

Special Issue:

Special Issue on COVID-19 Aerosol
Drivers, Impacts and Mitigation (XI)

OPEN ACCESS 

Received: June 5, 2020

Revised: November 12, 2020

Accepted: November 15, 2020

*** Corresponding Author:**

runguang.janta@gmail.com

Publisher:

Taiwan Association for Aerosol
Research

ISSN: 1680-8584 print

ISSN: 2071-1409 online

 **Copyright:** The Author(s).

This is an open access article
distributed under the terms of the
[Creative Commons Attribution
License \(CC BY 4.0\)](https://creativecommons.org/licenses/by/4.0/), which permits
unrestricted use, distribution, and
reproduction in any medium,
provided the original author and
source are cited.

Effect of COVID-19 Prevention Measures on Air Quality in Thailand

Jenjira Kaewrat^{1,2}, Rungruang Janta^{1,2*}

¹ School of Languages and General Education, Walailak University, Nakhon Si Thammarat, 80160, Thailand

² Center of Excellence in Sustainable Disaster Management, Walailak University, Nakhon Si Thammarat, 80160, Thailand

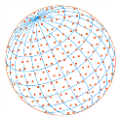
ABSTRACT

The coronavirus disease 2019 (COVID-19) has been a global pandemic since early 2020. In Thailand, the number of cases increased exponentially from the middle of March 2020. In response, Thailand's government has imposed various pandemic prevention measures, such as a rigorous stay-at-home measure to reduce viral transmission between humans. Many human activities ceased, such as transportation, businesses, and services. This has been associated with reductions in air pollutant emissions. This study thus aimed to measure air quality in metropolitan, industrial, and suburban cities of in Thailand. Data on the hourly concentrations of six criteria pollutants were obtained from Thailand's Pollution Control Department from five stations during three measurement periods: pre-COVID, early COVID, and working-from-home (WFH) periods. The results indicated that vehicle-emitted pollutants had significantly decreased during WFH periods. Moreover, the air quality of all city types ostensibly improved (50%–70%) because of reduced transportation in Thailand's central and eastern provinces. However, results for Northern provinces were unclear because PM_{2.5} concentrations were still high during WFH period due to effects from open burning activity as well as meteorological condition.

Keywords: Coronavirus, Air quality index, Criteria pollutants, Potential source contribution function

1 INTRODUCTION

Coronavirus disease 2019 (COVID-19) broke out in Wuhan in China's Hubei Province in late December 2019. On January 30, 2020, the World Health Organization (WHO) declared the COVID-19 outbreak a so-called Public Health Emergency of International Concern (Sohrabi *et al.*, 2020). COVID-19 spread rapidly worldwide, and the situation remains extremely serious at the time of writing. By May 19, 2020, over 4.7 million cases of COVID-19 had been reported worldwide, along with over 0.3 million deaths (WHO, 2020a). The older-adult population (aged ≥ 65 years) is significantly more likely to have severe COVID-19 infections (Li *et al.*, 2020). Thailand reported its first case of COVID-19 at the beginning of January 2020 in a Chinese tourist (WHO, 2020a). Many measures have been implemented by Thai authorities to reduce the risk of transmission, such as providing the public with information on COVID-19, giving recommendations for personal hygiene, and actively identifying and isolating patients. COVID-19 was in the early stage with fewer than 10 new cases per day until the middle of March 2020, and from then onward, the COVID-19 outbreak in Thailand began from clusters of pubs, restaurants, and boxing stadia. Cases increased exponentially from that period, with over 100 new cases reported daily (Thailand; WHO, 2020b). Thailand's government imposed urgent measures to curb the spread of COVID-19. The country's health authorities implemented several recommended measures to curb the transmission of the virus from infected cases. These measures included the immediate isolation of the patient and contact tracing. Moreover, rigorous measures have been implemented, including a stay-at-home order as well as the postponement of national holidays, stoppage of public transportation, cancellation of all international and domestic flights, suspension of business



operations, and control of movement between provinces. Economic and social activities have been greatly disrupted since the spread of COVID-19 in Thailand, and traffic density and industrial emissions have been greatly reduced because of the shutdowns. Such evidence has provided an opportunity to reduce air pollution related to human activity. Satellite data suggest that air pollution has decreased in many countries because of the COVID-19 outbreak (NASA, 2020), as has been the case in other countries around the globe, including China, Brazil, and Malaysia (Abdullah *et al.*, 2020; Dantas *et al.*, 2020; Xu *et al.*, 2020). Studies investigating such reduced pollution have been mainly conducted in metropolitan cities. However, reduced air pollution has been evident in suburban cities, which are predominant in Southeast Asia (SEA).

Air pollution in SEA stems mainly from transportation, industry, open burning, and transboundary haze in rural and border areas. Particulate matter (PM), carbon monoxide (CO), nitrogen dioxide (NO₂), volatile organic compounds (VOCs), and polycyclic aromatic hydrocarbons (PAHs) are well-known traffic-related pollutants in cities. The composition of air pollutants in industrial areas is complicated. The composition of air pollutants including VOCs, PM, SO₂, NO₂, and heavy metals depend on industry type; by contrast, open burning is greatly associated with PM concentration in the area (Han and Naeher, 2006; Khamkaew *et al.*, 2016; Saeaw and Thepanondh, 2015). Therefore, how COVID-19-prevention measures influence the quantity and quality of air pollution potentially depend on the type of area in question. Thus, this study aimed to compare variations in air pollutants and the Air Quality Index (AQI) in metropolitan, industrial, and suburban cities in Thailand during the COVID-19 outbreak. The results elucidate COVID-19's effects on air pollution in SEA.

2 METHOD

2.1 Description of Study Sites

Five provinces in Thailand were studied (Fig. 1), which were classified into three groups (metropolitan cities, industrial city and suburban cities) based on the size of their economy.

2.1.1 Metropolitan cities

Bangkok (BKK) is Thailand's capital city, located in the center of the country (13°45'N, 100°29'E). BKK has a tropical savanna climate with annual temperatures in the range of 10–40°C and rainfall of 1,600 mm. BKK has a total area of 1,568.7 km² and a population of 6 million, with a density of approximately 4,000 per km². This area is the center of Thailand's economy and the

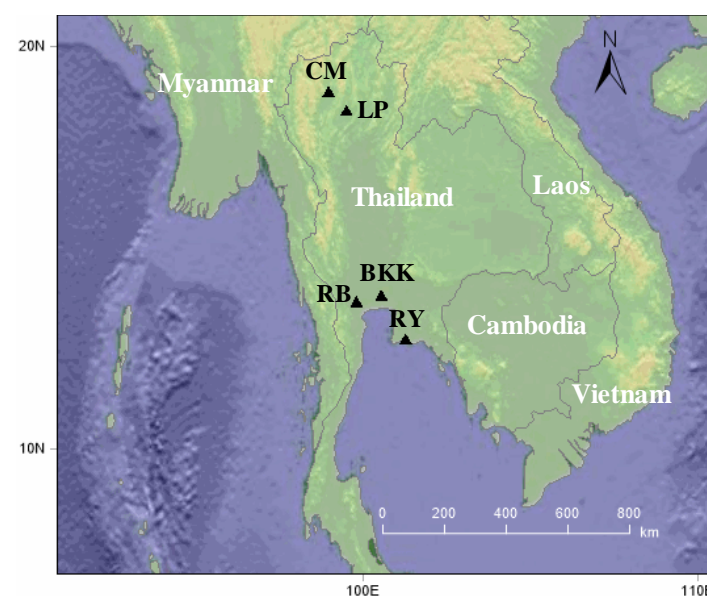
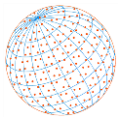


Fig. 1. The air pollution monitoring stations in each city: Chiang Mai (CM); Lampang (LP); Ratchaburi (RB); Bangkok (BKK) and Rayong (RY).



hub of government and business. Ten million vehicles are registered in BKK (Department of Land Transport, 2020). A high population density coupled with an inadequate road and public transport network have led to heavy traffic congestion in BKK. Air quality data of BKK was obtained from air quality monitoring (AQM) stations installed in community areas 200 meters from main roads. Transportation is a major source of air pollution in this area.

Chiang Mai Province (CM) is the largest province in northern Thailand. The city of Chiang Mai (18°47'N, 98°59'E) is located on a flat plain among mountains. CM has an area of 20,107 km² and a population of 2 million with a density 100 people per km² (3,200 per km in Chiang Mai Municipality). The climate of CM is influenced by the South Asian monsoon system. Annual temperatures range between 4 and 42°C, and the annual rainfall is 1,100 mm. CM is a popular tourist destination, attracting over 10 million visitors every year. The Department of Land Transport reported the number of registered vehicles in CM at over 1.5 million in 2020. This province is rapidly expanding and becoming urbanized, with traffic congestion beginning to seriously affect air quality. The AQM station is installed at Chiang Mai City Hall, surrounded by community areas, agricultural areas and forest. Transportation and open burning are the main air pollution sources in CM, with extra impact of open burning from neighboring countries during the dry season.

2.1.2 Industrial city

Rayong Province (RY) is located on the east coast of the Gulf of Thailand (12°40'N, 101°16'E). RY has an area of 3,552 km², with a population of 0.7 million people at a density of 200 per km². RY has a tropical climate, with annual rainfall of 1,370 mm. Annual temperatures range between 20 and 33°C. Both industrial and tourism sectors are crucial for the population's income. An AQM station is installed at Rayong Provincial Agriculture Offices, surrounded by a community area and 15 km from the Map Ta Phut Industrial Estate to the west. RY has 0.8 million registered vehicles (Department of Land Transport, 2020). Air quality in this area is affected by both community and industrial emissions.

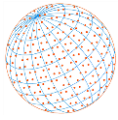
2.1.3 Suburban cities

Lampang Province (LP) is located in northern Thailand (18°18'N, 99°30'E) with an area of 12,534 km² and a population of 0.7 million at a density of 59 people per km² (2,600 per km² in the city). LP has a large coal-fired power plant (Mae Moh Power Plant), which can produce 2,400 MW of electricity per year (20% of Thailand's total capacity). The climate of LP is similar to that of CM. Annual temperatures range from 4 to 44°C, with annual rainfall of 1,000 mm. The number of registered vehicles in LP in 2020 was only 0.5 million. The AQM station is installed near the domestic airport in the city center, 30 km from the power plant to the northeast. This city also has an air quality problem during the dry season caused by open burning.

Ratchaburi Province (RB) is located in the west of Thailand (13°32'N, 99°49'E) and is surrounded by mountains. RB has an area of 5,196 km² and a population of 0.9 million at a density of 168 people per km². Annual rainfall and average temperature are 1,100 mm and 27°C, respectively. Local industry and livestock are essential to the economy of RB. Air quality data were obtained from the AQM station installed in the city of Ratchaburi. RB has only 0.5 million registered vehicles but traffic volume is very high along the roadway connecting BKK with the south of Thailand. Many activities including open burning, local industry (manual factories), transportation and construction are sources of pollution. In RB, PM_{2.5} exceeding the 24-h Thailand standard of 50 µg m⁻³ is usually observed during the dry season.

2.2 Air Pollutant Concentrations

The Thai government measures real-time hourly concentrations of six criteria pollutants, including particulate matter (PM_{2.5} and PM₁₀), sulfur dioxide (SO₂), nitrogen dioxide (NO₂), carbon monoxide (CO), and ozone (O₃) at various AQM stations. Air quality data was obtained on such measurements, for the period of November 2019 to May 2020, from the website of Thailand's Pollution Control Department (PCD; <http://air4thai.pcd.go.th/webV2/history>). The study period was divided into three periods according to the government's responses to COVID-19. These periods were the (1) pre-COVID period (November–December 2019, when Thailand had no instances of COVID-19); (2) early COVID period (January–February 2020, when the government



provided information on COVID-19 and promoted personal hygiene), and (3) working-from-home (WFH) period (March–May 2020, when the government implemented strict measures to control the spread of the virus, such as suspending businesses and curbing inter-regional movement).

2.3 Air Quality Index

The PCD developed and is responsible for monitoring Thailand's AQI. The AQI combines the concentrations of six criteria pollutants (PM_{2.5}, PM₁₀, CO, SO₂, NO₂, and O₃) into a single numerical value to indicate the level of air pollution. The concentration of six criteria pollutants, including the 24-h average concentrations of PM_{2.5} and PM₁₀, daily average of the 8-h moving average concentrations of CO and O₃, and average 1-h NO₂ and SO₂ concentrations, is applied to calculate the sub-AQI of each pollutant, as shown in Eq. (1). The highest sub-AQI contributor is defined as the AQI on that day (PCD, 2020). Some stations measured only the critical pollutant in their area; the AQIs of those areas were then calculated from the measured pollutants.

$$I_i = \left[\frac{I_{high} - I_{low}}{C_{high} - C_{low}} \times (C_i - C_{low}) \right] + I_{low} \quad (1)$$

AQI: maximum value among $I_1, I_2, I_3, \dots, I_n$.

I_i : sub-AQI of criteria air pollutant i .

C_i : concentration of air pollutant i .

C_{high} : breakpoint concentration $\geq C_i$.

C_{low} : breakpoint concentration $\leq C_i$.

I_{high} : I value corresponding to C_{high} .

I_{low} : I value corresponding to C_{low} .

Based on Thailand's AQI, the AQI values can be classified into five classes: Grade I: 0–25 (*excellent*; light blue); Grade II: 26–50 (*satisfactory*; green); Grade III: 51–100 (*moderate*; yellow); Grade IV: 101–200 (*unhealthy*; orange), and Grade V: over 201 (*very unhealthy*; red) (PCD, 2020).

2.4 Potential Source Contribution Function Analysis

The potential source contribution function (PSCF) is applied to estimate the potential source of a dominant pollutant in a given set of study areas using backward trajectories (Punsompong and Chantara, 2018; Li *et al.*, 2020). The PSCF is the ratio of the number of trajectory segment endpoints associated with an AQI value higher than a threshold value (falling in the i^{th} grid cell m_{ij}) with the total number of endpoints (falling within the i^{th} cell n_{ij}). The threshold is set at the AQI value of 100 because AQI values over 100 are at an unhealthy level. Cells with high PSCF values indicate a high potential source of the pollution at the receptor site. The PSCF value for the i^{th} cell can be derived using Eq. (2).

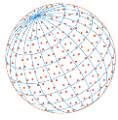
$$PSCF_{ij} = \frac{m_{ij}}{n_{ij}} \quad (2)$$

In this study, the *TrajStat* modeling system proposed by Wang *et al.* (2009) was used to compute backward trajectories and for the PSCF analysis. Moreover, meteorological data ($1^\circ \times 1^\circ$) and the Global Data Assimilation System (GDAS) were used for calculations. The 3-day backward trajectories at 7:00 am and 7:00 pm local time at a height of 10 m above ground level were calculated for each study site. In total, 120 and 162 trajectories were computed in the early COVID-19 and WFH periods, respectively. The grid cell at $0.3^\circ \times 0.3^\circ$ resolution was generated for PSCF calculation. The weight function $w(n_{ij})$ was applied to multiply the PSCF values to reduce uncertainties from the small value of n_{ij} (Zhang *et al.*, 2015).

3 RESULTS AND DISCUSSION

3.1 Air Pollutant Concentrations

The average concentrations of air pollutants in metropolitan and suburban cities during the



pre-COVID-19, early COVID-19, and WFH periods are presented in Table 1. The concentrations of air pollutants in the early COVID-19 period increased from those of the pre-COVID-19 period. This is attributable to 1) the COVID-19 spread being brought under control by Thailand’s public health authority and 2) the government measures being mainly focused on personal hygiene and isolation of patients with COVID-19. Businesses were operating as usual. Moreover, this period marked the seasonal transition from winter to summer, with low humidity and wind speeds because of the decreased influence of monsoons. Additionally, temperature inversion was commonly noted in the early morning. These resulted in increased pollutant concentrations (Cichowicz *et al.*, 2017). The concentration of particulate pollutants, including PM_{2.5} and PM₁₀ in RB, RY, and BKK, were the lowest during the WFH period and had decreased by approximately 42%–55% from the early COVID-19 period (Fig. 2). An exception was observed in LP and CM, where the concentrations had been increasing since the end of the year because that period was marked by haze episodes in northern Thailand, of which the main source was the open burning of biomass. However, a decrease in concentrations was observed at the end of April because of heavy rain. In the case of gas pollutants, the concentrations of CO and NO₂ exhibited significant reductions in the WFH period for all cities. As indicated in Fig. 2, COVID-19-induced decreases in human activity, especially in transportation, most significantly affected the levels of both pollutants. The findings indicated that CO and NO₂ in Thailand are mainly generated from incomplete combustion and the internal combustion of vehicles (El-Fadel and Abi-Esber, 2009; Carslaw *et al.*, 2019). In case of the secondary pollutant, O₃ exhibited different pattern between

Table 1. Air pollutants concentration and AQI in suburban, industrial and metropolitan cities during COVID-19 period.

Air pollutants		Suburban cities		Industrial and metropolitan cities		
		RB	LP	RY	CM	BKK
PM _{2.5} (µg m ⁻³)	pre-COVID	47.0 ± 12.0 ^a	34.0 ± 14.0 ^a	25.2 ± 7.3 ^a	31.3 ± 9.3 ^a	29.8 ± 8.7 ^a
	early COVID	54.5 ± 18.8 ^b	66.6 ± 24.1 ^b	33.5 ± 14.4 ^b	49.3 ± 17.4 ^b	36.7 ± 14.0 ^b
	WFH	24.5 ± 8.6 ^c	49.6 ± 29.1 ^c	18.5 ± 2.7 ^c	64.9 ± 39.1 ^c	18.3 ± 6.1 ^c
	% reducing*	−55%	−26%	−45%	32%	−50%
PM ₁₀ (µg m ⁻³)	pre-COVID	88.9 ± 17.1 ^a	55.9 ± 14.8 ^a	56.9 ± 18.1 ^a	46.4 ± 8.7 ^a	46.7 ± 11.3 ^a
	early COVID	100.0 ± 24.2 ^b	92.2 ± 32.6 ^b	58.8 ± 21.6 ^a	74.9 ± 22.3 ^b	54.5 ± 17.0 ^b
	WFH	54.9 ± 9.9 ^c	78.0 ± 32.0 ^c	34.3 ± 4.8 ^b	91.0 ± 47.2 ^c	30.9 ± 7.7 ^c
	% reducing*	−45%	−15%	−42%	21%	−43%
O ₃ (ppb)	pre-COVID	40.3 ± 8.4 ^a	25.8 ± 4.0 ^a	18.7 ± 7.5 ^a	31.4 ± 5.5 ^a	32.6 ± 8.7 ^a
	early COVID	35.0 ± 9.1 ^b	36.3 ± 6.6 ^b	18.1 ± 1.0 ^a	34.5 ± 7.8 ^a	36.1 ± 8.8 ^b
	WFH	25.5 ± 4.7 ^c	47.1 ± 11.0 ^c	28.0 ± 8.1 ^b	41.7 ± 8.3 ^b	32.1 ± 8.0 ^a
	% reducing*	−27%	30%	55%	21%	−11%
CO (ppm)	pre-COVID	0.8 ± 0.4 ^a	0.6 ± 0.1 ^a	1.0 ± 0.2 ^a	N/A	0.4 ± 0.2 ^a
	early COVID	0.7 ± 0.1 ^b	0.9 ± 0.2 ^b	1.1 ± 0.2 ^b		0.5 ± 0.2 ^b
	WFH	0.4 ± 0.1 ^c	0.7 ± 0.3 ^a	0.6 ± 0.3 ^c		0.3 ± 0.1 ^c
	% reducing*	−43%	−22%	−45%		−40%
NO ₂ (ppb)	pre-COVID	10.9 ± 2.4 ^a	9.2 ± 2.1 ^a	11.9 ± 2.9 ^a	10.7 ± 3.0 ^a	25.5 ± 6.2 ^a
	early COVID	11.3 ± 4.0 ^a	12.6 ± 4.0 ^b	12.5 ± 4.3 ^a	15.9 ± 3.2 ^b	20.5 ± 7.5 ^b
	WFH	5.2 ± 1.2 ^b	7.5 ± 3.1 ^c	5.7 ± 2.1 ^b	11.1 ± 5.7 ^a	9.0 ± 4.3 ^c
	% reducing*	−54%	−40%	−54%	−30%	−56%
SO ₂ (ppb)	pre-COVID	1.8 ± 0.7 ^a	1.5 ± 0.4 ^a	1.1 ± 0.2 ^a	1.1 ± 0.2 ^a	N/A
	early COVID	1.6 ± 0.5 ^{ab}	1.8 ± 0.5 ^b	1.2 ± 0.4 ^a	1.0 ± 0.2 ^a	
	WFH	1.3 ± 0.4 ^b	1.4 ± 0.5 ^a	1.5 ± 0.5 ^b	1.2 ± 0.3 ^a	
	% reducing*	−18%	−22%	25%	20%	
AQI	pre-COVID	87 ± 33 ^a	49 ± 37 ^a	38 ± 14 ^a	43 ± 22 ^a	42 ± 17 ^a
	early COVID	108 ± 49 ^b	135 ± 55 ^b	50 ± 36 ^b	90 ± 49 ^b	59 ± 35 ^b
	WFH	33 ± 18 ^c	98 ± 59 ^c	23 ± 9 ^c	127 ± 67 ^c	28 ± 13 ^c
	% reducing*	−70%	−28%	−54%	41%	−50%

^{a, b, c} present significant difference among of concentration from ANOVA test.

N/A; data is not available.

* is percentage of pollutant concentration reduction in WFH period from early COVID-19 period.

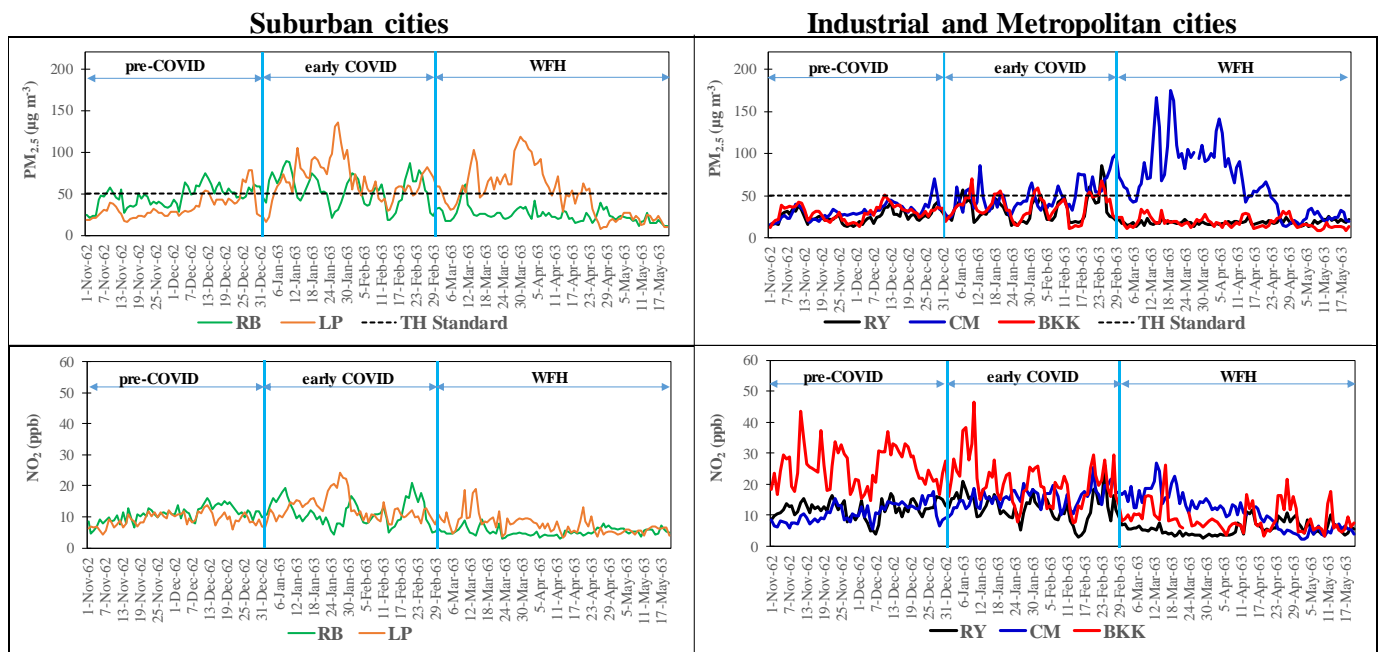
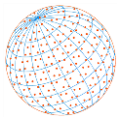


Fig. 2. Concentration of $PM_{2.5}$ and NO_2 in suburban, industrial and metropolitan cities.

cities. The ozone concentration decreased in RB and BKK, where road traffic is a source of O_3 precursors, such as nitrogen oxides (NO_x) and hydrocarbons. The lower traffic volume and faster traffic flow on the roads during the WFH period potentially contributed to the reduced emission of O_3 precursors (Munir *et al.*, 2012). By contrast, LP, CM and RY presented increasing of O_3 level because its precursors (the volatile organic compounds (VOCs) and NO_x) were emitted from both transportation and other sources such as open burning in LP and CM and industrial activities in RY (Rubio *et al.*, 2015; Saeaw and Thepanondh, 2015). Moreover, the stronger solar intensity from March to April encourages greater photochemical activity and, by consequence, O_3 production (Pochanart *et al.*, 2001). Additionally, the faster ozone formation caused by high temperature in dry season in LP and CM could be the result of the greatest ozone level in LP and CM during WFM period (Coates, *et al.*, 2016). SO_2 concentration also increased in CM and RY, which was potentially influenced by biomass burning and industrial regions, respectively.

The diurnal variations of air pollutants in each city are presented in Fig. S1 of the Supplement. The blue, black, and red lines denote the hourly averages in the pre-COVID-19, early COVID-19, and WFH periods, respectively. Because the pre-COVID-19 period occurred during late winter in Thailand, whereas the other periods occurred in summer during which the same pollutant sources and metrological conditions were present. The hourly trends of pollutants in the WFH period were similar to those at the early COVID-19 period. Traffic-related pollutants such as NO_2 and CO in the WFH period were significantly decreased from the corresponding levels at the early COVID-19 period especially at night because the government had imposed a curfew from 10:00 pm to 4:00 am as noted in Figs. S1(a) and S1(b). As indicated in Fig. S1(c) and S1(d) for the case of secondary pollutants (O_3) and PM, a decreasing trend was observed in RB and BKK where the major sources are related to road-traffic characteristics but noted a negative result in cities such as LP, RY, and CM which have various pollutant sources. The results of pollutant concentrations indicated that the WFH measure was more likely to affect traffic-related pollutants than other pollutants.

3.2 Air Quality Index during the COVID-19 Period

Fig. 3 depicts the change in the AQI during the COVID-19 period. A significant improvement in air quality was discovered for most cities with the exception of CM, which was considerably affected by open burning causing smoke haze episode (Yabueng *et al.*, 2020). Overall, the AQI during the WFH period exhibited a 28–70% decrease. RB exhibited the greatest decrease in the AQI (approximately 70%), where air quality changed from an unhealthy to a satisfactory level

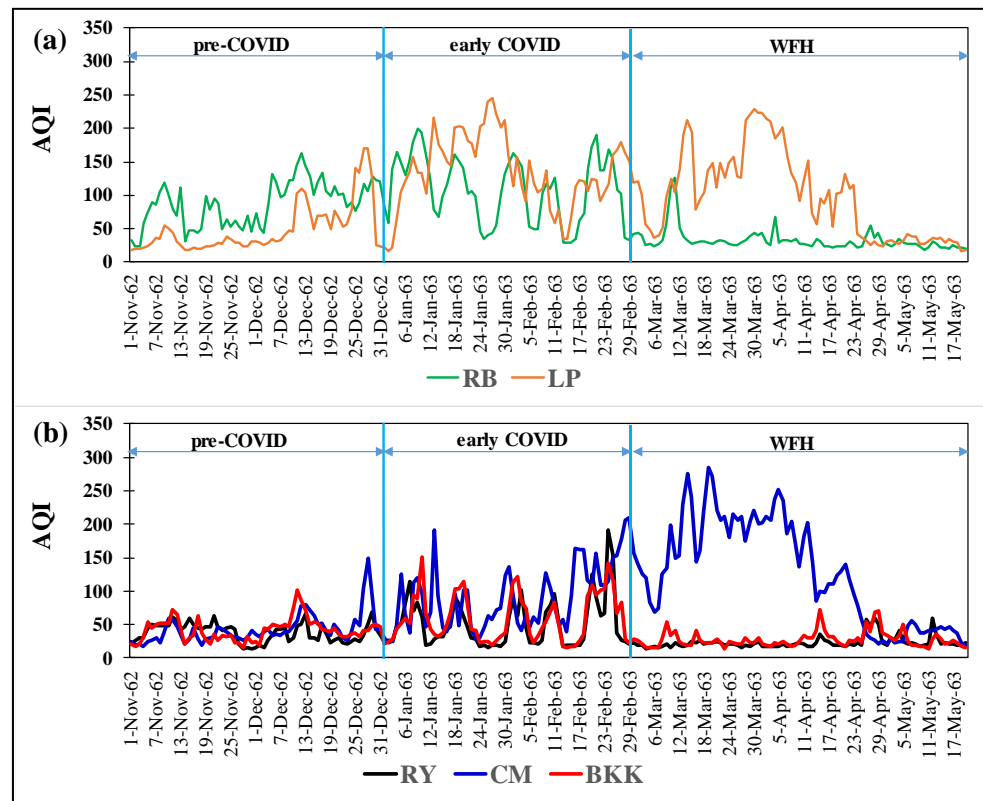
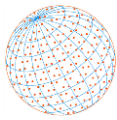


Fig. 3. Variation of AQI value during COVID-19 periods (a) suburban cities (b) industrial and metropolitan cities.

through a reduction in $PM_{2.5}$. The AQI of RB before WFH period was the highest as a result of many human activities such as transportation, agricultural burning and manual factories. Moreover, Ratchaburi City is located in a valley and pollutants accumulate due to thermal inversion. Pollutant levels particular PM in RB were the highest but decreased when control of human activities was implemented. This result was similar to those for BKK and RY, where the air quality improved (50% reduction in AQI value) from moderate to satisfactory and from moderate to excellent for BKK and RY, respectively. In the case of the cities in northern Thailand (LP and CM), the official ban on most human activity did not affect air quality because of uncontrolled activity e.g., open burning. However, this result suggests that $PM_{2.5}$ is the dominant pollutant with the most significant influence on air quality in Thailand.

3.3 Estimation of Potential Contributors to Air Pollution

To estimate the potential source of unhealthy air quality from aerosol transactions, the PSCF was calculated and compared between the early COVID-19 and WFH periods. The PSCF threshold was set at the AQI value of 100, an AQI over 100 indicates when a healthy individual experience health effects and when members of sensitive groups experience severe health effects. The PSCF results of the cities are presented in Fig. 4. The warmer grid color represents a greater potential source of the polluted area, one that contributes more to a high AQI value. As indicated in Fig. 4(a), both local area and the surrounding provinces presented the areas potentially contributing to the high AQI value in RB during the early COVID-19 period. The provinces to the south of RB are popular tourist destinations, such as Phetchaburi and Prachuap Khiri Khan. Moreover, the metropolitan cities in the center of Thailand, such as BKK, are located to the east of the province. The major sources of air pollution in RB were likely to be local human activities and pollutants being transported from neighboring metropolitan cities. Therefore, the reduction in human activity from the COVID-19 outbreak in metropolitan cities improved air quality in RB. Fig. 4(b) presents the potential sources of air pollution in BKK. This area is influenced by the northwest trade wind and the east coast current. However, the BKK air quality was mainly

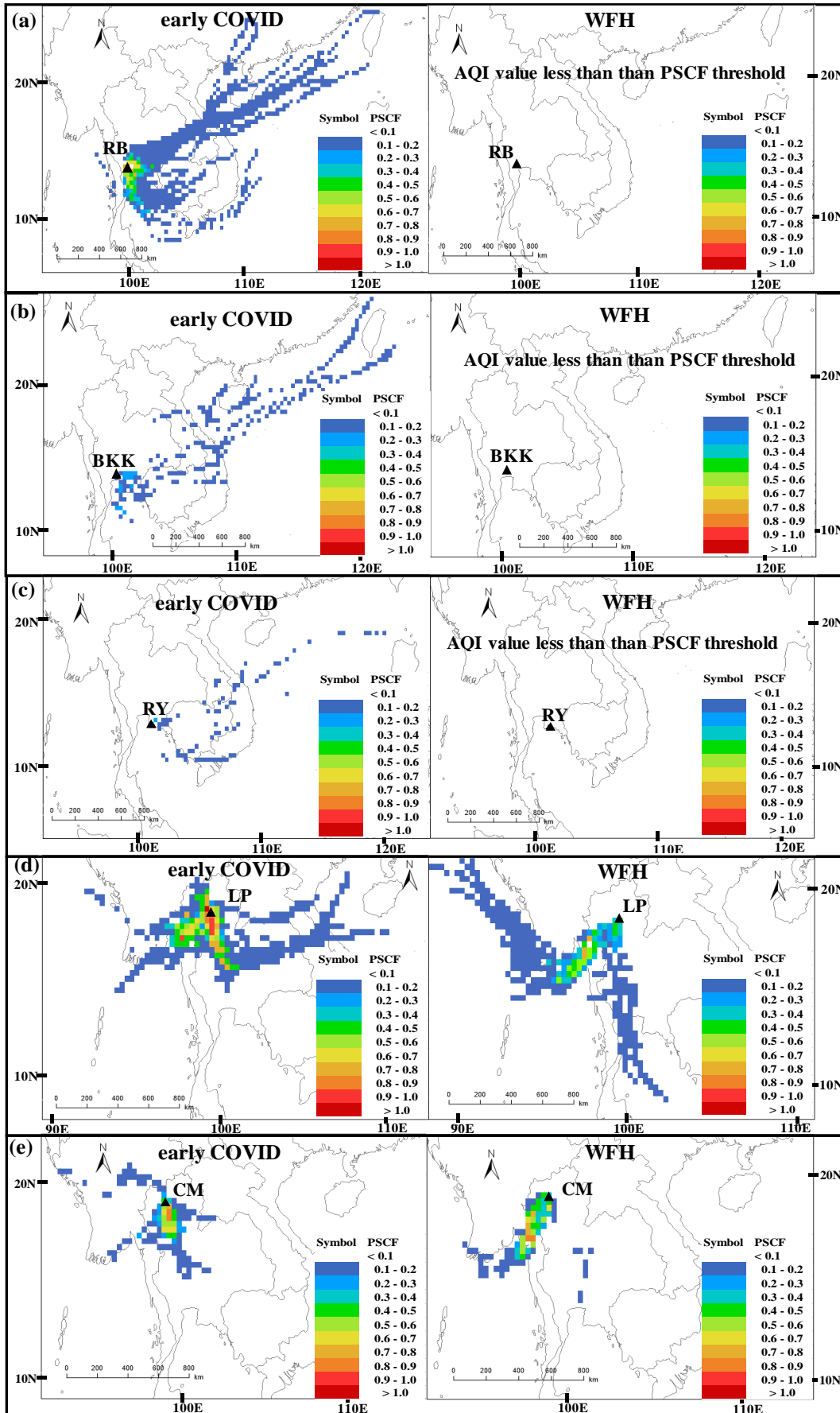
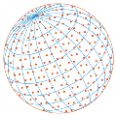
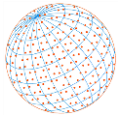


Fig. 4. PSCF of unhealthy AQI level during COVID-19 periods; (a) RB; (b) BKK; (c) RY; (d) LP; (e) CM.



affected by local sources because of the city's prominent concentration of businesses. An improvement in air quality was also observed in BKK during the WFH period. The potential sources of air pollution in RY are presented in Fig. 4(c). Although air pollution in Rayong city was contributed from both neighboring countries and the local area, it seemed to be mainly influenced by local activities, as indicated by the small blue grid in Fig. 4(c). Additionally, the average pollution levels for the abovementioned cities improved to a satisfactory or excellent level (daily AQI value < 100). The results indicated that the dominant air pollutants (PM_{2.5}) contributing to these cities were influenced by human activities.

In the case of LP and CM, which are located in northern Thailand, their respective compositions of pollution sources were complex. As illustrated in Figs. 4(d) and 4(e), in the early COVID-19 period, the major sources were contributions from local and nearby cities. Because the study periods fell during a haze episode in the northern region of Thailand, both traffic-related pollutants and pollutants from forest fires, particularly PM were generated in those areas. After the WFH measure had been implemented, the source of pollution changed from the local area to the neighboring country and forested areas. However, the air parcels in the northern region of Thailand during this period normally move from cities in the southwest because of metrological conditions (Punsompong and Chantara, 2018). Therefore, whether WFH measures could reduce human-related pollutants in northern Thailand was not clearly indicated.

4 CONCLUSION

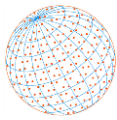
In response to the COVID-19 pandemic in Thailand, which began in January 2020, Thailand's government has implemented various measures to control the spread of infections. The measures began from the promotion of self-hygiene at the beginning of January 2020 to suspending business operations and ordering a WFH measure in the middle of March 2020. This study investigated the effect of restricting human activity on air quality in three classes of cities: metropolitan, industrial, and suburban. Significant decreases (20%–50%) in CO and NO₂, which are pollutants primarily from transportation, were observed for all classes of cities. Secondary pollutants were also reduced in the cities; some secondary pollutants include PM and O₃, which are primarily from transportation. By contrast, pollutants from other sources, such as forest fires and industries, increased. Although the trends of average hourly concentrations during the early COVID-19 and WFH periods were similar, pollutant levels were generally lower during the WFH period, especially at night during the rigorously enforced stay-at-home measure. A significant improvement in air quality was observed in the recipient cities of traffic-related sources. Nevertheless, the relationship between air quality improvement and city class was not clearly indicated in this study; hence, the effects of emission sources and meteorological conditions should be further evaluated.

SUPPLEMENTARY MATERIAL

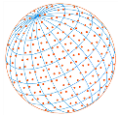
Supplementary data associated with this article can be found in the online version at <https://doi.org/10.4209/aaqr.2020.06.0344>

REFERENCES

- Abdullah, S., Mansor, AA, Napi, NNLM, Mansor, W.N.W., Ahmed, A.N., Ismail, M., Ramly, Z.T.A. (2020). Air quality status during 2020 Malaysia Movement Control Order (MCO) due to 2019 novel coronavirus (2019-nCoV) pandemic. *Sci. Total Environ.* 729, 139022. <https://doi.org/10.1016/j.scitotenv.2020.139022>
- Carslaw, D.C., Farren, N.J., Vaughan, A.R., Drysdale, W.S., Young, S., Lee, J.D. (2019). The diminishing importance of nitrogen dioxide emissions from road vehicle exhaust. *Atmos. Environ.* 1, 100002. <https://doi.org/10.1016/j.aeaoa.2018.100002>
- Cichowicz, R., Wielgosiński, G., Fetter, W. (2017). Dispersion of atmospheric air pollution in summer and winter season. *Environ. Monit. Assess.* 189, 605. <https://doi.org/10.1007/s10661-017-6319-2>



- Coates, J., Mar, K.A., Ojha, N., Butler, T.M. (2016). The influence of temperature on ozone production under varying NO_x conditions – A modelling study. *Atmos. Chem. Phys.* 16, 11601–11615. <https://doi.org/10.5194/acp-16-11601-2016>
- Dantas, G., Siciliano, B., Franca, B.B., Silva, C.M., Arbilla, G. (2020). The impact of COVID-19 partial lockdown on the air quality of the city of Rio de Janeiro, Brazil. *Sci Total Environ.* 729, 139085. <https://doi.org/10.1016/j.scitotenv.2020.139085>
- Department of Land Transport (2020). Number of Vehicle Registered in Thailand. <https://web.dlt.go.th/statistics/index.php> (accessed 5 September 2020).
- El-Fadel, M., Abi-Esber, L. (2009). In-vehicle exposure to carbon monoxide emissions from vehicular exhaust: A critical review. *Environ. Sci. Technol.* 39, 585–621. <https://doi.org/10.1080/10643380701798264>
- Han, X., Naeher, L.P. (2006). A review of traffic-related air pollution exposure assessment studies in the developing world. *Environ. Int.* 32, 106–120. <https://doi.org/10.1016/j.envint.2005.05.020>
- Khamkaew, C., Chantara, S., Janta, R., Pani, S.K., Prapamontol, T., Kawichai, S., Wiriya, W., Lin, N.H. (2016). Investigation of biomass burning chemical components over Northern Southeast Asia during 7-SEAS/BASELInE 2014 Campaign. *Aerosol Air Qual. Res.* 16, 2655–2670. <https://doi.org/10.4209/aaqr.2016.03.0105>
- Li, L., Li, Q., Huang, L., Wang, Q., Zhu, A., Xu, J., Liu, Z., Li, H., Shi, L., Li, R., Azari, M., Wang, Y., Zhang, X., Liu, Z., Zhu, Y., Zhang, K., Xue, S., Ooi, M.C.G., Zhang, D., Chan, A. (2020). Air quality changes during the COVID-19 lockdown over the Yangtze River Delta Region: An insight into the impact of human activity pattern changes on air pollution variation. *Sci. Total Environ.* 732, 139282. <https://doi.org/10.1016/j.scitotenv.2020.139282>
- Li, X., Xu, S., Yu, M., Wang, K., Tao, Y., Zhou, Y., Shi J., Zhou M., Wu. B., Yang, Z., Zhang, C., Yue, J., Zhang, Z., Renz, H, Liu, X., Xie, J., Xie, M., Zhao, J. (2020). Risk factors for severity and mortality in adult COVID-19 inpatients in Wuhan. *Journal of Allergy and Clinical Immunology*. Article impress. <https://doi.org/10.1016/j.jaci.2020.04.006>
- Munir, S., Chen, H., Ropkins, K. (2012). Modelling the impact of road traffic on ground level ozone concentration using a quantile regression approach. *Atmos. Environ.* 60, 283–291. <https://doi.org/10.1016/j.atmosenv.2012.06.043>
- NASA (2020). Airborne nitrogen dioxide plummets over China. <https://earthobservatory.nasa.gov/images/146362/airborne-nitrogen-dioxide-plummets-over-china> (accessed 5 May 2020).
- Pochanart, P., Kreasuwun, J., Sukasem, P., Geeratithadaniyom, W., Tabucanon, M.S., Hirokawa, J., Kajii, Y., Akimoto, H. (2001). Tropical tropospheric ozone observed in Thailand. *Atmos. Environ.* 35, 2657–2668. [https://doi.org/10.1016/S1352-2310\(00\)00441-6](https://doi.org/10.1016/S1352-2310(00)00441-6)
- Pollution control department (PCD) (2020). Thailand's air quality Information. http://air4thai.pcd.go.th/webV2/aqi_info.php (accessed 15 May 2020).
- Punsompong, P., Chantara, S. (2018). Identification of potential sources of PM₁₀ pollution from biomass burning in northern Thailand using statistical analysis of trajectories. *Atmos. Pollut. Res.* 9, 1038–1051. <https://doi.org/10.1016/j.apr.2018.04.003>
- Rubio, M., Lissi, E., Gramsch, E., Garreaud, R., (2015). Effect of nearby forest fires on ground level ozone concentrations in Santiago, Chile. *Atmosphere* 6, 1926–1938. <https://doi.org/10.3390/atmos6121838>
- Saeaw, N., Thepanondh, S. (2015). Source apportionment analysis of airborne VOCs using positive matrix factorization in industrial and urban areas in Thailand. *Atmos. Pollut. Res.* 6, 644–650. <https://doi.org/10.5094/APR.2015.073>
- Sohrabi, C., Alsafi, Z., O'Neill, N., Khan, M., Kerwan, A., Al-Jabir, A., Losifidis, C., Agha, R. (2020). World Health Organization declares global emergency: A review of the 2019 novel coronavirus (COVID-19). *Int. J. Surg.* 76, 71–76. <https://doi.org/10.1016/j.ijsu.2020.02.034>
- Wang, Y.Q., Zhang, X.Y., Draxler, R.R. (2009) TrajStat: GIS-based software that uses various trajectory statistical analysis methods to identify potential sources from long-term air pollution measurement data. *Environ. Modell. Software* 24, 938–939. <https://doi.org/10.1016/j.envsoft.2009.01.004>
- World Health Organization (WHO) (2020a). Coronavirus disease (COVID-2019) situation reports. <https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports> (accessed 15 May 2020).



- World Health Organization (WHO) (2020b). COVID-19 - WHO Thailand Situation Reports. <https://www.who.int/thailand/emergencies/novel-coronavirus-2019/situation-reports> (accessed 15 May 2020).
- Xu, K., Cui, K., Young, L.H., Hsieh, Y.K., Wang, Y.F., Zhang, J., Wan, S. (2020). Impact of the COVID-19 event on air quality in central China. *Aerosol Air Qual Res.* 20, 915–929. <https://doi.org/10.4209/aaqr.2020.04.0150>
- Yabueng, N., Wiriya, W., Chantara, S. (2020). Influence of zero-burning policy and climate phenomena on ambient PM_{2.5} patterns and PAHs inhalation cancer risk during episodes of smoke haze in Northern Thailand. *Atmos. Environ.* 232, 117485. <https://doi.org/10.1016/j.atmosenv.2020.117485>
- Zhang, Z.Y., Wong, M.S., Lee, K.H. (2015). Estimation of potential source regions of PM_{2.5} in Beijing using backward trajectories. *Atmos. Pollut. Res.* 6, 173–177. <https://doi.org/10.5094/APR.2015.020>