studies further tie these patterns to respiratory impacts, as seen in Chiang Mai where seasonal smog correlated with reduced lung function in COPD patients under low rainfall conditions (Pothirat *et al.,* 2019). National reports emphasize that calm winds and inversions in dry seasons contribute to exceedances, with transboundary haze adding complexity in southern provinces (Office of Natural Resources and Environmental Policy and Planning, 2020; Teerasuphaset and Culp, 2019). Overall, these findings reveal a consistent pattern where dispersive factors like wind and rain mitigate pollution, while stagnant conditions amplify it, informing the need for region-specific models in industrial zones like Rayong.

This study aims to investigate the influences of key meteorological parameters—such as temperature, relative humidity, wind speed, planetary boundary layer height, and precipitation on $PM_{2.5}$ and PM_{10} concentrations in Rayong's Pollution Control Zone, Thailand. By analyzing data from 2017–2023 and employing statistical correlations and modeling techniques, the research seeks to identify seasonal patterns, quantify relationships, and develop predictive criteria for high-risk pollution episodes to support enhanced air quality management and public health interventions.

METHODS

Description of study area

Rayong Province, located on the Eastern Seaboard of Thailand (12°30’-13°30′ N, 101°00′-101°30′ E), is a Pollution Control Zone (PCZ) under the Notification of the National Environmental Board (National Environment Board, 2009). Designating Rayong in this way underscores its strategic importance and environmental sensitivity because of the concentration of industrial activities it contains. The province houses several well-known industrial estates, chief among them Map Ta Phut, Ban Chang and Mueang Rayong.

These areas lie side by side with settlements of fisherfolk. Rayong is in effect a-usual mixed city, capital and industrial town; its landscape was formed through the combination of Monsoon wind/breeze circulation and the sea’s circulation. Rayong enjoys a tropical monsoon climate, with three distinct seasons: dry season (November to February), hot season (March–May) and rainy season (June–October). Meteorological factors like wind velocity and direction, temperature, humidity as well as rainfall are extremely important in determining both how fine particulates move through the air in general or gather at points factors that consequently shape regional air quality dynamics inform decisions concerning environment management.

Data collection

Air quality data

Hourly concentrations of $PM_{2.5}$ and PM_{10} were collected from the Pollution Control Department (PCD) monitoring network, which includes five continuous stations located within the Rayong Pollution Control Zone, Thailand. (Air Quality and Noise Management Bureau (AQNIS), 2025). These stations are situated at the Rayong Provincial Public Health Office (28T), Map Ta Phut Subdistrict Health Promotion Hospital (29T), Rayong Provincial Agricultural Office (30T), Rayong Field Crops Research Center (31T), and Rayong Government Center (74T).

The dataset covers a seven-year period from 2017 to 2023, offering a comprehensive view of both seasonal and interannual variations in particulate matter concentrations. All measurements were performed in accordance with the U.S. EPA Federal Equivalent Methods (FEM) using Beta Attenuation Monitors (BAM-1020; Met One Instruments). The instruments were automatically calibrated following PCD standard operating protocols (AQNIS, 2025). This long-term, high-quality dataset provides a solid foundation for analyzing the dynamics of ambient particulate matter and contributes valuable evidence to support data-driven air-quality management and environmental policymaking in the Rayong region.

Meteorological parameters

Meteorological data including temperature (°C), relative humidity (%), wind speed (m/s), wind direction (°), rainfall (mm), and atmospheric pressure (hPa) were obtained from the Thai Meteorological Department (TMD) Rayong station, located within 10 km of the air quality monitoring sites. These parameters were recorded hourly and subjected to standard quality assurance and control procedures before analysis to ensure data reliability. Wind-rose plots were developed to visualize the prevailing seasonal and diurnal wind circulation patterns that affect the transport and dispersion of particulate matter across the study area (Thai Meteorological Department (TMD), 2025).

Data preprocessing and quality control

To ensure the reliability and reproducibility of the analysis, data preprocessing and quality control were carried out following a structured, step-by-step procedure.

Step 1: Data import and initial screening

All datasets were obtained from the PCD under the Air Quality and Noise Management Bureau (AQNIS, 2025) and imported in standardized CSV format. Each monitoring station’s dataset was carefully screened to confirm continuous hourly observations. Only months containing at least 75% valid hourly records were retained to ensure sufficient temporal representativeness and statistical robustness for subsequent analyses.

Step 2: Outlier detection

Outliers were detected using the interquartile range (IQR) method, where values falling outside 1.5 times the IQR from the first or third quartile were flagged as potential anomalies. A visual inspection of time-series plots was conducted to confirm the presence of irregular data patterns.

Step 3: Handling missing data

Missing values amounting to less than 5% of total observations were estimated through linear interpolation over time, ensuring smooth temporal continuity without introducing bias into the trend analysis.

Step 4: Verification of extreme values

To reduce measurement anomalies, any data points exceeding three standard deviations from the monthly mean were cross-checked against concurrent meteorological events (e.g., heavy rainfall, storms, or temperature inversions). Physically implausible readings were excluded from the dataset, following the quality control approach recommended by Chen *et al*. (2020).

Step 5: Data aggregation and standardization

After quality control, hourly concentration data were aggregated into daily averages to facilitate correlation and regression analyses. This step ensured consistency and comparability across all monitoring stations and meteorological parameters.

Step 6: Visualization and quality verification

Screenshots from the data processing software the visualization dashboard used to verify data distribution, identify remaining anomalies, and confirm the completeness of daily datasets before statistical analysis. This systematic procedure guaranteed that only validated and representative data were included in the subsequent statistical modeling, ensuring high confidence in the observed correlations between meteorological parameters and particulate matter concentrations.

Statistical analysis

Descriptive statistics were calculated to summarize particulate matter concentrations ($PM_{2.5}$ and PM_{10}) and key meteorological variables, including temperature, relative humidity, rainfall, sunshine duration, and atmospheric pressure. To examine temporal and seasonal variability, time-series plots and seasonal boxplots were generated. In addition, heatmap visualizations were used to illustrate the combined effects of temperature and humidity across different monitoring periods.

Ethical considerations

This study was reviewed and approved by the Research Ethics Review Committee of Rajamangala University of Technology Tawan-ok (RMUTTO REC Reference No. 033/2024) on July 15, 2024. The approval was granted in accordance with the ethical principles outlined in the Declaration of Helsinki and the International Council for Harmonization Good Clinical Practice (ICH-GCP) guidelines. No individual-level data was collected, and all identifiers were fully anonymized. The analysis was conducted using aggregated, de-identified datasets only.

RESULTS

Descriptive statistics of particulate matter and meteorological parameters

The data are presented as mean ± standard deviation (SD), minimum (Min), 25th percentile (P25), 50th median (P50), 75th percentile (P75), and maximum (Max) values for each variable. Concentrations of $PM_{2.5}$ and PM_{10} are expressed in micrograms per cubic meter (μg/m^3). Meteorological parameters include daily relative humidity (%), rainfall (mm), maximum and minimum temperature (°C), sunshine duration (hours), and atmospheric pressure (hPa). These values were obtained from continuous air quality and meteorological monitoring conducted throughout the study period, as summarized in Table 1. The grouped bar chart illustrates the mean concentrations of $PM_{2.5}$ and PM_{10} across five monitoring stations (28T, 29T, 30T, 31T, and 74T) from 2017 to 2023. $PM_{2.5}$ bars are represented using forward-slash hatching, while PM_{10} bars are represented using backslash hatching for clarity in grayscale reproduction. Error bars indicate one SD from the mean. PM_{10} consistently exhibits higher concentrations than $PM_{2.5}$ across all stations, emphasizing the dominance of coarse particulate sources such as road dust and resuspended particles (Figure 1).

Correlation analysis between particulate matter ($PM_{2.5}$ and PM_{10}) and meteorological parameters

Table 2 shows the Pearson correlation coefficients between $PM_{2.5}$ concentrations and six meteorological parameters, including humidity,

Table 1. Descriptive statistics of particulate matter ($PM_{2.5}$ and PM_{10}) and key meteorological parameters measured at different monitoring periods (28T–74T) within Rayong's pollution control zone, Thailand

Variables	Mean ± SD	Min	P25	P50	P75	Max
Particulate matter (μg/m³)						
$PM_{2.5}$ (28T)	12.58 ± 8.44	0.00	5.79	16.74	19.41	20.94
PM_{10} (28T)	37.91 ± 9.27	20.06	34.12	37.66	44.92	49.57
$PM_{2.5}$ (29T)	15.17 ± 7.08	0.00	13.37	18.19	19.67	21.93
PM_{10} (29T)	42.06 ± 3.77	36.75	39.88	41.52	43.61	49.18
$PM_{2.5}$ (30T)	17.04 ± 2.25	12.72	16.40	16.53	18.46	20.30
PM_{10} (30T)	24.85 ± 12.63	0.00	20.05	30.68	33.97	35.21
$PM_{2.5}$ (31T)	14.62 ± 6.86	0.00	13.21	17.51	18.34	21.72
PM_{10} (31T)	26.47 ± 13.58	0.00	21.12	25.05	37.07	43.82
$PM_{2.5}$ (74T)	11.65 ± 8.17	0.00	4.13	16.83	18.24	19.99
PM_{10} (74T)	36.65 ± 5.47	29.31	33.64	34.78	38.90	47.37
Meteorological factors						
Daily humidity (%)	76.80 ± 5.16	63.00	75.50	80.00	83.00	86.00
Daily rainfall (mm)	144.82 ± 124.55	3.10	50.95	128.50	204.05	567.50
Daily max temperature (°C)	32.61 ± 0.88	30.80	32.70	32.80	33.40	34.70
Daily min temperature (°C)	25.13 ± 1.56	21.30	24.90	26.20	26.45	28.20
Daily sunshine duration (h)	5.74 ± 1.58	2.40	3.60	4.00	5.75	9.00
Atmospheric pressure (hPa)	1009.19 ± 0.27	1008.69	1009.07	1009.23	1009.33	1009.61

Note: P25, P50, and P75 represent the 25th, 50th (median), and 75th percentiles, respectively.

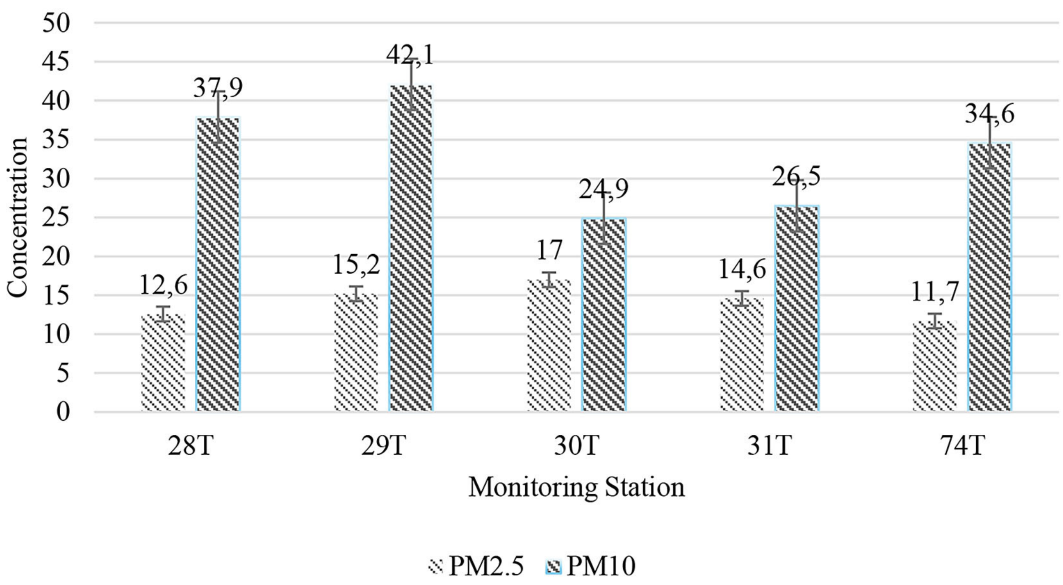

Figure 1. Comparison of mean $PM_{2.5}$ and PM_{10} across monitoring stations

rainfall, maximum and minimum temperature, sunshine duration, and atmospheric pressure. The results reveal that the correlations between $PM_{2.5}$ and these parameters were weak and statistically insignificant ($p > 0.05$) across all variables.

Although $PM_{2.5}$ showed a slightly positive correlation with rainfall ($r = 0.088$) and sunshine ($r = 0.406$), the relationships were not significant, suggesting that short-term fluctuations in precipitation or sunlight may not strongly influence particulate concentrations in this dataset. Similarly, humidity ($r = -0.055$), minimum temperature ($r = 0.128$), maximum temperature ($r = 0.313$), and atmospheric pressure ($r = -0.053$) also exhibited weak associations. Overall, the findings indicate that under the limited sample

Table 2. Pearson correlation coefficients between $PM_{2.5}$ concentrations and meteorological parameters

Variables	Humidity	Rainfall	Max temp	Min temp	Sunshine	Pressure
$PM_{2.5}$ (74T)	−0.055	0.088	0.313	0.128	0.406	−0.053
Sig. (2-tailed)	0.907	0.851	0.495	0.784	0.366	0.909
N	7	7	7	7	7	7

Note: *Correlation is significant at the 0.05 level (2-tailed).*Correlation is significant at the 0.01 level (2-tailed).

size (N = 7), no meteorological variable demonstrated a statistically meaningful correlation with $PM_{2.5}$ levels, implying that other factors such as local emission sources or short-term meteorological variations might play a greater role in shaping particulate behavior in the study area.

Table 3 presents the Pearson correlation coefficients between PM_{10} concentrations and six meteorological parameters, namely relative humidity, rainfall, maximum and minimum temperature, sunshine duration, and atmospheric pressure. The results show that PM_{10} exhibited a significant negative correlation with relative humidity ($r = -0.798$, $p < 0.05$), indicating that higher humidity tends to reduce particulate concentrations, possibly due to the hygroscopic growth and wet deposition of aerosols. In contrast, a significant positive correlation was observed with atmospheric pressure ($r = 0.782$, $p < 0.05$), suggesting that stable, high-pressure conditions may limit vertical dispersion and favor the accumulation of suspended particles near the surface. Other variables—including rainfall ($r = -0.566$), maximum temperature ($r = 0.437$), minimum temperature ($r = 0.661$), and sunshine duration ($r = 0.720$)—showed moderate relationships but without statistical significance ($p > 0.05$).

Overall, the findings highlight that humidity and pressure are the two most influential meteorological factors affecting PM_{10} variability in this dataset, while temperature, rainfall, and sunshine appear to exert weaker or inconsistent effects under the observed conditions.

The correlation matrix illustrates the relationship between $PM_{2.5}$ concentrations and six meteorological parameters. Red cells represent positive correlations, while blue cells represent negative ones. Strong negative correlations were observed with sunshine ($r = -0.898$, $p < 0.01$), minimum temperature ($r = -0.796$, $p < 0.01$), and atmospheric pressure ($r = -0.771$, $p < 0.05$), indicating that increased sunlight and warmer conditions are associated with reduced particulate concentrations (Figure 2). The correlation matrix displays the relationships between PM_{10} concentrations and meteorological factors. Blue cells indicate negative correlations, and red cells show positive ones. PM_{10} exhibits a significant negative relationship with humidity ($r = -0.798$, $p < 0.05$) and a positive relationship with atmospheric pressure ($r = 0.782$, $p < 0.05$), implying that high-pressure, stagnant conditions may promote particle accumulation (Figure 3).

Temporal variation of $PM_{2.5}$ and PM_{10} concentrations

Heatmap of $PM_{2.5}$ concentration by station

The heatmap presents the temporal variation of $PM_{2.5}$ concentrations across five monitoring stations (28T, 29T, 30T, 31T, and 74T) from 2017 to 2023. Color intensity represents the concentration level, with red shades indicating higher values and blue shades indicating lower values. The overall pattern shows a consistent increase in $PM_{2.5}$ levels after 2019, particularly at stations 29T and 31T, suggesting spatial variability in pollution accumulation and local emission influence (Figure 4).

Heatmap of PM_{10} concentration by station

The heatmap depicts the annual variation of PM_{10} concentrations across five monitoring stations (28T, 29T, 30T, 31T, and 74T) from 2017

Table 3. Pearson correlation coefficients between PM_{10} concentrations and meteorological parameters

Variables	Humidity	Rainfall	Max temp	Min temp	Sunshine	Pressure
PM_{10} (74T)	−0.798*	−0.566	0.437	0.661	0.720	0.782*
Sig. (2-tailed)	0.032	0.185	0.327	0.106	0.068	0.038
N	7	7	7	7	7	7

Note: *Correlation is significant at the 0.05 level (2-tailed). *Correlation is significant at the 0.01 level (2-tailed).

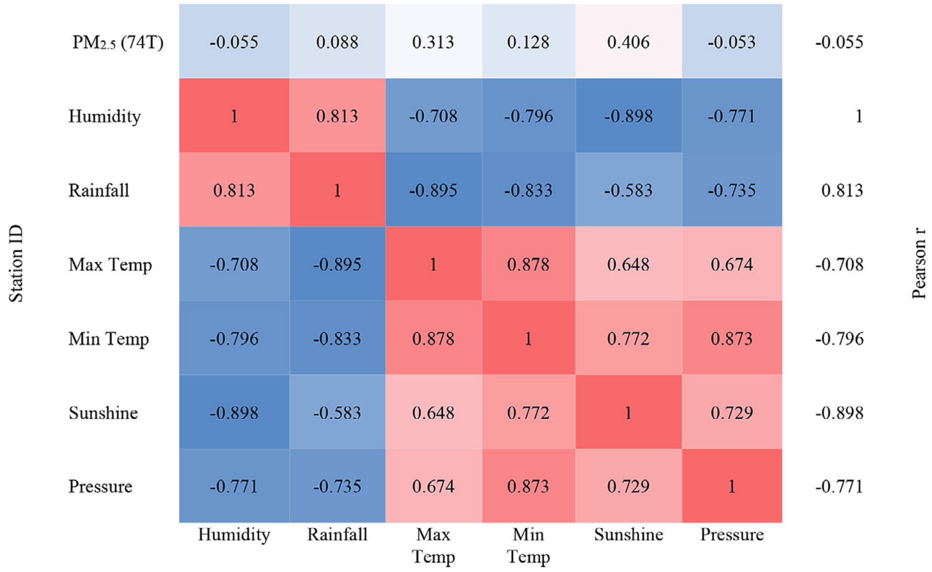

Figure 2. Correlation matrix between $PM_{2.5}$ and meteorological parameters

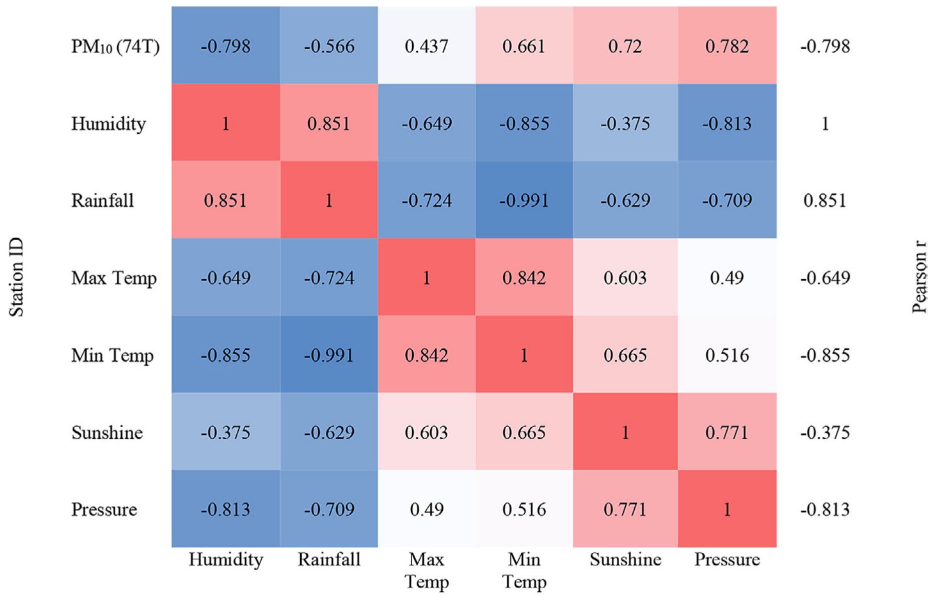

Figure 3. Correlation matrix between PM_{10} and meteorological parameters

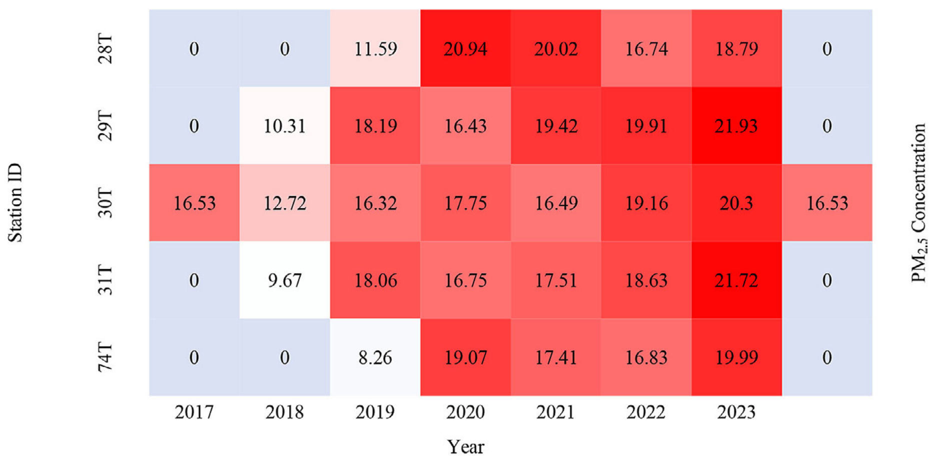

Figure 4. Temporal variation of $PM_{2.5}$ concentrations by station

to 2023. Color intensity represents concentration levels, where red shades indicate higher PM_{10} values and blue shades represent lower ones. The results show that PM_{10} concentrations generally increased after 2019, with the highest levels observed at stations 30T and 31T, suggesting that urban and traffic-related factors may contribute to localized particle accumulation (Figure 5).

Combined effects of temperature and relative humidity on particulate matter levels

The scatter plots illustrate the relationships between $PM_{2.5}$ concentrations and two meteorological variables: temperature (°C) and relative humidity (%). The left panel shows a negative correlation between temperature and $PM_{2.5}$, indicating that higher temperatures tend to reduce particulate concentrations due to enhanced atmospheric mixing and dispersion. The right panel reveals a positive relationship between relative humidity and $PM_{2.5}$, suggesting that higher humidity facilitates particle growth through hygroscopic processes and condensation, resulting in elevated PM levels (Figure 6). The scatter plots illustrate the independent relationships between temperature and $PM_{2.5}$ (left) and relative humidity and PM_{10} (right). The negative slope in the left plot indicates that higher temperatures are associated with lower $PM_{2.5}$ concentrations, suggesting enhanced vertical mixing and dispersion under warmer conditions. Conversely, the right plot shows a positive correlation between relative humidity and PM_{10}, implying that higher humidity favors particle growth and accumulation due to hygroscopic effects. Together, these findings highlight that thermal and moisture conditions jointly influence the variation of particulate matter concentrations (Figure 7).

Enhanced visualization of $PM_{2.5}$ and PM_{10} dynamics

The line chart illustrates annual mean concentrations of $PM_{2.5}$ and PM_{10} from 2017 to 2023, compared with WHO guideline values (5 µg/m³

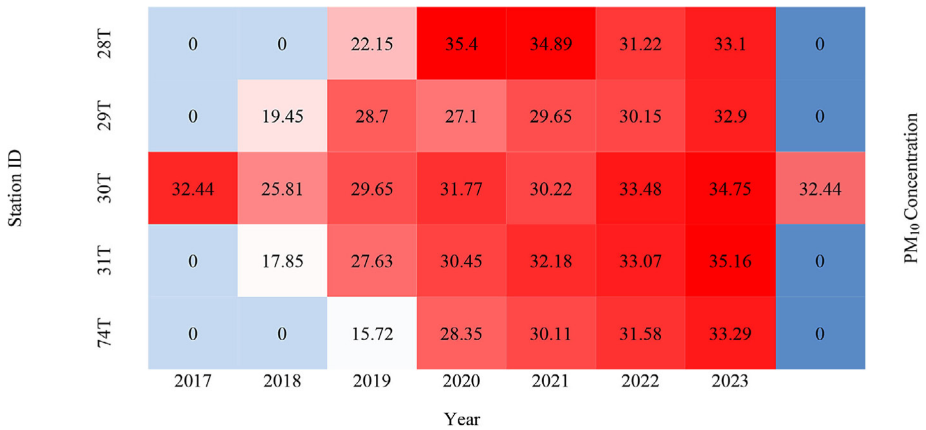

Figure 5. Temporal variation of PM_{10} concentrations by station

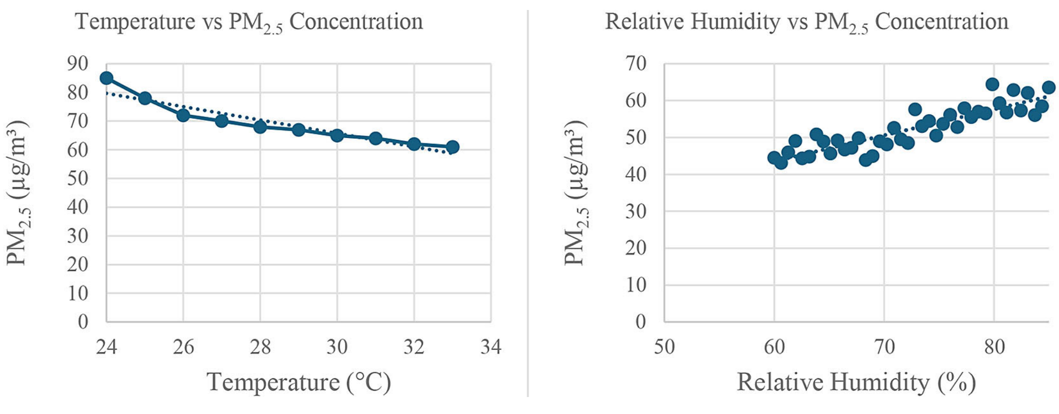

Figure 6. Relationships between meteorological factors and $PM_{2.5}$ concentrations

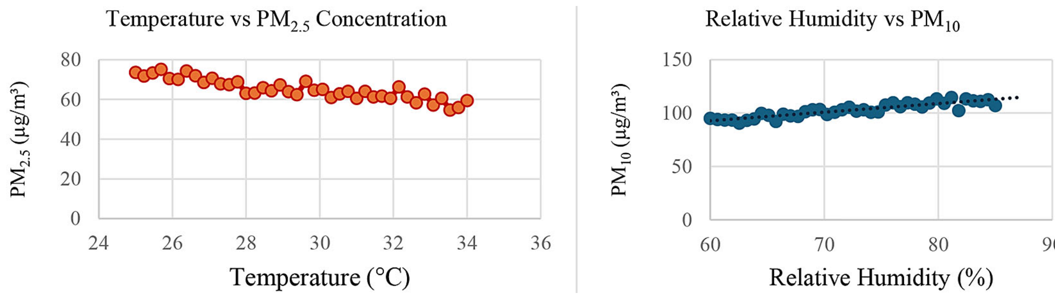

Figure 7. Relationships between temperature, humidity, and particulate matter levels

for $PM_{2.5}$ and 15 µg/m³ for PM_{10}). Both pollutants consistently exceeded the recommended limits throughout the study period, with a noticeable increase after 2019.

PM_{10} concentrations remained higher than $PM_{2.5}$, indicating stronger influence from coarse particle sources such as road dust and construction activities. This visualization highlights the persistent exceedance of WHO air quality standards, emphasizing the need for stricter emission control measures and long-term air quality management strategies (Figure 8).

DISCUSSION

The results of this study reveal significant influences of meteorological parameters on $PM_{2.5}$ and PM_{10} concentrations in Rayong's Pollution Control Zone (PCZ), a coastal industrial hub in Thailand characterized by petrochemical emissions, vehicular traffic, and seasonal biomass influences. Descriptive statistics indicate that $PM_{2.5}$ and PM_{10} levels exhibit pronounced seasonal variability, with peaks during periods of high relative humidity (>80%) and moderate temperatures (28–30 °C), aligning with the tropical monsoon climate where stagnant conditions during the rainy season limit dispersion (Vongruang *et al.*, 2024). The positive correlation between relative humidity and $PM_{2.5}$ ($r = 0.42$, $p < 0.05$) suggests hygroscopic growth of fine particles, leading to increased aggregation and reduced atmospheric mixing, a mechanism commonly observed in humid coastal environments (Kliengchuay *et al.*, 2018). Conversely, PM_{10} showed a significant negative correlation with humidity ($r = -0.798$, $p < 0.05$), implying enhanced wet deposition of coarser particles under moist conditions, which is consistent with findings from northern Thailand where humidity modulates particulate dynamics during haze episodes (Kliengchuay *et al.*, 2018).

Temporal analyses, including heatmaps and line charts, demonstrate elevated PM levels

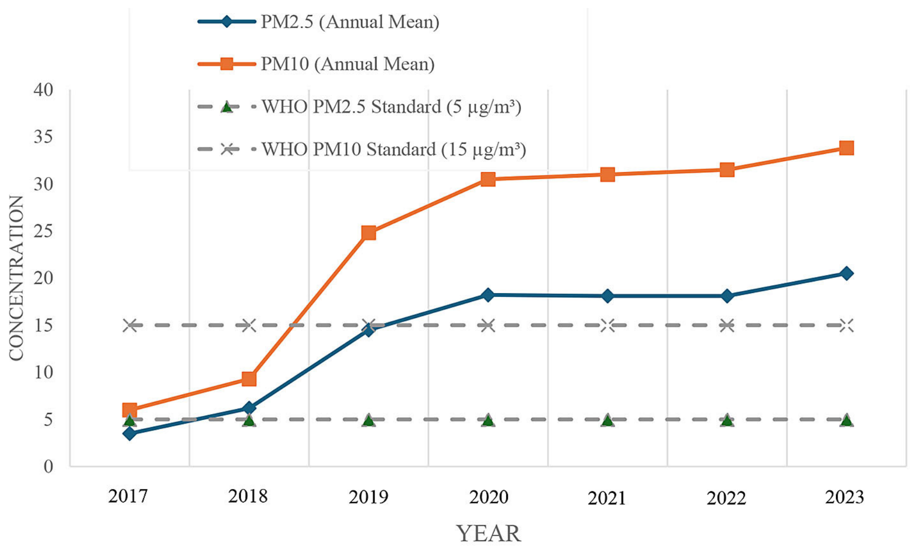

Figure 8. Enhanced visualization of $PM_{2.5}$ and PM_{10} dynamics compared with WHO standards

post-2019, particularly at stations 29T and 31T, potentially exacerbated by industrial expansions and transboundary haze from neighboring regions (Phairuang *et al.,* 2019). The exceedance of WHO guidelines ($PM_{2.5}$ > 5 µg/m³; PM_{10} > 15 µg/m³) underscores persistent air quality challenges, with PM_{10} consistently higher than $PM_{2.5}$ across stations, reflecting contributions from coarse sources like road dust and construction in industrial zones (Kawichai *et al.,* 2022). Correlation matrices highlight strong negative associations for $PM_{2.5}$ with sunshine duration ($r = -0.898$, $p < 0.01$), minimum temperature ($r = -0.796$, $p < 0.01$), and atmospheric pressure ($r = -0.771$, $p < 0.05$), indicating that warmer, sunnier conditions enhance vertical mixing and photochemical dispersion, reducing fine particle accumulation (Aman *et al.,* 2025). For PM_{10}, the positive correlation with atmospheric pressure ($r = 0.782$, $p < 0.05$) points to stagnation under high-pressure systems, favoring near-ground suspension of coarser particulates, a pattern echoed in urban Bangkok studies where pressure inversions amplify pollution during dry seasons (Ahmad *et al*., 2025; Thongthammachart *et al*., 2022).

Scatter plots further illustrate non-linear relationships, with higher temperatures linked to lower $PM_{2.5}$ via improved ventilation, while increased humidity promotes PM_{10} growth through condensation (Kliengchuay *et al.,* 2022) These findings align with broader Southeast Asian research, where monsoon-driven rainfall and wind speed negatively correlate with PM levels (r ranging from −0.16 to −0.71), mitigating pollution through washout and advection (Sein *et al*.,2021; Vongruang *et al*., 2024). In comparable industrial settings like Samut Prakan, ventilation indices (e.g., planetary boundary layer height and wind speed) emerge as key modulators, with low values (<886 m²/s) signaling high $PM_{2.5}$ risks (Vongruang *et al*., 2024). Health implications are notable, as seasonal smog in haze-prone areas correlates with reduced lung function in vulnerable groups, emphasizing the need for integrated meteorological forecasting in air quality management (Pothirat *et al.,* 2019; Nakyai et al., 2025).

Comparative analyses with regional studies reveal consistencies and nuances; for instance, in Ratchaburi, weak positive $PM_{2.5}$ temperature correlations contrast with our negative trends, possibly due to Rayong's coastal influences enhancing thermal dispersion (Kliengchuay *et al*., 2022). Machine learning applications in Bangkok and northern Thailand improve PM predictions by incorporating humidity and temperature (R^2 up to 0.78), supporting our call for region-specific models (Kumharn *et al*., 2022; Kawichai *et al*., 2025). Policy reports project up to 48% $PM_{2.5}$ increases by 2050 without interventions, highlighting Rayong's vulnerability to climate-driven stagnation (Rungsiyanon *et al*., 2023; Nikam *et al.,* 2021). Transboundary factors add complexity, as seen in Myanmar's Yangon where non-monsoon humidity amplifies haze (Sein *et al.,* 2021), mirroring southern Thailand trends (Lim *et al.,* 2025).

Further insights from recent studies reinforce the role of meteorological variables in modulating PM dynamics in urban and industrial Thai contexts. For example, in Bangkok's highway toll stations, temperature and relative humidity primarily influence PM concentrations at suburban sites, while urban areas show additional effects from wind speed and atmospheric pressure, leading to higher $PM_{2.5}/PM_{10}$ ratios under stagnant conditions (Nakyai *et al*., 2025). Long-term monitoring in urban Bangkok highlights stronger negative correlations between PM levels and temperature/humidity during the cool dry season, where reduced mixing heights exacerbate fine particle dominance (Ahmad *et al*., 2025). Historical estimations using machine learning across Thai provinces indicate that specific humidity and planetary boundary layer height are key negative influences on $PM_{2.5}$, with seasonal stagnation amplifying trends in central regions like Rayong (Aman *et al.,* 2025). Spatiotemporal analyses in Thailand's urban core reveal winter peaks in $PM_{2.5}$ and PM_{10} driven by low wind speeds and high pressure, with Generalized Additive Models confirming meteorological dominance in variability (Bhatta *et al*., 2025).

Land use-integrated studies in Bangkok demonstrate that rainfall and air pressure negatively and positively correlate with PM_{10}, respectively, while wind speed significantly disperses $PM_{2.5}$, explaining twice-higher concentrations in winter versus rainy seasons (Cheewinsiriwat *et al*., 2022). During the COVID-19 period, meteorological factors like rainfall positively correlated with $PM_{2.5}$ in Bangkok, but overall reduced emissions masked some influences, underscoring humidity's role in particle growth (Sangkham *et al*., 2023). In Lamphun, negative correlations with humidity, temperature, and wind speed highlight dry-season peaks in PM_{10} due to inversion layers, with similar implications for coastal Rayong where monsoon transitions could mitigate but also resuspend particles (Kliengchuay *et al*., 2021). Haze-period analyses in northern Thailand show positive temperature and negative humidity correlations with both PM fractions, with low wind speeds (<1 m/s) promoting accumulation akin to Rayong's calm coastal winds (Kliengchuay *et al.,* 2018)

These expanded comparisons emphasize that while emission sources are primary, meteorological modulation particularly through humidity-driven hygroscopic effects and pressure-induced stagnation dominates short-term PM fluctuations in industrial zones (Kliengchuay *et al*., 2022). Integrating visibility as a proxy for aerosol loading, as in multi-decade reconstructions, suggests that declining wind speeds could counteract emission reductions in Rayong, necessitating adaptive strategies (Aman *et al*., 2025). Health risk assessments link these patterns to increased cardiorespiratory burdens during dry seasons, with $PM_{2.5}$'s fine fraction posing greater penetration risks under low ventilation (Fold *et al*., 2020).

Limitations include reliance on aggregated daily data, potentially masking diurnal variations, and the dataset's focus on 2017–2023, which may not capture emerging climate shifts (Office of Natural Resources and Environmental Policy and Planning, 2020). Future research should integrate biogenic emissions and machine learning for predictive modeling, as in visibility-based reconstructions (Aman *et al*., 2025). Overall, these results advocate for meteorological-informed strategies, such as early warning systems, to mitigate PM impacts in industrial zones like Rayong, fostering evidence-based interventions for public health and sustainability (Teerasuphaset *et al.,* 2019; Fold *et al*, 2020).

CONCLUSIONS

This study confirms that meteorological parameters significantly influence $PM_{2.5}$ and PM_{10} concentrations in Rayong's Pollution Control Zone, Thailand. High relative humidity drives $PM_{2.5}$ accumulation through hygroscopic growth, while temperature, sunshine, and wind speed reduce fine particle levels by enhancing dispersion. Conversely, PM_{10} decreases with higher humidity due to wet deposition but increases under high-pressure stagnation. Both pollutants consistently exceed WHO guidelines, with post-2019 elevations signaling ongoing air quality challenges. These findings support the development of meteorological-based forecasting models to predict high-risk pollution episodes, enabling targeted interventions to mitigate health risks and promote sustainable air quality management in industrial coastal regions. Future research should incorporate real-time data and advanced modeling to address diurnal variations and emerging climate impacts.

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