Environmental Challenges 16 (2024) 100991

Contents lists available at ScienceDirect

Environmental Challenges

journal homepage: www.elsevier.com/locate/envc

Constructing an AQHI as a health risk communication tool for Bangkok, Thailand

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ARTICLE INFO

Keywords:
Air quality health index (AQHI)
Air quality index (AQI)
Bangkok
Ambient air pollutant
Respiratory disease
Cardiovascular disease

ABSTRACT

In this study, we established an air quality health index (AQHI) based on the associations between multiple air pollutants and respiratory and cardiovascular outpatient department (OPD) visits to communicate the health risks from air pollution in Bangkok, Thailand. The associations between various air pollutants, namely, suspended particulate matter (PM) with an aerodynamic diameter smaller than 2.5 μm and 10 μm ($PM_{2.5}$ and PM_{10}, respectively), sulphur dioxide (SO_2), and ozone (O_3) and the number of OPD visits for respiratory and cardiovascular diseases in Bangkok from 2016 to 2019 were assessed using generalised additive models with a Poisson link function. Significant associations were established between most cases of cardiovascular and respiratory diseases and these pollutants with a lag time of 0–7 days. The total excess risk was calculated to construct the AQHI, which was then adjusted to an arbitrary scale and banded into four groups based on the calculated score, where 1–3, 4–6, 7–10, and 10+ represented low risk, moderate risk, high risk, and very high risk, respectively. We found that the AQHI captured both high and very high risk levels during the day for most stations. The constructed AQHI also recorded a greater number of high and very high risk days than the currently used AQI but fewer than the WHO-based AQI. Our findings suggest that the AQHI can capture the combined effects of multiple air pollutants, which makes it an effective tool for communicating air pollution-related health risks.

1. Introduction

Ambient air pollutants are regarded as a major problem for public health. A report from the World Health Organization (WHO) in 2006 revealed that 4.2 million people die from environmental air pollution globally each year. Moreover, the results showed that 91 % of people live in areas where the levels of air pollution exceed the WHO's air quality guidelines (WHO 2016, 2022). Long-term particulate matter (PM) exposure can cause lower respiratory infections and cancer (Chen and Hoek, 2020; Manisalidis et al., 2020; Nakharutai et al., 2022). The effects of air pollution on public health are thus very serious, so it is necessary to develop effective communication tools that can comprehensively assess daily air quality and predict the impact of air pollution on health.

The air quality index (AQI) represents air quality categories ranging from good to severe. It is commonly used as a tool to convert the measured values of air pollutant concentrations into simple terms to communicate, and facilitate an understanding of, the air quality in a particular area. Many countries report daily air quality using the AQI because it is easy to understand. However, numerous studies have

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https://doi.org/10.1016/j.envc.2024.100991
Received 27 June 2024; Received in revised form 3 August 2024; Accepted 9 August 2024
Available online 14 August 2024

revealed the weak points of the AQI, which mostly centre around the additive effects of multiple air pollutants on health. The AQI represents the air quality situation from the perspective of only an ultimate concentration of a single air pollutant in a day and does not capture the combined health effects of multiple air pollutants. In addition, it does not reflect the linear non-threshold concentration response relationships between air pollutant exposure and health risks (Sicard et al., 2011, 2012; Stieb et al., 2008; Tan et al., 2021 Wang et al., 2022; Tang et al., 2024).

To overcome concerns regarding the health risks associated with multiple air pollutants, Health Canada and Environment Canada pioneered the development of the air quality health index (AQHI) (Stieb et al., 2008), which is an effective tool that estimates the combined health effects of exposure to multiple air pollutants. This index has been adopted by many countries, such as South Africa (Cairncross et al., 2007) and Sweden (Olstrup et al., 2019), and selected cities in China, among them, Shanghai (Chen et al., 2013), Guangzhou (Li et al., 2017), Tianjin (Zeng et al., 2020), and Hong Kong (Wong et al., 2013). A nationwide AQHI was subsequently developed in China based on the data of 272 major Chinese cities (Du et al., 2020). Most studies have compared the AQHI to the AQI, and the results have shown that the AQHI has a stronger association with health outcomes over the short term and can predict mortality and morbidity more accurately (Chen et al., 2013). Because the AQHI is a smart air quality index that is better than the AQI for communicating air pollution-related health risks, it is beneficial for policymakers to use the AQHI as a tool to help protect people from the acute health impacts of air pollution.

Bangkok, the capital city of Thailand, has high levels of air pollution from various sources, including traffic, industry, and transcity open crop burning (Tesfaldet and Chanpiwat, 2023; Wang et al., 2020). The city has 12 air monitoring stations based on the United States Environmental Protection Agency (US EPA) standard, and these are maintained by the Thai Pollution Control Department (PCD). In addition, like other capital cities, the population density in Bangkok is high, at 5294.3 per square kilometre. An annual report from the PCD showed that Bangkok has faced an air pollution problem for a long period, and it is worse in the winter season (October–February). Generally, Thai people perceive air quality based on the AQI, where the score is divided into five air quality levels with five colours depending on the severity of the pollution: blue (0–25), green (26–50), yellow (51–100), orange (101–200), and red (>200). Bangkok has over 100 hospitals located around the city, and these are administered by different organisations, such as the Ministry of Public Health, the Ministry of Higher Education, Science, Research and Innovation, and the local government. The primary obstacle to health data collection in Bangkok is the reporting of the individual hospitals into the central management system. For example, data obtained from the system may not be complete. We thus proposed an area-based study to develop a Bangkok AQHI using the health data from the individual hospitals located in the selected area and to link these with the daily air quality in the city.

The aim of the present study was therefore to develop an AQHI based on the associations between outpatient department (OPD) visits for cardiovascular and respiratory diseases and the air pollutants in Bangkok from 2016 to 2019. This study will increase the understanding of the air quality situation in the city and provide a scientific risk communication tool based on pollution-related health effects. We also expect the results of this study to be used as an effective tool to communicate health risks from air pollution in Thailand.

2. Data and methodology

2.1. Study area

Bangkok is located in the Chao Phraya River delta in central Thailand and has an estimated population of over 10 million. The city occupies 7762 km^2s (Chalermpong, 2007; Thanvisitthpon et al., 2018) and has a tropical climate with three distinct seasons: summer (March–May), rainy (May–October), and winter (October–March). The period March–May is the warmest, with air temperatures reaching 40 °C (United Nations Environment Programme, 2009). Bangkok is currently divided into 50 administrative districts under the authority of the Bangkok Metropolitan Administration (BMA), which is the local government of Bangkok. The district subgroups can be divided into six groups: central, northern, southern, eastern, northern Thon Buri, and southern Thon Buri. The healthcare system is complicated. Over 100 hospitals are distributed around the city and administered by different organisations, such as the Ministry of Public Health, the Ministry of Higher Education, Science, Research and Innovation, and the local government. For this study, we decided to collect health data from individual hospitals for analysis and selected particular areas for this purpose. The representative areas we chose for this study were the central BMA districts of Ratchathewi, Phaya Thai, Dindang, Dusit, Phranakorn, Huai Khwang, Wang Thonglang, Pom Prap Sattru Phai, and Samphantawong. Many hospitals, which are managed by diverse government agencies and the private sector, are located in this area (Fig. 1). There are various types of land use and activities, including sensitive areas, such as hospitals, preschools, schools, and universities. The central BMA districts face air pollution problems continuously, particularly during the winter season (November–February) each year (Fig. 2).

2.2. Exposure and health outcomes

2.2.1. Air quality data

We obtained the air quality data from 13 air quality monitoring stations located at several places in Bangkok, Thailand. The data sets were organised by Thailand's PCD for 12 stations and the BMA for one station. Six of the stations were located within 10 m of the road and were classified as roadside stations, while the other seven were situated in residential areas (Table 1). Due to the large amounts of missing data (generally >90 %), stations 50t and 53t were excluded from our analysis. The concentrations of suspended particulate matter (PM) with an aerodynamic diameter smaller than 2.5 µm ($PM_{2.5}$) and 10 µm (PM_{10}) were measured using the Beta Attenuation Monitor 1020, as recommended by the EPA. The ozone (O_3), sulphur dioxide (SO_2), nitrogen dioxide (NO_2) and carbon monoxide (CO) concentrations were measured using ultraviolet absorption photometry, ultraviolet fluorescence, cavity attenuated phase shift spectroscopy and Non-Dispersive Infrared Detection techniques. The corresponding atmospheric data, including atmospheric pressure, relative humidity, and temperature, and each station's location coordinates were also retrieved. All the air pollutant monitoring equipment used met the requirements of the PCD and the standards of the US EPA.

2.2.2. Time-series variations and spatial interpolation for the air quality data

Time-series plots are beneficial for displaying oscillations in pollutant concentrations that change across various timescales. The diurnal, weekday, and intra-annual variations of the time-series plots were used to present the situations for $PM_{2.5}$, PM_{10}, O_3, SO_2, NO_2, and CO.

To link the air pollution data with the health data from the hospitals, we used two approaches: (1) we manually assigned the air monitoring station data, and (2) we performed inverse distance weighting (IDW) using the data from all 11 stations. First, we constructed a distance matrix between the centroid of the area related to the postcode of the central BMA and the 11 air monitoring stations. To interpolate the air quality concentrations at the centroid of the area, we then performed the IDW methods described by Shepard (1968).

2.2.3. Sources of health effects data

As the main outcomes data, the number of OPD visits due to respiratory and cardiovascular diseases from the 24 tertiary hospitals located

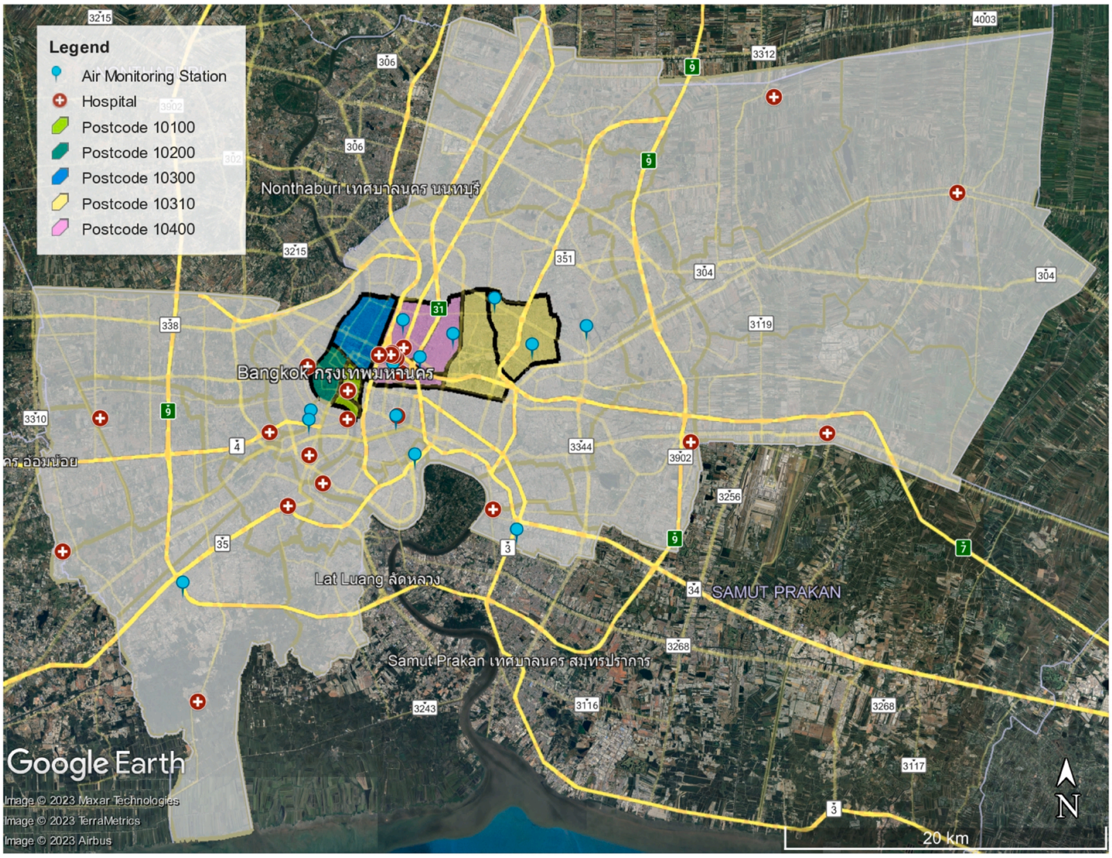

Fig. 1. District map of Bangkok, Thailand, with locations of air quality monitoring stations and hospitals.

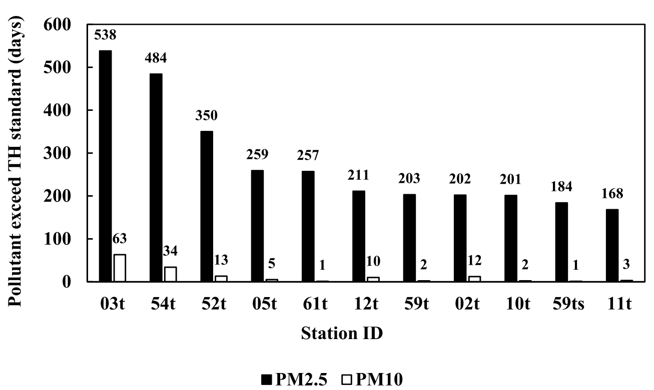

Fig. 2. Summary of the number of days pollutants (PM2.5: □ and PM10: ■) exceed the standard for all air quality monitoring stations in Bangkok, Thailand.

around the Bangkok Municipality were collected after obtaining approval from the ethics committees of the Faculty of Tropical Medicine, Mahidol University (COA no MUTM2022–003–02-YMID_M_64_003), Rajavithi Hospital (023/2565), Chulalongkorn University Faculty of Medicine (1386/2022), the BMA (AL04.1), and the naval medical department (046 COA-NMD-REC 046/65), as well as permission from the different hospitals. Nine hospitals were located in the central district area (Fig. 1). The data were obtained from the medical records department or information technology division of each hospital and exported as individual patient data in text files with de-identified (hashed) hospital numbers. We prepared the health data by separating the postcodes related to the central BMA districts. The postcodes of the central districts are 10,100, 10,200, 10,300, 10,310, and 10,400. The centroid of the boundary of each postcode was designated the exposure area and linked with the health data. The OPD visits were recorded and coded by medical coders using the 10th revision of the International Statistical Classification of Diseases and Related Health Problems-Thailand Modification (ICD-10-TM) after physician diagnoses. The patient records with respiratory and cardiovascular morbidity identified as J00-J99 and I00-I99, respectively, were retrieved from each hospital.

The patient data for the period 1 January 2016 to 31 December 2019 (i.e. before the COVID-19 pandemic) were retrieved. The diseases and symptoms were identified and classified into respiratory (i.e. bronchitis, common cold, chronic obstructive pulmonary disease [COPD] with acute exacerbation, overall asthma, overall COPD, pharyngitis, and upper respiratory tract infection) and cardiovascular diseases (i.e. heart failure, arrythmia, haemorrhagic stroke, all ischaemic heart diseases [IHDs], acute coronary syndrome, subacute coronary syndrome, peripheral arterial disease, hypertension, ischaemic stroke, and overall stroke). The total number of hospital visits per day for each disease group was calculated for each exposure area. Some patients may have visited more than one hospital in a day, that would have resulted in an overestimation of the number of visits, as the identifying personal data were not available for duplication checks. However, the unit of analysis was the daily number of visits, so we postulated that the likelihood of patients visiting multiple hospitals on the same day was low.

2.2.4. Missing data imputation

No data were missing from the medical records since the ICD-10-TM codes, which are generally used for reimbursement, were the only data required. For the missing air quality data, we used the multivariate imputation by chained equations (MICE) method described by Buuren and Groothuis-Oudshoorn (2011). The parameters used were date, hour, wind speed, temperature, humidity, latitude and longitude of the air monitoring station, $PM_{2.5}$, PM_{10}, O_3, SO_2, NO_2, and CO. To select the appropriate imputation for each parameter, the convergence was

Table 1
Location of air quality monitoring stations.

Station ID	Station Name	Description	Lat	Lon
02t	Bansomdejchaopraya Rajabhat University Hiran Ruchi, Khet Thon Buri	Residential area	13.7328 N	100.4877 E
03t	Highway NO.3902 km.13 + 600 Kanchanaphisek Rd, Bang Khun Thian	Roadside	13.6365 N	100.4143 E
05t	Thai Meteorological Department Bang Na, Khet Bang Na	Residential area	13.6662 N	100.6057 E
10t	National Housing Authority Klongchan Khlong Chan, Khet Bang Kapi	Residential area	13.7799 N	100.6460 E
11t	National Housing Huaykwang Din Daeng, Khet Din Daeng	Residential area	13.7755 N	100.5692 E
12t	Nonsi Witthaya School Chong Nonsi, Khet Yannawa	Residential area	13.7081 N	100.5473 E
50t	Chulalongkorn Hospital Rama IV Rd. Khet Pathum Wan	Roadside	13.7299 N	100.5365 E
52t	Thonburi Power Sub-Station Intarapitak Rd. Khet Thon Buri	Roadside	13.7276 N	100.4866 E
53t	Chokchai Police Station Lat Phrao Rd. Khet Wang Thonglang	Roadside	13.7954 N	100.5930 E
54t	National Housing Authority Dindaeng Din Daeng Rd. Khet Din Daeng	Roadside	13.7925 N	100.5502 E
59t	The Government Public Relations Department Phaya Thai, Khet Phaya Thai	Residential area	13.7832 N	100.5405 E
59ts	Ratchathewi District Office, Bangkok Phayathai Roadside, Ratchathewi	Roadside	13.7592 N	100.5349 E
61t	Bodindecha Sing Singhaseni School Pubpla, Khet Wang Thonglang	Residential area	13.7697 N	100.6146 E

assessed virtually by plotting the means of the parameters against the number of iterations. The missing continuous variables of the hourly pollution concentrations were imputed using the predictive mean matching method with MICE. The imputed data were then calculated as the average daily air pollution concentrations.

2.3. Associations between air pollutants and morbidity (OPD visits for cardiovascular and respiratory diseases)

The continuous atmospheric data (i.e. the daily concentrations of $PM_{2.5}$, PM_{10}, SO_2, O_3, temperature, relative humidity, and wind speed) were described using the corresponding means and standard deviations (Table 2). The associations between the daily ambient concentrations of $PM_{2.5}$, PM_{10}, SO_2, and O_3 and the daily OPD visits due to respiratory and cardiovascular diseases were assessed using Poisson regression. Generalised additive models with a Poisson link function were applied to obtain the coefficients of the concentration–response relationship using a single pollutant model:

$$\log[\text{ respiratory / cardiovascular}] = \beta i^{*}(\text{Xi}) + \text{wkday} + \text{ns}(\text{ humid, } \text{df} = 7) + \text{ns}(\text{Temp}, \text{df} = 6) + \text{ holiday} \tag{1}$$

where respiratory/cardiovascular is the number of OPD visits on day t, Xi is the concentration of the pollutant (PM2.5, PM10, SO2, and O_3), βi is the regression coefficient for Xi, ns () indicates a smoother based on penalised smoothing splines (this captures the nonlinear relationships of the covariates of the time trend and the weather parameters with OPD visits), and df is the degree of freedom. The daily mean temperature and relative humidity were used in all the models to control for confounding. The adjusted variables in the models were Thai national holidays, weekends, and atmospheric parameters (i.e. temperature, relative humidity, and wind speed). The incident rate ratios with their corresponding 95 % confidence intervals (CIs) were then calculated and accounted for lag times of 0–7 days because associations were found between $PM_{2.5}$, PM_{10}, SO_2, and O_3 and respiratory and cardiovascular diseases up to 7 days after exposure. The statistical significance was determined based on a p-value of 0.05. We adjusted the covariates: (1) an indicator variable for 'day of week' to account for possible variations in the week and (2) natural smooth functions with 6 df for the present-day temperature and 7 df for the present-day relative humidity to

Table 2
Distribution of air pollutants and atmospheric parameters.

Station	Ambient Concentration and Atmospheric Data Median [Min, Max]								
	PM_{10}	$PM_{2.5}$	NO_2	SO_2	CO	O_3	Wind Speed	Temperature	Humidity
02t	36.0 [1, 340]	19.0 [2, 167]	9.00 [0, 89.0]	1.08 [0.00, 4.38]	0.55 [0.08, 1.64]	12.0 [0, 117]	0.500 [0, 6.30]	29.9 [17.9, 39.7]	63.0 [20.0, 90.0]
03t	56.0 [3, 466]	28.0 [2, 287]	26.0 [0, 169]	1.13 [0.38, 3.25]	0.69 [0.11, 3.19]	4.00 [0, 107]	1.10 [0, 6.10]	28.8 [15.7, 47.4]	NA [NA, NA]
05t	32.0 [3, 273]	17.0 [1, 173]	13.0 [0, 114]	1.46 [0.00, 6.42]	0.49 [0.05, 1.38]	17.0 [0, 133]	1.40 [0.100, 5.80]	28.5 [16.1, 38.1]	74.0 [20.0, 99.0]
10t	31.0 [3, 188]	17.0 [1, 114]	15.0 [0, 146]	2.63 [1.38, 5.83]	0.77 [0.36, 1.70]	17.0 [0, 177]	0.80 [0, 4.10]	29.3 [16.3, 39.0]	NA [NA, NA]
11t	29.0 [1, 188]	18.0 [1, 105]	24.0 [1.00, 111]	2.29 [0.00, 6.04]	0.83 [0.20, 2.00]	16.0 [0, 182]	0.50 [0, 2.80]	29.1 [16.6, 39.5]	62.0 [4.00, 100]
12t	44.0 [1, 297]	17.0 [1, 110]	21.0 [1.00, 103]	1.38 [0.00, 8.54]	0.65 [0.09, 2.49]	11.0 [0, 132]	0.60 [0, 2.70]	29.8 [18.2, 41.7]	77.0 [15.0, 100]
52t	38.0 [2.00, 300]	21.0 [1, 148]	15.0 [0, 119]	1.33 [0.00, 5.54]	0.62 [0.03, 1.67]	14.0 [0, 141]	0.60 [0, 4.10]	29.1 [17.3, 38.5]	67.0 [16.0, 99.0]
59t	29.0 [0, 300]	17.0 [1, 168]	13.0 [0, 120]	1.75 [0.79, 4.42]	0.67 [0.02, 2.14]	21.0 [0, 158]	0.50 [0, 2.20]	28.3 [16.4, 47.0]	70.0 [15.0, 100]
59ts	41.0 [0, 193]	22.0 [0, 133]	23.0 [1.00, 112]	1.83 [0.79, 4.63]	0.75 [0.13, 5.00]	9.00 [0, 104]	0.40 [0, 0.900]	29.9 [16.0, 42.0]	64.0 [16.0, 101]
61t	35.0 [1, 179]	19.0 [1, 149]	12.0 [0, 107]	2.29 [0.00, 7.33]	0.75 [0.37, 1.90]	16.5 [0, 178]	0.70 [0, 3.70]	28.9 [6.00, 39.5]	NA [NA, NA]
Overall	39.0 [0, 466]	20.0 [0, 287]	17.0 [0, 195]	1.75 [0.00, 8.54]	0.71 [0.02, 5.54]	14.0 [0, 182]	0.60 [0, 6.30]	29.2 [6.00, 47.4]	67.0 [4.00, 101]

NA = Not Available.

control for the potential nonlinear confounding effects of weather conditions. To select the most appropriate degree of freedom for a natural spline, generalised cross-validation (GCV) was used to compare the goodness of fit between the various degrees of freedom. The degrees of freedom with the lowest GCV rounded to the integer were selected as the most suitable degrees of freedom for humidity and temperature, as shown in Fig. 3. We used the Akaike information criteria (AIC) to check robustness. The model with the lowest AIC was the single air pollutant model with temperature and humidity.

We assessed a variety of single-day lags of air pollutant concentrations from 0 to 7, that is, same day exposure (lag 0), exposure the previous day (lag 1), exposure 2 days previously (lag 2), exposure 3 days previously (lag 3), exposure 4 days previously (lag 4), exposure 5 days previously (lag 5), exposure 6 days previously (lag 6), and exposure 7 days previously (lag 7). Finally, the lag that achieved the strongest effect estimate was used to develop the AQHI in this study (Li et al., 2017; Stieb et al., 2008).

To further develop the AQHI, we used the coefficients from the single-pollutant model. We subsequently predicted the excess risk (ER), which was defined as the percentage increase in daily OPD visits for each 10 $\mu g/m^3$ increase in PM_{10} and $PM_{2.5}$, and each unit ppb increase in SO_2 and O_3 with 95 % CIs. The ER was calculated using the following formula:

$$ER_{it} = 100^{*}[\exp(\beta i^{*}Xit) - 1] \tag{2}$$

where ER_{it} represents the percentage change in morbidity associated with the ith pollutant on the tth day, βi is the regression coefficient of pollutant i in the single-pollutant model, and Xit is the concentration of the pollutant i on the tth day.

2.4. Construction of the AQHI

The AQHI for all the air monitoring stations in Bangkok was constructed after calculating the total daily ER using the following formula:

$$\text{AQHI} = 10/c * \text{ dailytotal } ER_t \tag{3}$$

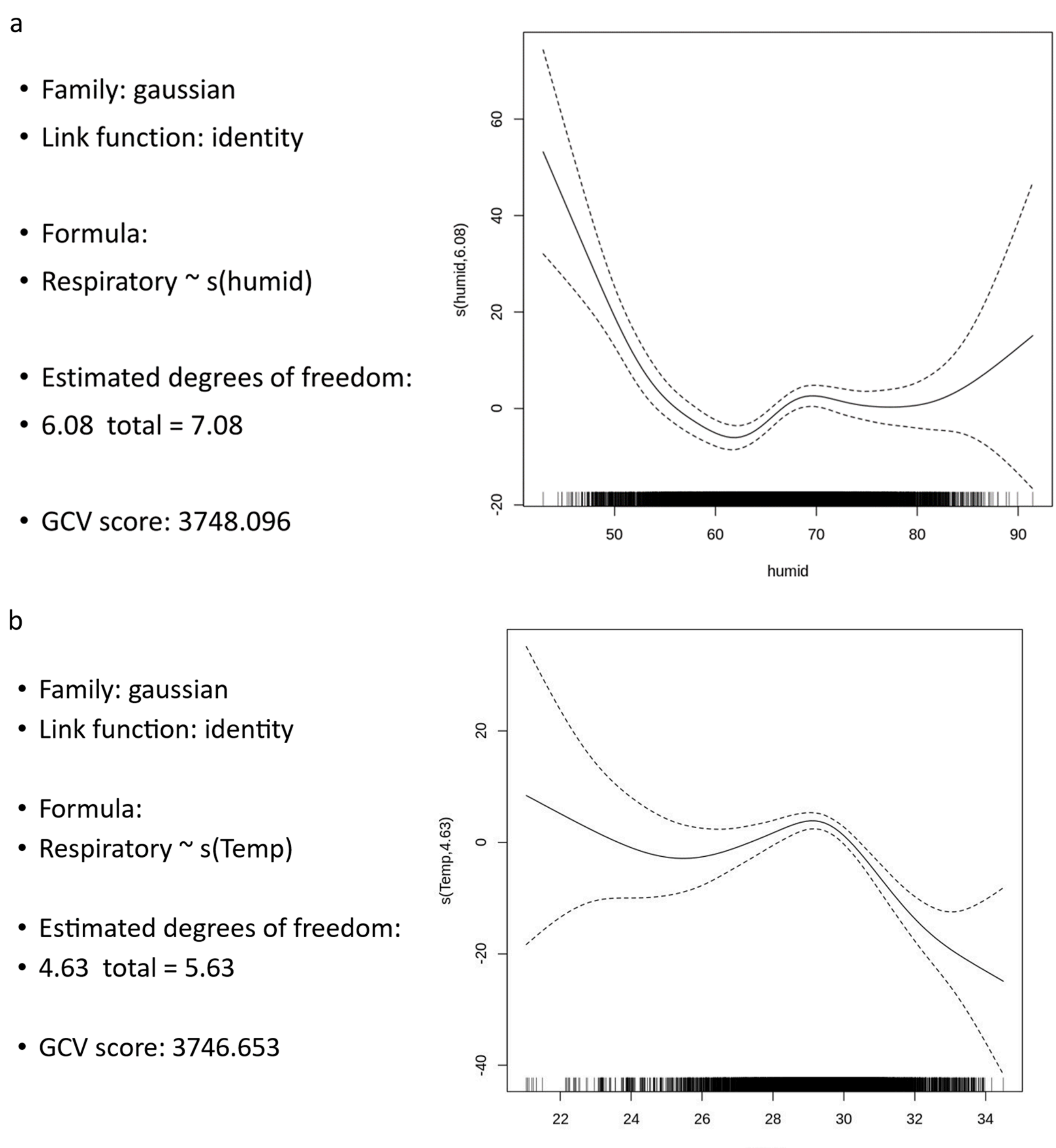

Fig. 3. Degrees of freedom for humidity(a), and temperature (b).

where the daily total ER_t expresses the sum of ER_{it} of the OPD visits associated with the ith pollutant on the tth day, and c is the maximum value of ER_t. A time series of daily AQHI values was created on a numerical scale from 0 to 10+ (Stieb et al., 2008).

The AQHIs were banded into four groups based on the calculated score, where 1–3, 4–6, 7–10, and 10+ represented low risk, moderate risk, high risk, and very high risk, respectively.

All the statistical analyses were conducted in R software, version 3.4.2. (R Core Team, Austria).

3. Results and discussion

3.1. Temporal variations in ambient air pollutants

Variations in the ambient air pollutants (PM_{10}, PM_{coarse}, $PM_{2.5}$, CO, SO_2, NO_2, O_3) were calculated by averaging the hourly concentrations for each period to view the fluctuations in the diurnal, weekday, and intra-annual variations, which represented the air quality situation for each area where the air monitoring stations were located across Bangkok using the time-series plot (Figs. S1–S11). The $PM_{2.5}$ trends were higher than those of PM_{coarse} during the period of high $PM_{2.5}$ concentrations (October–April) and lower in the low $PM_{2.5}$ season (May–September). This was observed at stations 02, 03, and 54t, while the trend of PM_{coarse} at station 12t was higher than that of $PM_{2.5}$ for all periods. The PM in the diurnal cycle related to the different sources or factors that affected the measured concentrations of PM at each station. For example, at the 02t station, fuel combustion from traffic resulted in increased concentrations of $PM_{2.5}$, CO, and NO_2 (only in the mornings). Peaks in PM_{10} hourly concentrations were observed at 8 a.m., 2 p.m., and 11–12 p.m., while $PM_{2.5}$ had no peaks in the afternoon. This suggested that the factor affecting the peak concentrations of PM_{10} and $PM_{2.5}$ in the morning and at night were the same, whereas the peak of PM_{10} in the afternoon was different because PM_{coarse}, which is a component of PM_{10}, showed a peak in the afternoon. Generally, the sources of PM_{coarse} are mechanical activities, such as the dispersion of fugitive dust from wind and construction. At the 02t monitoring station, the construction of the MRT Gold Line and Blue Line or another source may have contributed to the PM_{10} readings. The diurnal cycle pattern did not differ during the days of the week, and the lowest concentration was observed on Sundays. Monthly variations showed that the trend of PM concentrations for the period May–September was lower than that for the October–April period. In terms of diurnal variations in NO_2, the NO_2 peak occurred once in the morning and once at night, which was the same as that for $PM_{2.5}$ and corresponded with fuel combustion from traffic. The NO_2 concentrations decreased on Saturdays and Sundays. O_3, the secondary pollutant generated from photochemical reactions, peaked at 1–2 p.m. each day. The pattern of diurnal variation of CO was similar to those for PM_{10}, $PM_{2.5}$, and NO_2, while the peak of SO_2 was observed only in the morning. This indicated that the main factor inducing the CO peak in the morning and at night, including the SO_2 peak in the morning, was fuel emissions from traffic. Another key factor affecting the peak of pollutants at night was the reduction in the mixing height, which led to lower pollutants in that area of the 02t monitoring station.

At the 03t station, the main factor contributing to all the PM and gases may have been traffic, especially along Kanchanapisek, Rama II, and Ekkachai roads. The highest concentrations of PM_{10} and $PM_{2.5}$ presented at 8 a.m. and then decreased until 2 p.m. The second cycle started at 10–12 p.m. and decreased again until 4–5 a.m. This diurnal cycle pattern did not differ between the days of the week, but the lowest concentrations were observed on Saturdays and Sundays. The monthly variations showed that the PM concentration trend for the period May–September was lower than that for October–April. O_3 peaked at 1–2 p.m. on all days. The NO_2 peak occurred only at 6 p.m., which may have been the result of the photochemical reactions of O_3 and NO In addition, volatile organic compounds are a precursor that reacts with free radicals (hydroxyl radical) in the atmosphere to produce RO_2 and HO_2, which can react with NO and eventually convert to NO_2. Another source of NO_2 in the evening may have been the secondary road of Ekkachai Road (Soi 94–96), along which many industries and a large community are located. The diurnal variations of CO were the same as for PM_{10}, $PM_{2.5}$, and PM_{coarse} in that CO peaked at 8–9 a.m. and 8–9 p.m.

At the 05t station, all the pollutants peaked twice: once in the morning (8 a.m.) and once at night (8–10 p.m.). In the morning, the PM_{coarse} concentration remained at a high level until 12 a.m., while the PM_{10}, $PM_{2.5}$, CO, and NO_2 levels started to decrease at 10 a.m. This implies that traffic influenced the high concentrations in the period 8–10 a.m., and another mechanical factor was responsible for the increasing concentrations of PM larger than 2.5. The peak variations for all the pollutants, except NO_2, in the morning were higher than those at night. This may have been caused by the photochemical reactions of O_3 and NO in the afternoon, which resulted in the elevated concentration of NO_2 at night. SO_2 had fewer diurnal variations. Small peaks occurred throughout the day and night, so traffic may not have been a major contributor to the SO_2 concentrations. These small fluctuations may have been caused by other emissions near the station.

For the 10t station, the pattern of diurnal variations did not differ from that of the 05t station, while for the station 11t, an NO_2 peak was observed at 8 p.m., which was different from the peaks of the other pollutants at 10–11 p.m. The cause may have been the photochemical reactions of NO and O_3 in the afternoon. The peak of CO at night was higher than that in the morning, which resulted from other conditions, such as fuel combustion, household cooking, and the cooking of street food at night markets. These offer strong reasons for the higher CO concentrations compared to the SO_2 concentrations from evening to night. The CO concentrations did not peak during that time because most of the fuel used for cooking has no sulphur, so it differs from the oil fuel used in vehicles, of which sulphur is a component. The SO_2 concentrations measured at night were low.

The diurnal PM variations were quite stable at the 12t station. The peak of NO_2 at night (7 p.m.) was higher than that in the morning (7 a.m.). This implies that traffic in the morning could have contributed to lowering the NO_2 concentrations more than photochemical reactions. The PM_{10} concentrations tended to be higher than 120 $\mu g/m^3$, and the monthly variations in PM_{coarse} tended to be higher than those of $PM_{2.5}$ throughout the year.

The station 52t is located on a roadside, so the main source of all the pollutants was traffic. The construction of the MRT line caused the high concentrations of PM_{10} and $PM_{2.5}$ in the same way as for station 02t The diurnal variations of PM_{10}, $PM_{2.5}$, PM_{coarse}, NO_2, CO, and SO_2 had two peaks, one in the morning (8–9 a.m.) and one at night (7–10 p.m.), with the morning concentration higher than that at night. Our results showed that the main source of all the pollutants at the station was fuel combustion from traffic. Similarly, the peak of NO_2 at night was higher than that in the morning and was induced by the photochemical reactions of NO and O_3.

For the station 54t, the PM_{10}, $PM_{2.5}$, PM_{coarse}, and CO concentrations started at 6 a.m. and peaked at 10 a.m. before decreasing continuously until 4 p.m. They subsequently peaked again at 9–10 p.m. The CO peaks in the morning and at night were observed earlier than the other PM peaks. This may have been caused by secondary particles or other factors that collected PM. An analysis of the secondary PM is recommended.

At station 59t, none of the PM peaks were clear. $PM_{2.5}$ tended to increase at 8–10 a.m. and decrease in the afternoon. On the other hand, $PM_{2.5}$ and PM_{10} were low in the morning but tended to increase at 2–5 p.m. CO peaked during the two periods 8–9 a.m. and 8–9 p.m. and was generated from incomplete combustion, such as traffic. However, the diurnal variations for station 59t were low. The station may thus have had some conditions or buffers that could maintain the PM levels, as the PM concentrations were quite stable throughout the day.

For the 61t station, the NO_2 peak started earlier (8–9 p.m.) than those of the other pollutants at night (10–11 p.m.). This may have been caused by the photochemical reactions of O_3 and NO_2. The $PM_{2.5}$, PM_{10}, and O_3 levels tended to be higher than the National Ambient Air Quality Standards (NAAQS). The most likely sources were the main roads on the east and southeast sides of the station (Ramkamhaeng and Romklao roads). The patterns of concentration variations of the air pollutants implied correlations between the source emissions for each pollutant in all the areas. Time variations can be applied to present the trends, cycles, and magnitudes of pollutants (Hayes et al., 2013; Kanchanasuta et al., 2020; Munir et al., 2017; Szulecka et al., 2017).

3.2. Associations between air pollutants and respiratory and cardiovascular OPD visits

In this study, we assessed the associations between $PM_{2.5}$, PM_{10}, O_3, and SO_2 and respiratory diseases. The daily ambient concentrations of the air pollutants were linked to the number of OPD visits at 24 hospitals in Bangkok, and the air pollutant concentrations were generally as high as the WHO standards for ambient concentrations of air pollutants. We observed a significant association between the daily concentrations of $PM_{2.5}$, PM_{10}, O_3, and SO_2 and respiratory diseases, namely, bronchitis, the common cold, COPD with acute exacerbation, overall asthma, overall COPD, pharyngitis, pneumonia, and upper respiratory infection, with a lag time of 0–7 days following exposure. We similarly noted lag times of 0–6 days for PM_{10} and O_3 and 1–5 days for $PM_{2.5}$ in cases of status asthmaticus (Fig. 4). No association was detected between SO_2 and status asthmaticus and pneumonia.

A significant association was observed with respect to the cardiovascular diseases heart failure, arrythmia, all IHDs, subacute coronary syndrome, hypertension, and overall stroke and the daily concentrations of $PM_{2.5}$, PM_{10}, O_3, and SO_2, with a lag time of 0–7 days following exposure. Haemorrhagic and ischaemic stroke similarly showed significant associations with $PM_{2.5}$ and PM_{10}; however, the lag times were 0–4 days for $PM_{2.5}$ and PM_{10} and 0–7 days for O_3 and SO_2. No association was observed between these pollutants and peripheral arterial disease. Our results indicated that lag 0 had the strongest association with most cases of respiratory and cardiovascular diseases, so lag 0 was selected to

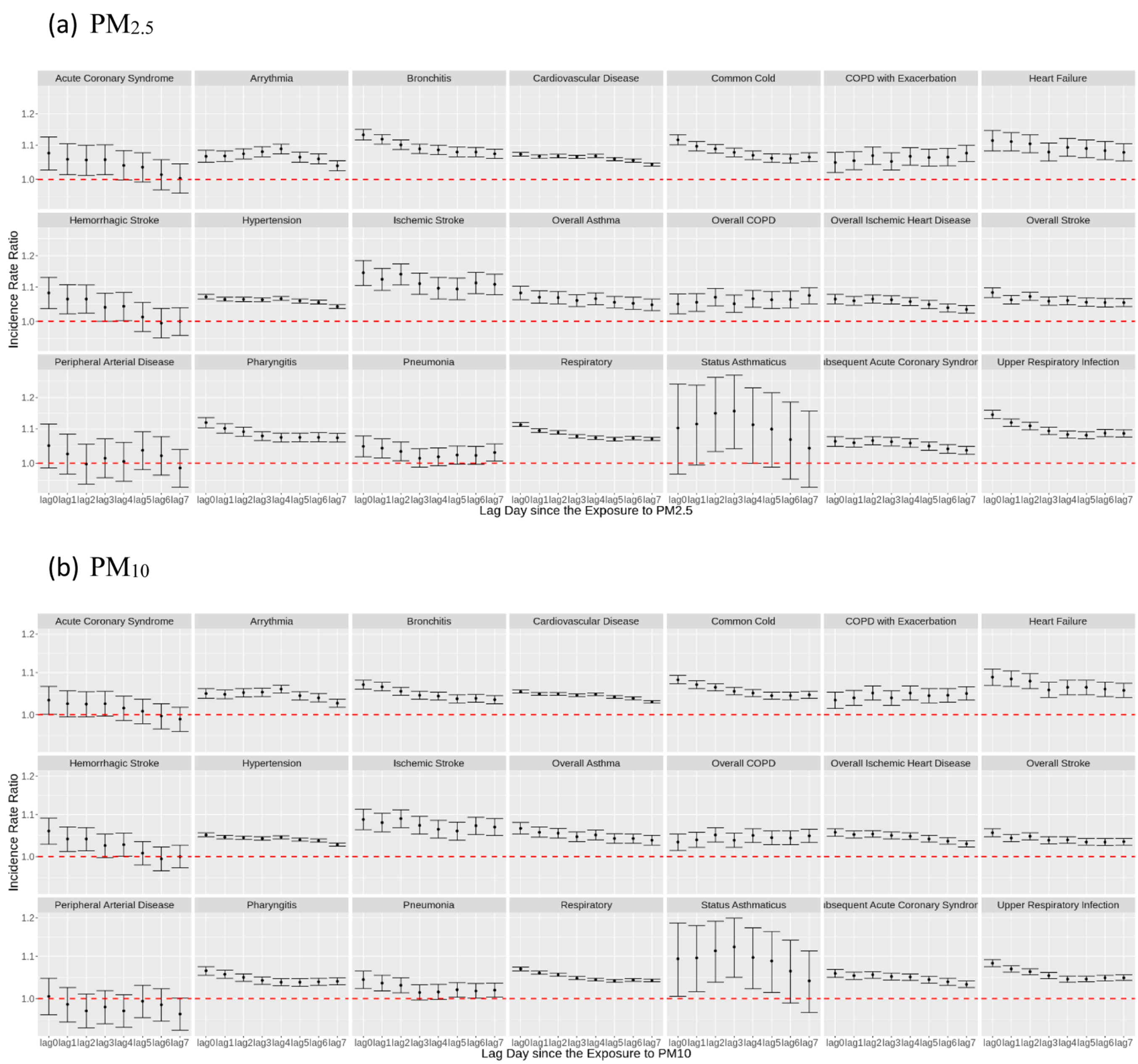

Fig. 4. Association between daily concentration of $PM_{2.5}$ (a), PM_{10} (b), O_3 (c) and SO_2 (d) and Diseases Group at Lag 0 to 7 days.

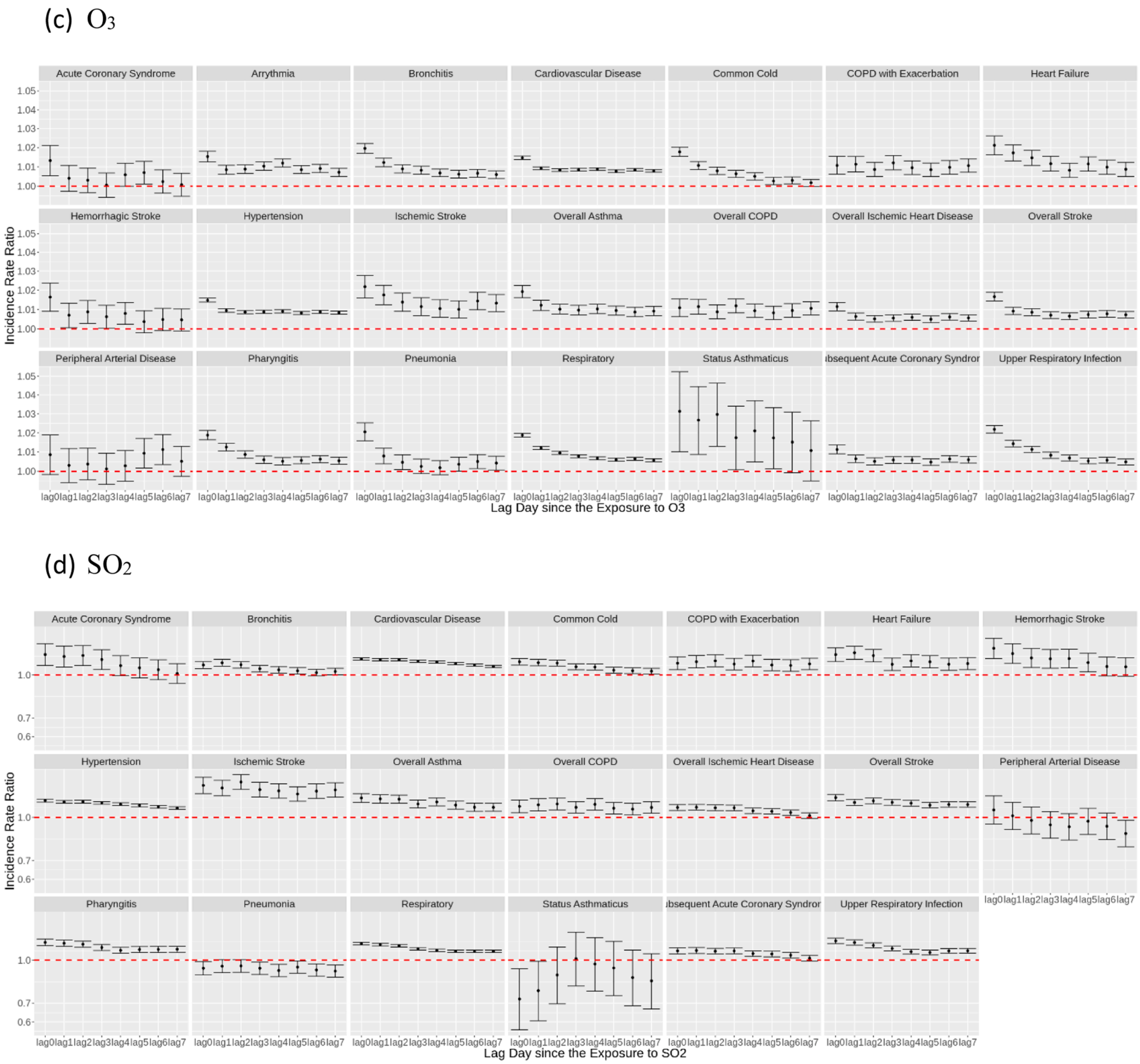

Fig. 4. (*continued*).

determine the coefficient (β) and further develop the AQHI.

Several previous studies have reported positive associations between the air pollutants $PM_{2.5}$, PM_{10}, and NO_2 and respiratory diseases, including COPD (Park et al., 2021), respiratory mortality (Areal et al., 2022), and bronchitis (Cai et al., 2014), but these links have not been observed for O_3. The effects of these air pollutants that increase the likelihood of respiratory diseases could be explained through the stimulation of the autonomic nervous system and inflammation processes (Wu et al., 2018). An in vitro study illustrated that exposure to PM led to inflammation of the endothelial cells by various mechanisms, including anti-tissue factor antibody synthesis, reactive oxygen species production, and the Nox-4 enzyme (Terzano et al., 2010). Following exposure to air pollutants, systemic vasoconstriction is augmented (Wu et al., 2018). Zhang et al. (2022) studied the association between short-term exposure to $PM_{2.5}$ constituents and hospital admissions for cardiovascular diseases. The effects of exposure to different $PM_{2.5}$ constituents produced variable risks of hospital admissions. The results showed that exposure to NH4+ was associated with the highest risk of IHD and ischaemic stroke, while polycyclic aromatic hydrocarbons were predominately associated with ischaemic stroke only. This therefore implies that $PM_{2.5}$ from various sources has different health outcomes depending on the constituents. O_3, a toxic air pollutant, can be found in urban areas, especially those with heavy traffic, and can cause damage to the bronchial and alveolar epithelial cells and thereby affect pulmonary function. A study by Lei et al. (2019) reported an association between O_3 and respiratory disease in the short term. Moreover, every 10 $\mu g/m^3$ increase in O_3 has been associated with a 0.05 % (95 % CI: 0.42 %–0.53 %) and 2.22 % (95 % CI: 0.56 %–3.90 %) increase in non-accidental and respiratory deaths, respectively. This may be because O_3 exposure can induce stress-related responses in the respiratory tract epithelia and thus produce symptoms of mucosal irritation and airway inflammation (Mudway and Kelly, 2004; Valacchi et al., 2004) and eventually induce respiratory diseases (Paffett et al., 2015; Raza et al., 2018). Several studies have also found that short-term O_3 exposure is associated with platelet activation and increased blood pressure, which may affect cardiovascular health over time and cause heart disease, high blood pressure, and stroke (Day et al., 2017; Han et al., 2016) as well as an increased risk of non-accidental death. Additionally, a study by Nascimento et al. (2020) confirmed associations between SO_2 and PM_{10} and acute respiratory diseases. The authors indicated a greater risk of acute respiratory events due to SO_2 exposure, with a relative risk of 1.28 (95 % CI: 1.22–1.34), and PM_{10} exposure, with a relative risk of 1.14 (95 % CI: 1.09–1.20), with a lag of 0 (i.e. on the day of exposure). A recent study reported an increased risk of asthma mortality with acute exposure to SO_2 in the Chinese population (Liu et al., 2023). The ER for each 10 μg/m^3 increase in SO_2 concentration was 7.78 % (95 % CI: 4.16–11.52 %) with a 7-day lag.

The results of our study support the possible effects of $PM_{2.5}$, PM_{10}, O_3, and SO_2 on respiratory and cardiovascular diseases in Asian populations. In addition, we demonstrated the advantages of using the ICD-10-TM to monitor the health effects of air pollutants. However, the support systems for health data collection should be managed homogeneously so that data can be made available for research with little effort.

3.3. Constructing the AQHI and comparisons with the conventional and WHO-based AQIs

One of the strengths of this work is the selected air pollutants. Furthermore, only the predominant urban air pollutants were included to establish the AQHI, which makes the AQHI more representative of the health effects of air pollution in the central districts of Bangkok because the latter are the primary location for shopping malls, large department stores, entertainment zones, temples, commercial communities, private offices, government offices, universities, schools, hospitals, etc. The pattern of activities thus makes this area a crowded zone. The traffic problems in Bangkok are considered among the worst in cities globally, and traffic is the main cause of air pollutants. $PM_{2.5}$ and PM_{10}, which stem from the combustion of fuel, are the main pollutants affecting the air quality of urban areas, and O_3 is the secondary pollutant (Guan et al., 2023). The sulphur content of the diesel fuel used for transportation in Thailand is controlled, and the measured value from the air monitoring stations around Bangkok did not exceed the hourly standard of 300 ppb. However, our statistical analysis indicated a strong association between the daily average concentration of SO_2 and adverse health outcomes. This may be due to the synergistic effects of SO_2 and PM (Yun et al., 2015). Based on our findings, the present AQHI for Bangkok included $PM_{2.5}$, PM_{10}, SO_2, and O_3. The selection of these pollutants for our AQHI was different from those of other AQHIs due to the use of local health statistics and air pollution data. In Canada, three pollutants (i.e. NO_2, O_3, and $PM_{2.5}$) were considered in the development of the AQHI (Stieb et al., 2008). The AQHI for South Africa and Europe was also developed from multiple pollutants (Cairncross et al., 2007; Sicard et al., 2011) and includes multiple exposures of fine PM (PM_{10}, $PM_{2.5}$) and other pollutants. A study by Li et al. (2017) in Guangzhou, China, used $PM_{2.5}$ to represent PM due to the collinearity and health effects of PM_{10} and $PM_{2.5}$. This guideline also differs from the AQHIs of Canada (Stieb et al., 2008), Shanghai (Chen et al., 2013a), and Hong Kong (Wong et al., 2013) based on the included pollutants. The AQHI developed for Shanghai comprises NO_2, PM_{10}, and $PM_{2.5}$ (Chen et al., 2013a), while SO_2, NO_2, O_3, and PM_{10} were included in the AQHI for Hong Kong (Wong et al., 2013). Many studies have reported correlations between the predominant pollutants and the ERs for air pollutants, which fluctuate in different areas. Zekun et al. (2015) reported that O_3 took the place of $PM_{2.5}$ as the predominant air pollutant in Guangzhou in 2014. The effects of SO_2 and NO_2 on mortality were also found to be higher than those reported in Europe, the United States, and many cities in Asia (Yu et al., 2012). The AQHI in this study could therefore provide more sensible and appropriate predictions that reflect regional differences in health risks stemming from short-term exposure to air pollution. Similarly, Wang et al. (2022) revealed that at-risk people, such as older adults, women, and people with respiratory diseases, are more vulnerable to the short-term health effects of air pollution, and the development of AQHIs for specific groups, such as those representing age, gender, and diseases, is unnecessary. Meanwhile, Tang et al. (2024) suggested that focusing constructed AQHIs on short-term adverse health outcomes from air quality may result in the underestimation of their cumulative impacts, although long-term health outcomes can be assessed using the beta coefficients from the WHO because it is limited by local health data. Reporting both short- and long-term health risks has been recommended. Local hospital admission data could be used as the health endpoint for short-term air exposure risks, while all-cause mortality could be employed to determine long-term air exposure risks. Notwithstanding, this is the first study to construct an AQHI for Bangkok, Thailand, and to compare it with the currently used AQI and the WHO-based AQI.

Time-series plots of the AQHI for all the air monitoring stations operated by the PCD (10 stations) and BMA (59ts) were applied and compared with the currently used AQI and the WHO-based AQI for the period 2017–2021 (Fig. 5, S12–S21). The number of days in which the risk levels were high and very high risk in our AQHI, the currently used AQI, and the WHO–based AQI are presented in Table 3. The results show that our AQHI captured both the high and very high daily risk levels for all the stations except station 03t, so the number of days included in our AQHI exceeded those of the currently used AQI for both high and very high risk levels. The results for station 03t may have occurred because the environment around the station differs from those of the other stations. The correlation between our AQHI and the currently used AQI showed that our AQHI achieved a 95 % stronger effect than the currently used AQI for all stations. Some lower risk levels (i.e. <1 % for stations 02t, 05t, 12t, 52t, 59ts, and 61t, <2 % for station 54t, and <6.5 % for station 03t) were obtained for our AQHI compared to the currently used AQI (Table 4). Our results also showed that the constructed AQHI covered a greater number of days with high and very high risk levels than the currently used AQI but fewer than the WHO-based AQI. The high-risk level captured by our AQHI was lower than that of the WHO-based AQI, and the values of the WHO air quality guidelines are lower than the NAAQS for each air pollutant. However, our AQHI was conducted based on the association of the concentration of air pollutants and local health data, which reflects the health risks for the people in the area. The different risk levels between the constructed AQHI and the currently used AQI resulted in a better understanding of the health risks for the local population. For example, at station 02t, the number of days where the risk levels were high based on our AQHI over 5 years totalled about 265; however, the currently used AQI reported the same risk level as our AQHI but for about 124 days. Accordingly, there were 141 days during which people thought that they had moderate or good air quality and could enjoy outdoor activities, but in fact the risk level was high. Using our AQHI to report the health risks from air pollution in daily air quality management and public health communications, especially for at-risk groups, would be beneficial for policymakers, as its use would help protect people's health and provide suitable health messaging for each population group based on real situations (Table 5).

A crucial limitation of this study was that the health data comprised a non-registered commuter population. These people could therefore not be classified by address. The use of postcodes may not have truly identified some groups because their offices and homes may have been located in different areas. Notwithstanding, this study provides the first step towards developing an AQHI to help ameliorate the acute health effects of air pollutant exposure in Bangkok. In terms of improving the system, a key issue regarding our AQHI was the health data collection, so the next step would be to adjust the coefficient (β) used in Eqs. (2), 3, and 4. The coefficient (β) was calculated from the individual data of each pollutant and represented specific areas. The data were mostly quite different from any other region or period (Wang et al., 2022). The health data for all the subgroup districts should therefore also be collected and analysed, and the AQHI equations should be adjusted to better represent the entire city of Bangkok. Longitudinal studies will need to be

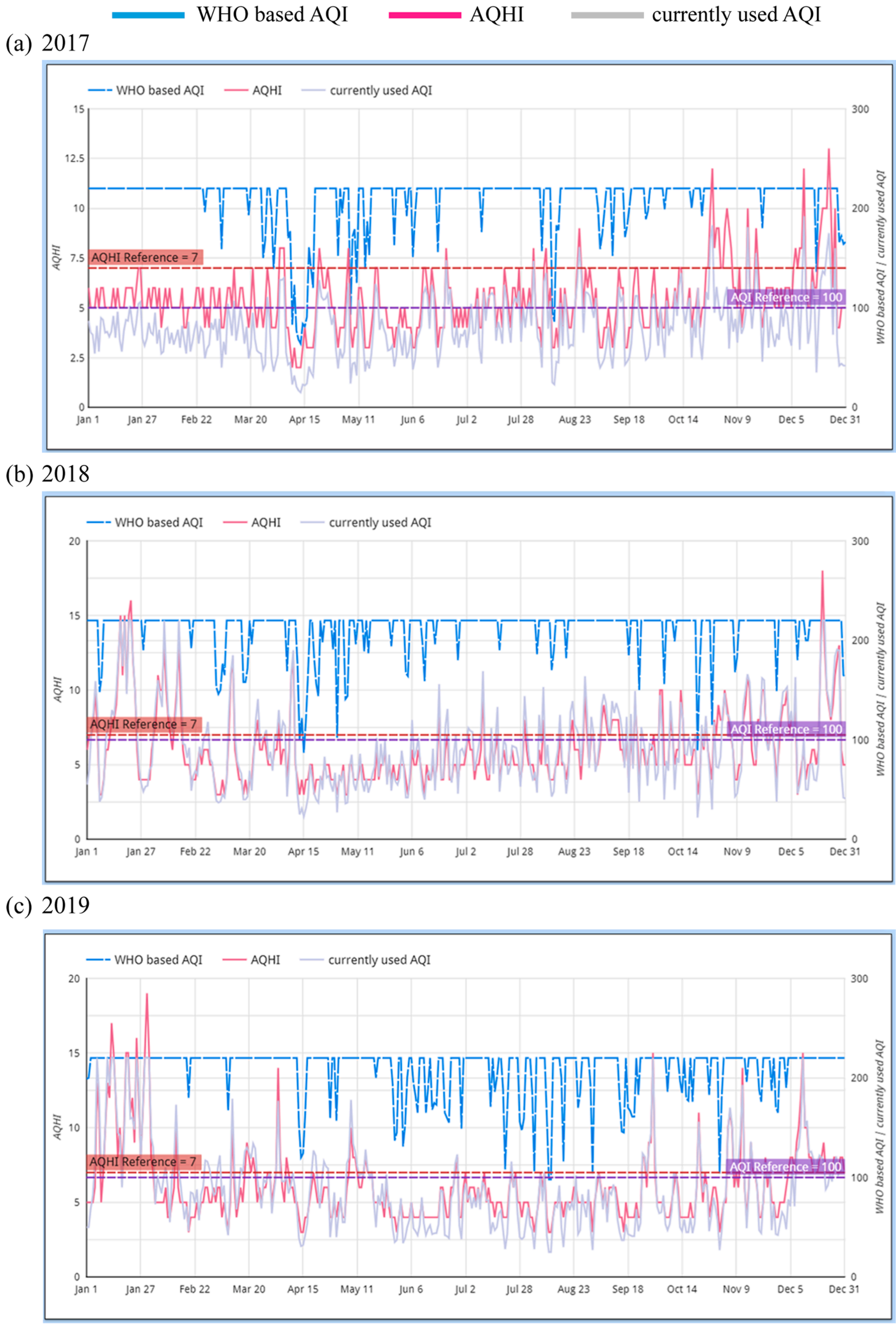

Fig. 5. Time-series plots of the AQHI for air monitoring station 03t by year: (a) 2017, (b) 2018, (c) 2019, (d) 2020, (e) 2021. Red, blue and gray line represent the constructed AQHI, currently used AQI and WHO based AQI respectively.

Fig. 5. (*continued*).

Table 3
The number of days related to high and very high risk in each index between 1 January 2017 – 31 December 2021.

Station	High risk level (days)			Very high risk level (days)		
	AQHI	currently used AQI	WHO based AQI	AQHI	currently used AQI	WHO based AQI
02t	330	202	1370	8	6	662
03t	492	539	1783	3	34	1243
05t	475	259	1032	20	7	534
10t	705	201	1253	161	1	570
11t	643	168	1356	96	2	643
12t	359	211	1451	83	5	775
52t	543	350	1400	133	24	742
54t	843	484	1817	166	23	1172
59t	602	203	1113	135	3	518
59ts	401	184	1660	55	1	682
61t	734	257	1333	206	6	616

conducted to track the effectiveness of our AQHI over time as well as its applicability in different environmental conditions. Studies should be conducted on the association between air pollution data and the health of the local population at specific periods and in specific areas. Differences in the relationships between air pollution and health outcomes among cities, regions, and countries mean that the AQHI of a specific location cannot be directly applied to another city, region, or country. Nevertheless, the AQHI can be used to accurately reflect the impact of air quality on public health and to communicate the associated health recommendations to local residents effectively. In terms of future works,

Table 4
The correlation between the AQHI and the currently used AQI during 1 January 2017 – 31 December 2021.

		AQHI Category / Number of Days				
Station	Thai AQI Category	1. Low Risk (1–3)	2. Moderate Risk (4–6)	3. High Risk (7–10)	4. Very High Risk (10+)	Total
02t	1. Low Risk (0–50)	414	738	12	–	1164
	2. Moderate Risk (51–100)	–	330	129	1	460
	3. High Risk (101–200)	–	14	124	58	196
	4. Very High Risk (201+)	–	–	–	6	6
	Total	414	1082	265	65	1826
03t	1. Low Risk (0–50)	87	494	2	–	583
	2. Moderate Risk (51–100)	–	633	71	–	704
	3. High Risk (101–200)	–	120	323	62	505
	4. Very High Risk (201+)	–	–	–	34	34
	Total	87	1247	396	96	1826
05t	1. Low Risk (0–50)	492	743	57	–	1292
	2. Moderate Risk (51–100)	–	113	158	4	275
	3. High Risk (101–200)	–	3	122	127	275
	4. Very High Risk (201+)	–	–	–	7	7
	Total	492	859	337	138	1826
10t	1. Low Risk (0–50)	54	1016	185	–	1255
	2. Moderate Risk (51–100)	–	51	298	21	370
	3. High Risk (101–200)	–	–	61	139	200
	4. Very High Risk (201+)	–	–	–	1	1
	Total	54	1067	544	161	1826
11t	1. Low Risk (0–50)	120	904	151	9	1184
	2. Moderate Risk (51–100)	–	159	306	9	474
	3. High Risk (101–200)	–	–	90	76	166
	4. Very High Risk (201+)	–	–	–	2	2
	Total	120	1063	547	96	1826
12t	1. Low Risk (0–50)	304	725	22	–	1051
	2. Moderate Risk (51–100)	–	431	125	8	564
	3. High Risk (101–200)	–	7	129	70	206
	4. Very High Risk (201+)	–	–	–	5	5
	Total	304	1163	276	83	1826
52t	1. Low Risk (0–50)	402	641	41	–	1084
	2. Moderate Risk (51–100)	–	227	162	3	392
	3. High Risk (101–200)	–	13	207	106	326
	4. Very High Risk (201+)	–	–	–	24	24
	Total	402	881	410	133	1826
54t	1. Low Risk (0–50)	46	533	75	–	654
	2. Moderate Risk (51–100)	5	368	312	3	688
	3. High Risk (101–200)	–	31	290	140	461
	4. Very High Risk (201+)	–	–	–	23	23
	Total	51	932	677	166	1826
59t	1. Low Risk (0–50)	316	830	162	–	1308
	2. Moderate Risk (51–100)	–	78	218	19	315
	3. High Risk (101–200)	–	–	87	113	200
	4. Very High Risk (201+)	–	–	–	3	3
	Total	316	908	467	135	1826
59ts	1. Low Risk (0–50)	317	810	22	–	1149
	2. Moderate Risk (51–100)	–	295	193	5	493
	3. High Risk (101–200)	–	3	131	49	183
	4. Very High Risk (201+)	–	–	–	1	1
	Total	317	1108	346	55	1826
61t	1. Low Risk (0–50)	139	871	189	2	1201
	2. Moderate Risk (51–100)	–	80	248	40	368
	3. High Risk (101–200)	–	2	91	158	251
	4. Very High Risk (201+)	–	–	–	6	6
	Total	139	953	528	206	1826

we strongly recommend that multi-province studies that involve different pollutant levels and local exposure–response models be carried out so that localised AQHIs can be applied across Thailand.

4. Conclusion

In this study, we developed an AQHI for Bangkok, Thailand, based on a comprehensive analysis of the associations between ambient air pollutant criteria ($PM_{2.5}$, PM_{10}, O_3, and SO_2) and daily OPD visits for respiratory and cardiovascular diseases in the central districts of Bangkok. The established AQHI could be used to communicate the air pollution-related health risks in Bangkok to the public and, in particular, could be an effective tool that helps policymakers and relevant agencies protect and manage at-risk groups during air pollution crises. We first developed the AQHI by using data from the city's central districts to represent Bangkok because of the limitations of health data collection, such as the obstacles to data centralisation by the authorised agency. We therefore encourage policymakers to develop a health data collection system to manage all data, as this will be beneficial in improving the AQHI, and the resulting data analyses will assist in planning health promotion policies and protecting the health of the people in Bangkok.

Table 5
Air Quality Health Index Categories and Health Recommendations.

AQHI	Risk Level	Health Recommendations	
		General Population	At-Risk Groups
1–3	Low	➢ Enjoy normal outdoor activities.	➢ Enjoy normal outdoor activities. ➢ Monitor the AQHI as usual.
4–6	Moderate	➢ Consider rescheduling strenuous outdoor activities.	➢ Consider rescheduling and reducing strenuous outdoor activities. ➢ Use personal equipment, such as a $PM_{2.5}$ protection mask, when spending time outdoors.
7–10	High	➢ Consider reducing strenuous activities or the amount of time spent outdoors. ➢ Take appropriate preventive equipment, such as a $PM_{2.5}$ protection mask, to protect one's health when spending time outdoors.	➢ Limit and minimise the amount of time spent outdoors. ➢ Consider staying in a safer area with air quality controls or an air purifier or using a $PM_{2.5}$ protection mask at home. ➢ Take appropriate preventive equipment, such as a $PM_{2.5}$ protection mask, to protect one's health when staying outdoors, if necessary. ➢ Have sufficient quantities of one's medications available and follow the doctor's normal recommendations for taking them.
10+	Very high	➢ Avoid physical exertion outdoors and spending time outdoors. ➢ Consider staying in a safer area with air quality controls or an air purifier or using a $PM_{2.5}$ protection mask at home and avoid physical exertion. ➢ Take appropriate preventive equipment, such as a PM2.5 protection mask, to protect one's health when staying outdoors, and only spend time outdoors if absolutely necessary.	➢ Avoid outdoor physical exertion and staying outdoors. ➢ Staying in the safer area with air quality controlling or air purifier or using PM2.5 protection mask at home and avoid physical exertion .

Funding

This work was supported by Thailand Center of Excellence for Life Science (Public Organization) (Grant no. TC-A (ERP) 9/2564) and Mahidol University.

CRediT authorship contribution statement

Suwimon Kanchanasuta: Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Thammasin Ingviya:** Validation, Software, Methodology, Formal analysis, Data curation. **Narongpon Dumavibhat:** Visualization, Writing – review & editing. **Chathaya Wongrathanandha:** Visualization, Writing – review & editing. **Nakarin Sansanayudh:** Visualization, Writing – review & editing. **Piti Chalongviriyalert:** Visualization, Writing – review & editing. **Dittapol Muntham:** Visualization, Writing – review & editing. **Wichayaporn Chusut:** Software, Resources, Data curation. **Natthaya Bunplod:** Software, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Suwimon Kanchanasuta reports financial support was provided by Mahidol University. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Data availability statement

All data generated or analyzed during this study are included within the submitted manuscript and the Supplementary Materials.

Acknowledgments

The authors acknowledge the Pollution Control Department and Air Quality and Noise Management Division, Department of Environment, Bangkok Metropolitan Administration, Thailand for providing the air monitoring data. We also thank all 24 hospitals for providing the health data.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.envc.2024.100991.

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