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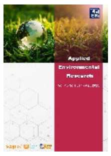

Research Article

Meteorological Conditions and $PM_{2.5}$ Impact on COVID-19 Case Fatality Ratios (CFR) in Bangkok Metropolitan Region

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Abstract

The emergence of a novel coronavirus strain triggered a global health crisis, impacting both health and economies worldwide, including Thailand since 2019. While prior research hinted at connections between environmental factors and rising COVID-19 cases, these links remained inconclusive. This study investigated indoor and outdoor (I/O) ratios and explored potential correlations between fine particulate matter ($PM_{2.5}$), meteorological conditions, and the case fatality rate (CFR%) of COVID-19 in Bangkok and its metropolitan area from January to December 2021. In Spearman's Rank correlation analysis, the results found that CFR% exhibited a positive correlation with relative humidity (RH) (r=0.187) and a negative correlation with $PM_{2.5}$ (r=-0.190) and wind speed (WS) (r=-0.039). The generalized additive model (GAM) indicated that RH, $PM_{2.5}$, temperature, and WS adversely affect the CFR% of COVID-19. Consistent relationships between $PM_{2.5}$, RH, and WS were observed in both Spearman's Rank correlation and the GAM model. This study underscored the complexity of understanding pandemic dynamics across seasons, I/O ratios, and the influence of lag days. By presenting the results, they may serve as a valuable reference for planning interventions during future pandemics.

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Introduction

The novel coronavirus outbreak, identified in China in December 2019, primarily spreads through respiratory droplets, similar to SARS-CoV. This syndrome, known as COVID-19, has caused widespread illness and deaths globally, including in Thailand. Symptoms of COVID-19 vary from mild to severe, affecting the lungs' ability to clear pathogens. Transmission occurs through direct or indirect contact with infected individuals via respiratory droplets and can also happen by touching contaminated surfaces and subsequently touching the eyes, nose, or mouth.

There is growing concern about the connection between meteorological factors and the COVID-19 outbreak. In Asia, a systematic review indicated a consistent relationship between temperature, humidity and population density [1]. The top 20 countries with the highest confirmed cases showed strong correlations between climate variables and COVID-19 outcomes. High temperature and humidity have been found to influence local transmission of COVID-19 and reduce confirmed cases. Meteorological variables such as low temperature, wind speed, dew/frost, rainfall and surface pressure tended to prolong the virus [2–3]. In addition, Nath et al. (2021) revealed that extreme weather patterns and events, which are becoming more frequent and intense due to climate change, especially temperature and humidity, can play a crucial role in influencing the distribution and health risks associated with COVID-19 [4].

Additionally, air quality plays a role in exacerbating COVID-19 symptoms, especially in areas with poor air

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quality. Exposure to air pollutants, such as $PM_{2.5}$, PM_{10}, and O_3, has been strongly correlated with COVID-19 hospital admissions and mortality rates. Air pollution, which encompasses $PM_{2.5}$, PM_{10}, sulfur dioxide, nitrogen dioxide, and ozone, has detrimental effects on human physical health, leading to nonmalignant respiratory fatalities, lung cancer, and cardiovascular issues [5]. Short-term exposure to $PM_{2.5}$, PM_{10}, and O_3 strongly correlated with COVID-19 related hospital admissions and mortality in Iran [6]. In Thailand, Bangkok and surrounding areas consistently rank in the top ten for annual $PM_{2.5}$ concentrations. Studies have shown the positive impact of COVID-19 measures, such as lockdowns and restricted activities, on improving air quality [7]. However, limited research has explored the relationship between COVID-19 mortality and environmental factors. Meteorological factors are generally linked to seasonal variations, which in turn can influence the transmission and severity of COVID-19. While this hypothesis has been investigated in various regions to understand the potential impact of weather-related factors on the virus's spread, it remains relatively unexplored in the context of Bangkok and its nearby provinces.

Several past studies have used continuously monitored outdoor concentrations as a study factor. However, since the majority of people spend more than 90% of their time indoors, in this study, indoor-to-outdoor (I/O) ratios were employed to convert outdoor values from monitoring stations to indoor values. The focus was on $PM_{2.5}$ to compare whether outdoor values from monitoring stations and indoor values differ. The concentrations of ambient air pollutants can have a major effect on indoor air pollution and considering that people spend approximately 90% of their time indoors, there is a need to study the I/O ratios in relation of pollutants such as respirable particulate matter PMs) in major cities [8]. $PM_{2.5}$ is the most well-intentioned because its concentration can be an indicator of indoor air quality levels with potential impacts on health and work performance [9]. The I/O ratios is a straightforward, yet valuable parameter used to identify the sources of indoor and outdoor pollution and their correlations.

This study aimed to address the gaps in previous research and gain a better understanding of the relationship between the CFR of COVID-19 and environmental factors in urban areas, incorporating the I/O ratios and air pollution. Our study focused on Bangkok and five metropolitan provinces, which, due to their high population density and status as vital economic hubs, have been heavily impacted by the pandemic. These six provinces also have the highest number of COVID-19 infections and deaths in the country, and they are also provinces with high readiness in terms of meteorological data.

Materials and methods

1) Study area

The study was conducted in the Bangkok metropolitan region, including Bangkok, Nakhon Pathom, Nonthaburi, Pathum Thani, Samut Prakan, and Samut Sakhon provinces. Several factors influenced the selection of this study area. Bangkok is located in the central region of Thailand. It shares borders with Nonthaburi and Pathum Thani provinces to the north, Samut Prakan province to the south, and Nakhon Pathom and Samut Sakhon provinces to the west. These neighboring provinces are significantly influenced by the development and economic activities of Bangkok, the capital city. Moreover, this region serves as the economic hub of the country. The population density in these six provinces ranks among the highest in the nation, with an average of 1,471 people km^{-2}. This study collected data from the year 2021, spanning from January 1^{st} to December 31^{st}, as it was the year marked by the COVID-19 outbreak, witnessing up to three waves (the 2^{nd}, 3^{rd}, and 4^{th} waves) within a single year.

2) Data collection

This study spanned from J January 1^{st} to December 31^{st}, 2021, aligning with the timeframe specified by the COVID-19 Management Center (CDC). The CDC identified specific areas with the highest increase in infected individuals, designating them as the strictest control areas.

2.1) Meteorological and air pollution data

Daily average temperature, wind speed (WS), rainfall, and relative humidity (RH) were collected from the Thailand Meteorological Department. Daily average of $PM_{2.5}$ was retrieved from 18 monitoring stations operated by the Division of Air Quality Data, Air Quality and Noise Management Bureau, and the Pollution Control Department. In this study, the daily AQI is based on the 24-hour average of hourly readings.

2.2) COVID-19 confirmed positive cases and deaths

Data extraction was performed based on confirmed COVID-19 cases and deaths from the public organization's website (www.data.go.th) operated by the Digital Government Development Agency website. The published information is in a file format that can be displayed as a data sample, automated visualization, and APIs for publishable datasets.

The CFR is influenced by delays in reporting dates for cases and deaths (Eq.1). The formula restricts the analysis to resolved cases to mitigate delays in case resolution and estimate mortality from COVID-19. The formula is as follows Eq. 1.

2.3) Empirical indoor and outdoor $PM_{2.5}$ concentration measurement

Portable $PM_{2.5}$ meter (A25 series) was used to measure indoor and outdoor $PM_{2.5}$ concentrations. In each province, three communities nearby the TMD stations were randomly selected, each community comprising 50 sites. Each province, therefore, yielded 150 I/O $PM_{2.5}$ samples, resulting in a total collection of 900 samples. The meteorological monitoring stations and our empirical $PM_{2.5}$ measurement sites are illustrated in Figure 1.

3) Data analysis

The data obtained from this study were statistically and graphically analyzed with the R program (R Core Team, 2021). Descriptive statistics were employed to capture the characteristics of I/O ratios of $PM_{2.5}$ concentrations. The data used to study the correlation with the COVID-19 CFR patients included the following parameters: $PM_{2.5}$, wind speed, relative humidity, average temperature, rainfall, and season (wet and dry seasons). Spearman's correlation was performed to determine the monotonic association between the CFR and meteorological factors and $PM_{2.5}$. Generalized additive models (GAM) were executed to discover non-linear relationships among important factors that influence the CFR of COVID-19. We applied two types of GAMs families to address different response variables: Gaussian family for CFR values in percentage, and binomial family for CFR values represented by 0 and 1. We also considered the daily average lag effect for the 7-day period, compared to the daily baseline [10].

$$\text{CFR (\%)} = \frac{\text{Number of deaths from COVID}-19}{(\text{Number of deaths from COVID}-19)+(\text{Number of recovered from disease})} \text{x}100 \qquad \text{(Eq. 1)}$$

The data on the number of recoveries and deaths are obtained from the public organization under the Digital Government Development Agency website.

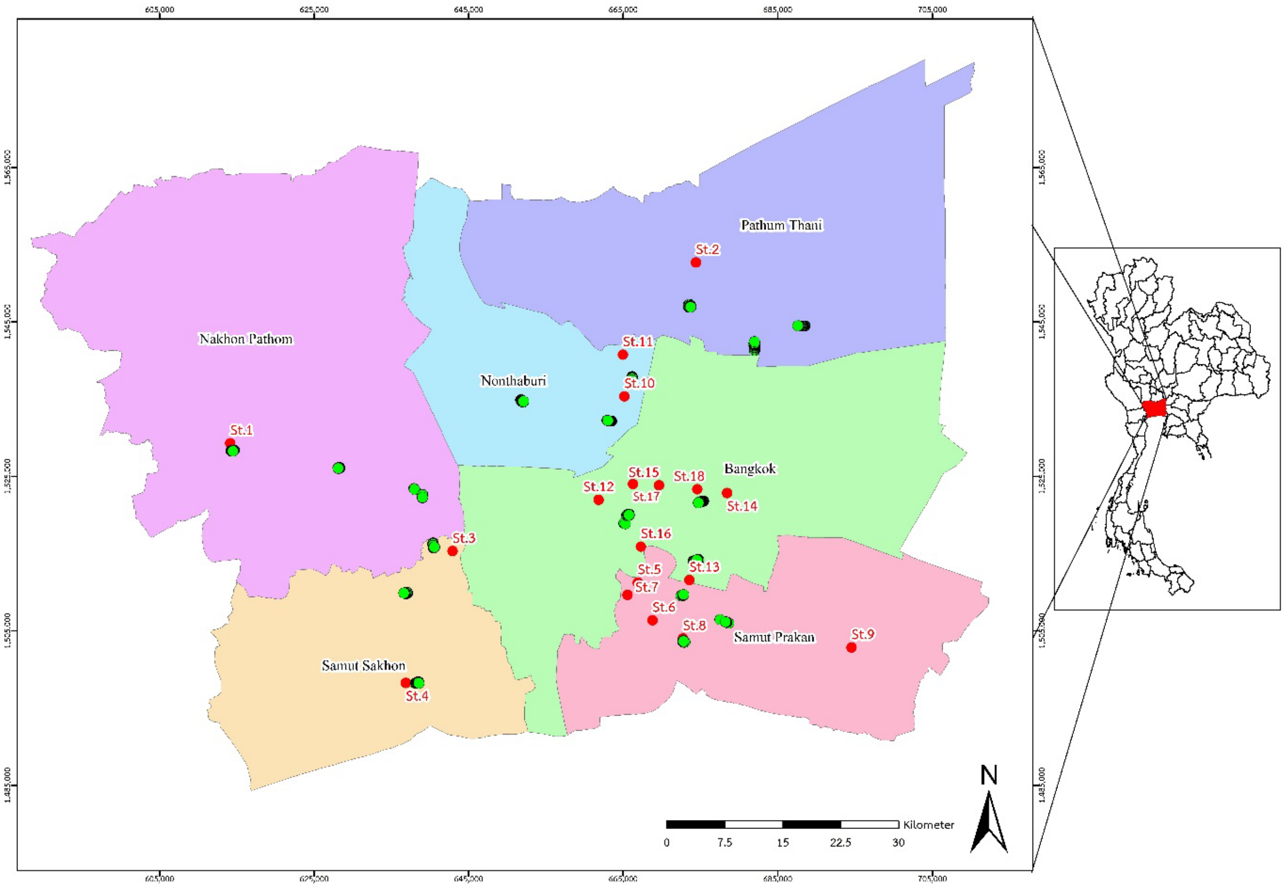

Figure 1 A map shows the Bangkok metropolitan area (Red points represent weather monitoring stations, totaling 18 points. Green points denote $PM_{2.5}$ sampling locations in each province (900 samples).

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Results and discussion

1) PM2.5 indoor/outdoor ratios

Prior to conducting further analysis, we identified outliers among the total of 900 samples, leading to the exclusion of 25 samples. The province with the most exclusions is Pathum Thani, where 15 samples were excluded. This was likely because the areas where PM2.5 samples were collected experienced strong air turbulence, resulting in significantly higher PM2.5 concentrations in shaded areas compared to open areas at several locations.

In a general sense, the I/O ratios has been utilized to assess the relationships between air pollutants. This ratios can be used to reflect the significant variability due to numerous factors, including outdoor pollutant levels, spatial variances, indoor activities, architectural designs, geographical locations, and equipment, among others. For the purposes of this study, the interpretation of the I/O ratios with respect to indoor air pollution is defined as follows [11]:

I/O ratios > 1.2 implies indoor pollutant concentrations surpass that outdoors, possibly as a result of indoor sources.

I/O ratios of 0.8 to 1.2 implies indoor pollutant concentrations are in a state of equilibrium with outdoor levels.

I/O ratios < 0.8 implies indoor pollutant concentrations are lower than outdoor levels, indicating the potential influence of outdoor factors.

From Table 1, the average I/O ratios for all provinces ranged from 0.86 to 0.99, indicating a state of equilibrium where the concentrations of PM2.5 inside and outside were relatively similar. Bangkok showed the lowest I/O ratios. In residential homes and public buildings, indoor PM2.5 levels were primarily influenced by outdoor sources when the I/O ratios was close to one. In such cases, it would be advisable for residents to remain indoors rather than venturing outside when outdoor PM2.5 concentrations are elevated.

In reviewing the relationship between indoor and outdoor environments we found that the I/O ratios observed in many countries falls within the range of 0.8 to 1.2, and our study aligns with this observation [12].

Figure 2 highlighted the statistical variabilities in I/O data among the provinces, with some provinces having a wider distribution of values than others. Bangkok and Pathum Thani have the widest range, with values ranging from 0.29 to 1.53 and 0.37 to 1.53, respectively. Samut Sakhon has the narrowest range, with values ranging from 0.53 to 1.34. Nakhon Pathom has the highest median value at 1.00, followed by Samut Sakhon at 0.98, while Bangkok has the lowest median value at 0.86.

Table 1 Descriptive statistics of PM2.5 I/O ratios by province

Province	Average PM2.5 indoor*	Average PM2.5 outdoor*	Average I/O	Min I/O	Max I/O	Median I/O	N
Bangkok	45.5	54.0	0.86	0.29	1.53	0.86	147
Nakhon Pathom	42.7	43.1	0.99	0.71	1.55	1.00	148
Nonthaburi	36.0	37.9	0.95	0.43	1.48	0.96	146
Pathum Thani	17.6	18.2	0.98	0.37	1.53	0.93	135
Samut Prakan	56.9	66.5	0.87	0.43	1.4	0.89	149
Samut Sakhon	48.0	49.4	0.98	0.53	1.34	0.98	150

Remark: *25µg m^{-3} (annual average standard value) (Announcement of the National Environment Board 2010, 2010)

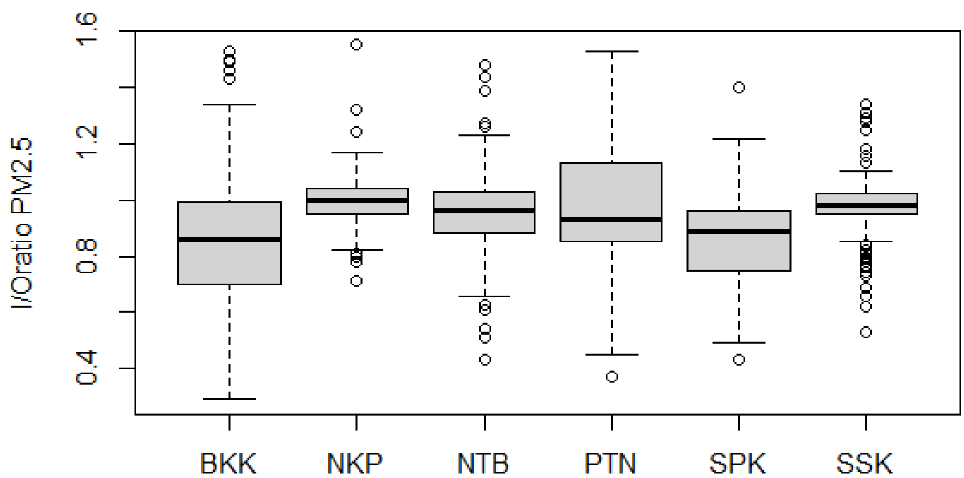

Figure 2 Box plot distribution of PM2.5 I/O ratios in Bangkok and metropolitan area. (BKK = Bangkok; NKP = Nakhon Pathom; NTB = Nonthaburi; PTN = Pathum Thani; SPK = Samut Prakan; SSK = Samut Sakhon)

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2) COVID-19 deaths and COVID-19 infections by season

Generally, meteorological factors are related to seasonal variations. Therefore, the number of COVID-19 cases and related deaths were analyzed in the context of wet and dry seasons. The wet season is defined as the period between May and October, when Thailand typically experiences more rainfall and elevated humidity levels. In contrast, the dry season occurs from November to April, and is characterized by lower rainfall and reduced humidity.

Table 2 demonstrates a noticeable disparity in COVID-19 cases and related deaths based on the season in these particular provinces. This seasonal variation implies that the number of cases and fatalities is not constant throughout the year. It appears that the dry season corresponds to lower counts of both COVID-19 cases and deaths, while the wet season is associated with higher numbers of cases and deaths. This contrast between the two seasons raises questions about what factors might be driving these variations.

Table 2 Cases of infection and deaths in 2021 by province in different seasons

Province	Case of covid-19	Season	
		Wet	Dry
Bangkok	New case	411,514	57,017
	New death	6,490	364
Nakhon Pathom	New case	34,021	2,564
	New death	600	23
Nonthaburi	New case	63,770	5,635
	New death	404	14
Pathum Thani	New case	39,018	4,435
	New death	795	34
Samut Prakan	New case	122,981	12,475
	New death	1,401	82
Samut Sakhon	New case	92,098	18,869
	New death	856	24

This analysis can provide valuable insights that inform public health strategies and responses. If the analysis reveals that the wet season is associated with higher cases and deaths, public health authorities might consider implementing stricter measures during this period to mitigate the impact of the virus. Understanding seasonality can help in allocating healthcare resources more effectively. For instance, more medical staff and hospital beds might be required during peak seasons. Through an investigation of the factors contributing to this pattern, public health measures can be more effectively designed to address the challenges posed by the seasonally fluctuating dynamics of COVID-19, ultimately enhancing pandemic preparedness and response.

Figure 3 presents the dispersion of each variable of interest in different provinces, categorized into wet seasons and dry seasons. Across six provinces, the mean and median values of $PM_{2.5}$ were higher during the dry season compared to the wet season. This contrasts with the CFR%, which showed higher dispersion during the wet season compared to the dry season. Another noteworthy finding in this research was that the wind speed values in Samut Prakan and Samut Sakhon provinces, exhibited greater dispersion than in other provinces. This may be attributed to the fact that both of these provinces are located near the sea, resulting in higher wind speeds compared to other provinces, although this did not lead to lower $PM_{2.5}$ values in these areas compared to others.

The high maximum CFR% of 28.57 in Bangkok indicated a substantial fatality rate, which could be due to various factors, such as a strain on healthcare resources or a surge in cases. Similar to Bangkok, Nonthaburi also exhibits a high maximum CFR. This could be indicative of critical challenges in managing the pandemic in this province. Samut Sakhon, similar to Bangkok and Nonthaburi, exhibited a high maximum CFR% of 33.33, indicating exceptional fatality rates. The median CFR% of 0.49 suggested that Pathum Thani experienced moderate fatality rates. Nakhon Pathom and Samut Prakan have a relatively low average CFR. However, the presence of any non-zero CFR values suggested the occurrence of fatalities. In summary, while some provinces revealed relatively low average CFR values, the presence of high maximum CFR values in several provinces raised concerns.

The CFR of COVID-19 was used to distinguish between the first and second waves in Ontario, Canada. The first wave CFR ranged from 0.004 to 0.146, whereas the second wave CFR ranged from 0.003 to 0.034 [13]. and South Korea and Germany have CFR values of approximately 1%, similar to those in Table 3, while Italy, Spain, the United Kingdom, and France have a CFR that is approximately 12% higher [14].

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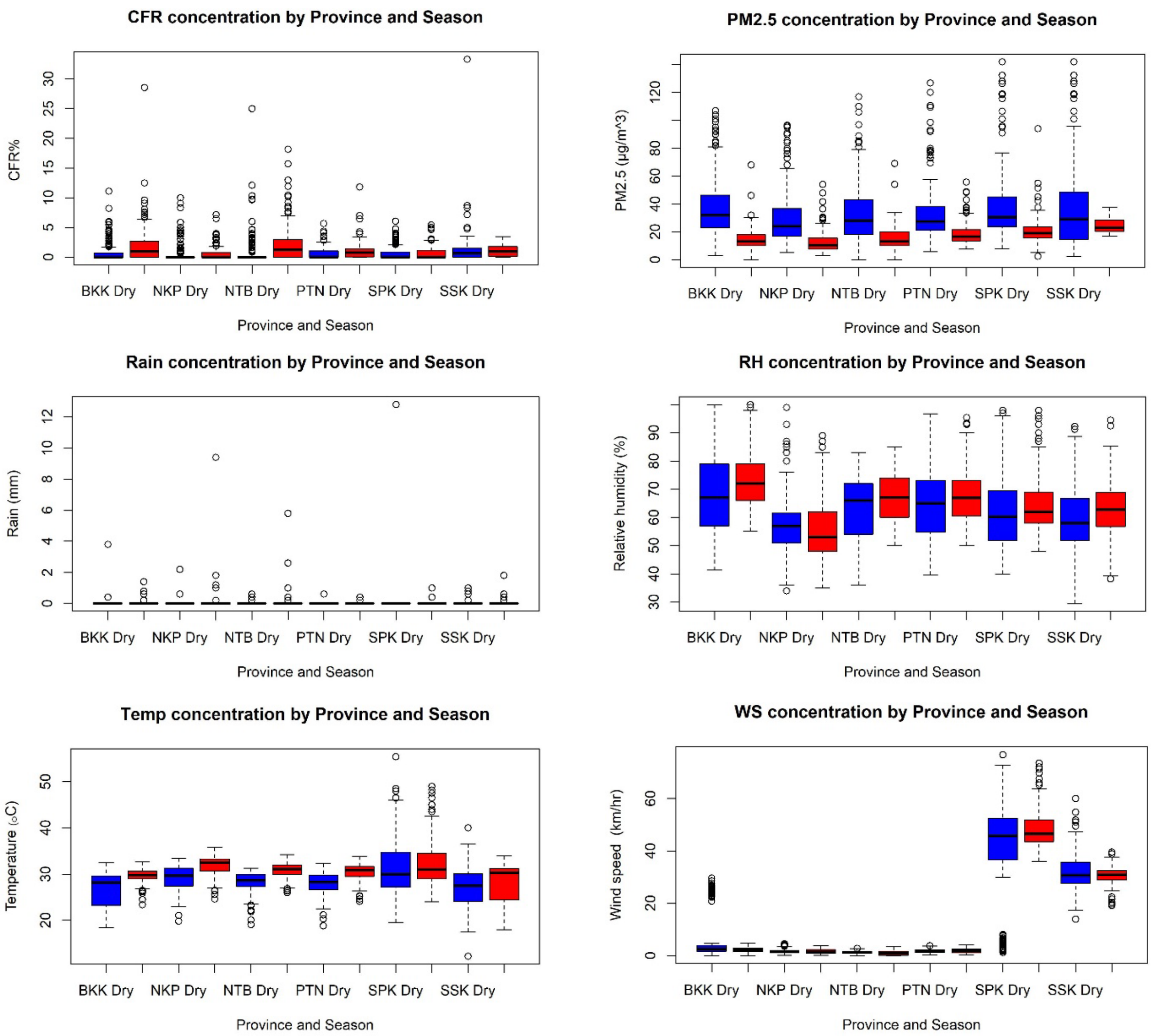

Figure 3 Box plots representing distribution of CFR% and meteorological parameters in Bangkok and metropolitan area.

Table 3 Data of CFR% and meteorological parameters in Bangkok and metropolitan area

Province	Statistical value	CFR	$PM_{2.5}$	Rain	RH	Temp	WS
Bangkok	Average	1.32	26.93	0.024	71.5	28.29	4.59
	Min	0	0	0	41.25	18.48	0
	Max	28.57	107	3.8	100	32.7	29.5
	Median	0	21	0	71	29.3	2.3
	n	357	357	357	357	357	357
Nakhon Pathom	Average	0.55	21.08	0.048	56.56	30.54	1.6
	Min	0	3	0	34	19.8	0.1
	Max	10	96	9.4	99	35.8	4.5
	Median	0	15.5	0	56	31	1.4
	n	363	363	363	363	363	363
Nonthaburi	Average	1.44	24.2	0.031	65.49	29.58	1.1
	Min	0	0	0	36	19.1	0
	Max	25	117	5.8	85	34.2	3.5
	Median	0	19	0	66.5	30	1.15
	n	360	360	360	360	360	360
Pathum Thani	Average	0.8	25.81	0.005	66.31	29.22	1.79
	Min	0	5.8	0	39.6	33.86	0.28
	Max	11.82	126.8	0.6	96.8	18.82	4.02
	Median	0.49	21.2	0	66.4	29.72	1.74
	n	363	363	363	363	363	363

Table 3 Data of CFR% and meteorological parameters in Bangkok and metropolitan area (*continued*)

Province	Statistical value	CFR	$PM_{2.5}$	Rain	RH	Temp	WS
Samut Prakan	Average	0.67	29.7	0.039	63.23	31.82	44.5
	Min	0	2.5	0	40	19.56	1.18
	Max	6.06	142	12.8	98	55.4	76.7
	Median	0	23.5	0	61.5	30.5	46.5
	n	364	364	364	364	364	364
Samut Sakhon	Average	1.09	30.4	0.017	61.38	27.7	31.17
	Min	0	2.5	0	29.5	12.24	13.9
	Max	33.33	142	1.8	94.5	40	60
	Median	0.86	23.5	0	61.5	28.5	30.8
	n	365	365	365	365	365	365

3) Relationships between CFR, $PM_{2.5}$, and meteorological factors

The weather significantly affects the transmission of infectious diseases by impacting how they spread, the susceptibility of hosts, and the survival of viruses in the environment. Research on weather conditions and COVID-19 shows that each weather factor has both beneficial and detrimental effects, especially in winter when host susceptibility increases and virus viability rises [15].

Figure 4 displays the results of a correlation study utilizing Spearman's Rank correlation coefficient to examine the relationships between meteorological factors and $PM_{2.5}$ levels, as well as CFR% of COVID-19 in Bangkok and metropolitan area from January to December 2021. The CFR% exhibited a positive correlation with relative humidity (RH) (r=0.187) and a negative correlation with $PM_{2.5}$ (r=-0.190) and wind speed (WS) (r=-0.039). In a similar fashion, previous research exploring the impacts of $PM_{2.5}$ and meteorological parameters also identified a positive correlation between RH with daily confirm cases of COVID-19 [10]. It was also found that the impact of weather and seasonality on the COVID-19 pandemic in Saudi Arabia was negatively related to relative humidity (RH) (r= -0.62) and minimum temperature (r = -0.61) [16]. This differs from our study where a positive correlation of RH was found. While there was an adverse correlation with $PM_{2.5}$, it remained essential to monitor $PM_{2.5}$ dust levels. Particulate matter ($PM_{2.5}$) has the potential to elevate the infection rate of SARS-CoV-2 and the severity of COVID-19. $PM_{2.5}$ can lead to a 1.5-fold upregulation of the angiotensin 2 converting enzyme (ACE2), a mechanism exploited by viral particles for entering human lung alveolar cells, resulting in a 1.5-fold increase in RAB5 protein [17].

In Baghdad [18], Iraq, a seasonal relationship was also observed, with the highest number of deaths occurring during the summer of 2020, accounting for 41% of the total. In Mumbai, India, a significant association between COVID-19 and various meteorological factors was observed, including temperature, dew point, relative humidity, as well as surface pressure [19]. In Italy, temperature showed a negative correlation with the CFR of COVID-19, as well as with the concentrations of air pollutants (NO_2, O_3, PM_{10}, and $PM_{2.5}$), while relative humidity was positively associated with the CFR [1]. In this Italian report, However for $PM_{2.5}$, the Italian report revealed a positive correlation with CFR, which differs from the findings presented in this report.

Numerous factors influence the rise or fall in the number of COVID-19 cases. These factors include the implementation of lockdown measures, population mobility in each region, contact with symptomatic and asymptomatic individuals, and the progress of COVID-19 vaccination efforts. The spread of COVID-19 is a complex interplay of various factors, not solely reliant on air pollution or meteorological conditions. By considering these multiple factors, we can engage in a more comprehensive discussion and arrive at more definitive conclusions regarding the dynamics of COVID-19 transmission.

4) Effects of $PM_{2.5}$ and meteorological parameters factors and CFR%

Nonparametric technique, GAM model, was applied to analyze $PM_{2.5}$ data and meteorological parameters from monitoring stations in relation to CFR% values. In the initial stage, two GAM models were compared between response types of CFR% as percentage and CFR% as binary codes. The binomial model performed better prediction, therefore, we decided to conduct the binomial analysis to investigate the relationship and analysis.

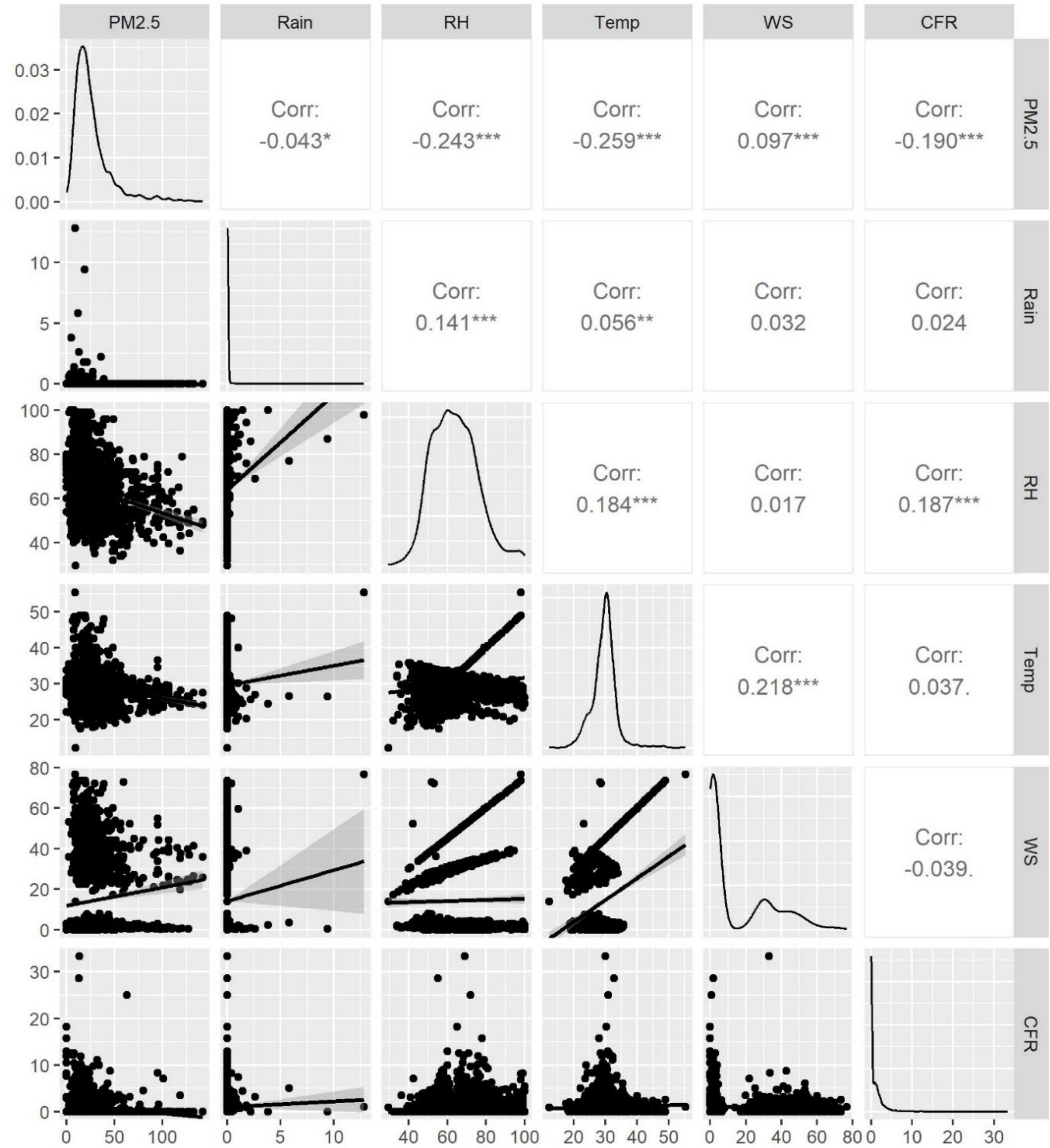

Figure 4 Scatter plots of the spearman's rank correlation coefficient between $PM_{2.5}$ and meteorological parameters factors and CFR% in Bangkok and metropolitan area from 1 January to 31 December 2021.

The GAM binomial model includes CFR% as CFR binary (0 and 1) and $PM_{2.5}$ values as $PM_{2.5I/O}$. Table 4 presents data from the GAM for $PM_{2.5I/O}$ and meteorological parameters across all seasons, affecting the CFR% of COVID-19. Using the GAM model with data from all six provinces yields the highest deviance explained value of 36% with the R^2 value of 0.42. Significant variables influencing the CFR percentage were $PM_{2.5I/O}$ (p-value: dry season = 0.0003, wet season <2e-16), RH (p-value: dry season = 0.000770, wet season <2e-16), and wind speed (p-value: dry season = 0.270985, wet season <2e-16). This underscored the statistical significance of these variables concerning CFR% in both dry and wet seasons.

In Wuhan, CFR% was found to be related to PM 2.5. The CFR% was positively related to the total lag0-lag5 concentrations of PM 2.5 and PM 10 ($r > 0.36$, $P < 0.03$). However, no significant relationship was found between temperature, RH, and CFR of COVID-19 ($r = 0.13$, $P = 0.44$, and $r = 0.21$, $P = 0.22$, respectively) [20].

5) Clustering of CFR magnitudes and various lags

This research categorized the main data into two groups: high CFR and low CFR, based on the CFR% values from Table 3. The High CFR group included Nonthaburi and Bangkok provinces, while the low CFR group comprised Pathum Thani, Nakhon Pathom, Samut Prakan and Samut Sakhon provinces.

Table 4 Data of GAM related to CFR% and meteorological parameters in Bangkok and the metropolitan area

Parameter	Season	edf	Ref.df	Chi.sq	p-value
$PM_{2.5I/O}$	Dry	1.65	1.88	16.90	0.0003***
	Wet	2.00	2.00	305.58	<2e-16***
Rain	Dry	2.13	2.49	0.45	0.7818
	Wet	1.00	1.00	0.60	0.4388
RH	Dry	3.11	3.78	19.30	0.0008***
	Wet	1.00	1.00	34.50	<2e-16***
Temp	Dry	4.20	4.66	29.59	1.49e-05***
	Wet	1.40	1.70	2.91	0.2710
WS	Dry	4.45	4.85	70.92	<2e-16***
	Wet	4.64	4.91	40.80	2.27e-07***

Remark: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
R-sq.(adj) = 0.42 Deviance explained = 36% -REML = 1007.6 Scale est. = 1 n = 2173

Table 5 Data of GAM model of lag Day-0 and lag Day-7

Province group	Lagged effect			P-value										R-sq.	Deviance explained (%)
	CFR	$PM_{2.5}$	Day	$PM_{2.5}$		Rain		RH		Temp		WS			
				Dry	Wet	Dry	Wet	Dry	Wet	Dry	Wet	Dry	Wet		
High CFR	CFR%	$PM_{2.5}$	Day-0	.	**					.		.	***	0.3	34.9
			Day-7		**		.						***	0.3	36.1
		$PM_{2.5I/O}$	Day-0	.	**					.		.	***	0.3	35.0
			Day-7		**								***	0.3	36.1
	CFR (Binary)	$PM_{2.5}$	Day-0	.						***		**		0.6	57.5
			Day-7	.						***		**		0.6	56.8
		$PM_{2.5I/O}$	Day-0	.						***		*		0.6	57.2
			Day-7	*						***		**		0.6	57.6
Low CFR	CFR%	$PM_{2.5}$	Day-0										*	0.1	12.2
			Day-7										*	0.1	10.8
		$PM_{2.5I/O}$	Day-0										*	0.1	12.0
			Day-7										*	0.1	10.6
	CFR (Binary)	$PM_{2.5}$	Day-0											0.4	33.8
			Day-7											0.4	31.8
		$PM_{2.5I/O}$	Day-0											0.4	33.4
			Day-7											0.3	31.0

Remark: Signif. (codes: ≤ 0 '***' ≤ 0.001), (0.001 ≤ '**' ≤ 0.01), (0.01 ≤ '*' ≤ 0.05), (0.05 ≤ '.' ≤ 0.1), (0.1 ≤ ' ' ≤ 1)

In Table 5, there is further differentiation of data compared to Table 4, allowing for greater insight into the connections between the effects. This includes data that distinguishes the CFR between the two groups over the lag periods of Day-0 and Day-7. The highest deviance explained values were found in the high CFR group, which CFR% values represented as CFR (Binary). This is particularly observed in the lag Day-7 data group of $PM_{2.5I/O}$ and p-values obtained for $PM_{2.5}$ and WS are consistent with those in Table 4. The GAM modes with binary CFR values exhibited better predictive models when compared to the percentage CFR. Lag days performed not much different predictive outputs when compared to the baseline model. In the north-central United States, day lag is related to variables. Most significantly, positive associations were found in lower levels of each selected meteorological factor from 3 to 11 lagged days. Our findings were contradictory to this study in which lagged days showed significance on COVID-19 incidence. In particular, a significantly positive association appeared in minimum relative humidity higher than 88.36% at a 5-day lag [21].

Conclusions

This research has unveiled a direct correlation between the average relative humidity and the case fatality percentage (CFR%) of COVID-19 in Bangkok and the surrounding metropolitan area. Additionally, using new data clustering techniques, our resulting generalized additive model (GAM) has the R^2 value of 0.6, explaining a substantial 57.6% of the variance in CFR% using the High CFR binary derived from lag Day-7 data associated with $PM_{2.5I/O}$. However, it is important to recognize that several complex factors come into play when assessing COVID-19 dynamics. These factors include the presence of asymptomatic COVID-19 patients, the progress of immunization campaigns, socioeconomic factors influencing healthcare access, the emergence of different SARS-CoV-2 variants, and the unique topography of the area. To gain a more comprehensive understanding, further research is warranted. This research should explore the potential influence of vaccination efforts and pollutant levels, as well as the medical histories of individuals who have contracted SARS-CoV-2. Such insights are important not only for responding to the current pandemic but also for predicting and preparing for future outbreaks. These findings can assist policymakers in making informed decisions to prevent and mitigate risks associated with respiratory infections. Furthermore, can suggest the need for increased public health policies, particularly in urban planning and environmental regulations. Due to diverse environmental conditions and lifestyles, the health impacts of air pollution vary across different regions. Therefore, it is essential to tailor air pollution policies according to local circumstances to strike a balance between economic costs and health benefits. Moreover, stricter air pollution regulations should be implemented in areas with severe pollution levels. Overall, the following limitations of the study should be considered in further research:

- Air pollution data obtained from environmental monitoring stations may not precisely reflect an individual's actual exposure level.
- This study is not representative of the entire general population.
- This study did not account for potential confounding factors that could influence the relationship between environmental factors and COVID-19, such as age, gender, smoking status, alcohol consumption, comorbidities, and vaccinations.

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