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Original article

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Short-term associations of PM_{10} attributed to biomass burning with respiratory and cardiovascular hospital admissions in Peninsular Malaysia

Muhammad Abdul Basit Ahmad Tajudin ,[1,2,*] Lina Madaniyazi ,[1] Xerxes Seposo ,[1,2] Mazrura Sahani ,[3] Aurelio Tobías ,[4] Mohd Talib Latif ,[5] Wan Rozita Wan Mahiyuddin ,[6] Mohd Faiz Ibrahim ,[7] Shingo Tamaki,[1] Kazuhiko Moji,[1] Masahiro Hashizume [1,8] and Chris Fook Sheng Ng [1,8]

[1]School of Tropical Medicine and Global Health (TMGH), Nagasaki University, Nagasaki, Japan, [2]Department of Hygiene, Department of Social Medicine, Graduate School of Medicine, Hokkaido University, Sapporo, Hokkaido, Japan, [3]Center for Toxicology and Health Risk Studies (CORE), Faculty of Health Sciences, Universiti Kebangsaan Malaysia, Kuala Lumpur, Malaysia, [4]Institute of Environmental Assessment and Water Research (IDAEA), Spanish Council for Scientific Research (CSIC), Barcelona, Spain, [5]Department of Earth Sciences and Environment, Faculty of Science and Technology, Universiti Kebangsaan Malaysia, Bangi, Selangor, Malaysia, [6]SEAMEO TROPMED Malaysia, Institute for Medical Research, National Institutes of Health, Ministry of Health Malaysia, Shah Alam, Selangor, Malaysia, [7]Environmental Health Research Center, Institute for Medical Research, National Institutes of Health, Ministry of Health Malaysia, Shah Alam, Selangor, Malaysia and [8]Department of Global Health Policy, Graduate School of Medicine, The University of Tokyo, Bunkyo-ku, Tokyo, Japan

*Corresponding author. Department of Hygiene, Department of Social Medicine, Graduate School of Medicine, Hokkaido University, Kita 15 Nishi 7, Kita ward, Sapporo 060-8638, Japan. E-mail: abdulbasit@pop.med.hokudai.ac.jp

Abstract

Background: Biomass burning (BB) is a major source of air pollution and particulate matter (PM) in Southeast Asia. However, the health effects of PM smaller than 10 µm (PM_{10}) originating from BB may differ from those of other sources. This study aimed to estimate the short-term association of PM_{10} from BB with respiratory and cardiovascular hospital admissions in Peninsular Malaysia, a region often exposed to BB events.

Methods: We obtained and analyzed daily data on hospital admissions, PM_{10} levels and BB days from five districts from 2005 to 2015. We identified BB days by evaluating the BB hotspots and backward wind trajectories. We estimated PM_{10} attributable to BB from the excess of the moving average of PM_{10} during days without BB hotspots. We fitted time-series quasi-Poisson regression models for each district and pooled them using meta-analyses. We adjusted for potential confounders and examined the lagged effects up to 3 days, and potential effect modification by age and sex.

Results: We analyzed 210 960 respiratory and 178 952 cardiovascular admissions. Almost 50% of days were identified as BB days, with a mean PM_{10} level of 53.1 µg/m^3 during BB days and 40.1 µg/m^3 during normal days. A 10 µg/m^3 increment in PM_{10} from BB was associated with a 0.44% (95% CI: 0.06, 0.82%) increase in respiratory admissions at lag 0–1, with a stronger association in adults aged 15–64 years and females. We did not see any significant associations for cardiovascular admissions.

Conclusions: Our findings suggest that short-term exposure to PM_{10} from BB increased the risk of respiratory hospitalizations in Peninsular Malaysia.

Keywords: Biomass burning, particulate matter, respiratory diseases, Southeast Asia.

Key Messages

- We estimated daily proportions of PM_{10} attributable to biomass burning using fire hotspots and wind trajectory information.
- PM_{10} from biomass and non-biomass burning sources increased the risk of respiratory hospital admission.
- The effects were more immediate for PM_{10} from biomass-burning compared to those from non-burning sources.

Introduction

Biomass Burning (BB) is a major source of air pollution that affects human health worldwide.[1] BB emits large amounts of particulate matter (PM) and gaseous pollutants into the atmosphere, causing poor air quality and health hazards.[1,2] Exposure to BB emissions could increase the risks of respiratory and cardiovascular diseases, hospitalizations and deaths.[3–6] Previous literatures have stated that BB events in

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Malaysia stems from both local and transboundary sources such as land use change, agricultural expansion and forest managements.[7–10] These days are known as 'haze days' by communities in the region to describe the obscurity of the atmosphere due to BB.

Most studies have used simple methods to define BB events and estimate PM levels from BB, which may not capture the complexity and variability of BB exposure.[11–15] Some studies have used a fixed PM threshold (PM_{10} >100 $\mu g/m^3$ or $PM_{2.5}$ >35 $\mu g/m^3$) to define a BB day,[4–6] or the Pollutant Index above a specific threshold,[11,15] while others have used a percentile threshold to identify bushfire events, such as the 90th percentile,[14] the 95th percentile[12] or the 99th percentile[13] of the observed PM distribution. These methods, however, may overlook smaller events with PM concentrations below the threshold or miss the variability of PM levels within BB events. They may also be influenced by other sources of PM that are not related to BB, such as traffic or industry.

As previous studies on BB/haze days in Southeast Asia have analyzed their impact on health outcomes using binary indicators,[5,14] they might not account for the source-specific contribution of PM_{10} from BB events, which may vary depending on the location, season and meteorology. Hence, since PM_{10} is a major pollutant during BB events and can have adverse health effects,[16,17] there is public health relevance in examining the health effects of PM_{10} by distinguishing between BB PM_{10} and non-BB PM_{10} while also considering the modifying effect of the events.

In this study, we examined the short-term association between source-specific PM_{10} (based on the occurrence of BB) and hospital admissions for respiratory and cardiovascular diseases in Peninsular Malaysia. To our knowledge, this investigation is the first to use a continuous measurement for BB-related PM_{10} and assess its association with hospital admissions in Southeast Asia.

Methods

Study location and period

We selected five major districts spanning north to south of Peninsular Malaysia (Figure 1). They include Kinta, Kuantan, Kuala Lumpur, Klang and Johor Bahru, with populations ranging from slightly below half a million in Kuantan to over 1.6 million in Kuala Lumpur (Table 1).[18] These districts were chosen to represent different geographical regions and urbanization levels in Peninsular Malaysia. The study period ranges from 2005 to 2015 depending on the availability of hospital admission data.

Environmental exposure data

We obtained daily air pollution and meteorological measurements from the Continuous Air Quality Monitoring (CAQM) stations managed by the Department of Environment Malaysia. Besides PM_{10} and temperature, other gaseous pollutants such as carbon monoxide (CO), sulphur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), as well as relative humidity were collected for sensitivity analyses. We downloaded daily fire hotspot data from the Fire Information for Resource Management System (FIRMS) archive covering an area from 4°S to 10°N and 95°E to 120°E. The fire hotspot data were measured by the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite by the National Aeronautics and Space Administration (NASA). We selected observations with high confidence from the MCD14DL fire identification product. We filtered for hotspots recorded with a confidence level of ≥80% to minimize false alarms[19] and as type 'presumed vegetation fires'[20] to focus on BB. We included all Fire Radiative Power values to account for smaller hotspots likely associated with agricultural residue burning.[21]

Health outcome data

We collected daily count of hospital admissions for respiratory diseases [International Classification of Diseases 10th revision (ICD-10): J00-J99] and cardiovascular diseases (ICD-10: I00-I99) from the Health Information Centre, Ministry of Health Malaysia. At least one major hospital in each city was included (seven in total, six state hospitals and one respiratory medical institute). The data were stratified by gender and age groups: 0–14 (child), 15–64 (adult) and 65 years and above (elderly). We paired each hospital with the closest CAQM station (within 10 km) for exposure matching.

Identification of BB days

We used the Hybrid Single Particle Lagrangian Integrated Trajectory (HYSPLIT) Model by the Air Resources Laboratory (ARL), National Oceanic and Atmospheric Administration (NOAA) to estimate the backward wind trajectories from each CAQM station with a resolution of 1° latitude and longitude. The trajectories were estimated at 500, 1000 and 1500 m above ground, twice a day at 12-hours interval at 00:00 and 12:00 hours, with a duration of 72-hours to cover the distance of both local and transboundary sources within the area as most peat fires in Kalimantan burned for more than 24 hours.[22] The procedure was accomplished using the *splitr* package in R. To identify BB days, we merged the daily information from the MODIS fire hotspots and the HYSPLIT backward wind trajectories. We created a buffer of 0.5° radius for all trajectory coordinates. Days with at least one buffer containing a fire hotspot were defined as 'BB days', while others as 'normal days' (Supplementary Figure S1, available as Supplementary data at *IJE* online). The process is automated using Python script.

PM_{10} attributable to BB

We adapted the European Union reference method[23,24] to estimate the daily levels of PM_{10} attributable to BB. This method had been proven to estimate source-specific PM levels in areas with natural or anthropogenic sources (i.e. dust storms or wildfires).[24,25] We removed the days with BB identified in the previous step, and calculated the 90-day moving average using the PM_{10} levels observed on the remaining normal days without BB. The moving average was based a 3-month period to accommodate locations that documented BB events continuously for 60 days. This provides a smoothed daily concentration to represent background PM_{10} unrelated to BB (essentially the non-BB PM_{10} on BB days). PM_{10} level attributable to BB (BB PM_{10}) was obtained by subtracting the moving average from the total concentration observed at a given station during a BB Day.

Statistical analysis

We conducted a two-stage analysis. We used a time series model to estimate the source-specific associations (BB PM_{10} and non-BB PM_{10}) during BB days or normal days represented by an interaction term with the BB indicator. We chose this model to account for the potential differences in the effects of PM_{10} from BB and non-BB sources during BB days and normal days. PM_{10} with a lag duration of up to

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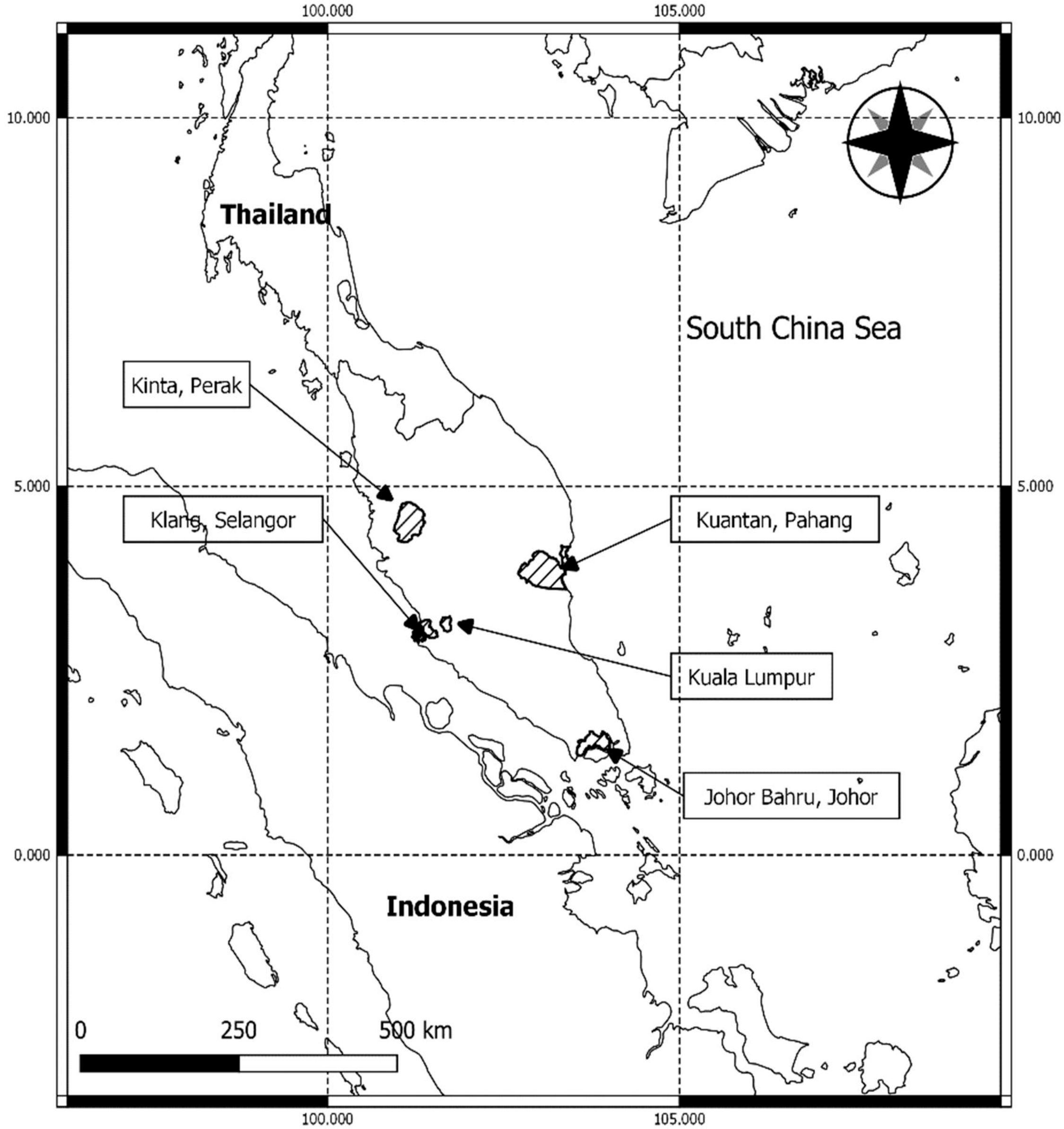

Figure 1. Study districts in Peninsular Malaysia

Table 1. Study location, period, population characteristics and hospital admissions

City[a]	State	Region	Study period	Population in 2010	No. of hospital beds	Respiratory admissions		Cardiovascular admissions	
						Total (n)	Daily mean (SD)	Total (n)	Daily mean (SD)
Kinta	Perak	North	2007–2014	767 794	990	43 971	15.1 (5.3)	43 670	14.9 (5.2)
Kuantan	Pahang	East coast	2009–2011	461 906	793	12 172	11.1 (4.1)	8132	7.4 (3.2)
Kuala Lumpur	Kuala Lumpur	Central	2005–2010	1 674 621	2131	62 501	28.5 (9.3)	47 656	21.7 (6.2)
Klang	Selangor	Central	2008–2010	861 189	1154	23 902	21.8 (8.7)	19 558	17.5 (5.5)
Johor Bharu	Johor	South	2009–2015	1 386 569	1206	68 414	26.8 (9.4)	60 027	23.5 (6.8)
Overall						210 960	22.2 (17.2)	178 952	18.9 (12.3)

[a] Ordered by latitude, north to south.
SD, standard deviation.

four previous days was examined based on previous studies that found significant associations between PM_{10} exposure and respiratory or cardiovascular outcomes at these lags.[16,26,27] In the second stage, we performed a random-effects meta-analysis to pool effect estimates across cities.[28,29] Heterogeneity was described using I^2, Qstatistic and τ^2.[30]

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The following quasi-Poisson regression model was fitted for each district:

$$E[\log(y_t)] = \beta_0 + \beta_1 \mathrm{BBPM}_{10_l} + \beta_2 \mathrm{nonBBPM}_{10_l} + \beta_3 \mathrm{BBday}_l + \beta_4 \mathrm{BBday}_l \times \mathrm{nonBBPM}_{10_l} + ns(\text{time}, \text{df} = 3 \times \text{number of years}) + bs(\text{temp}_0 \times I[\text{temp}_0 > \text{median}], \text{knots} = 66pct) + bs(\text{temp}_{ma3} \times I[\text{temp}_{ma3} < \text{median}], \text{knots} = 33pct) + \beta_5 \text{holiday}_t + \beta_6 H1N1_t + \beta_7 myhdw_t + \beta_k DOW_t^k, \quad (1)$$

where: y_t is the daily counts of admission on day t; BBPM_{10} is the BB-related PM_{10} exposure variable on lag day l, representing the number of cumulative lags (i.e. lag 0–1, 0–2, 0–3 and 0–4); $\mathrm{nonBBPM}_{10}$ is the non-BB-related PM_{10} exposure variable; BBday is the binary indicator variable for days with BB events; time is calendar day smoothed using natural cubic spline (*ns*) with three degrees of freedom (df) per year to account for seasonality and long-term trend; temp_0 and temp_{ma3} represent the current day (lag 0) and the average of the previous 3 days temperature (lag 1–3), respectively; and $I[x]$ is an indicator function with a value of 1 when condition x is true; a quadratic B-spline (*bs*) with one internal knot placed at the 33rd (for low temperature) or 66th percentile (for high temperature) was used to smooth the temperature terms, separately for high (above median value) and low temperatures (below median value) to allow possible delayed and nonlinear pattern;[23–25] holiday_t is an indicator variable for public holidays; $H1N1_t$ is an indicator variable for influenza A (H1N1) outbreak in 2009; $myhdw_t$ is an indicator variable for a change in reporting system by the Ministry of Health Malaysia after 2012; and DOW_t^k is an indicator variable for k days of the week. We also examined possible effect modification by age and gender.[4–6,31] We used R version 4.0.4[32] and *meta* package.[33] All results are reported as percent increases in risk (%IR) of admissions relative to a 10-μg/m^3 increment in PM_{10} with 95% confidence intervals (CI).

Additional analysis

Additional sensitivity analysis methods can be found in the Supplementary Analyses (available as Supplementary data at *IJE* online). We also used Bing Chat[34] to assist in revising our article, specifically employing the prompt 'improve the flow of this paragraph as a native speaker' to generate suggestions for enhancing the English language. We acknowledge that the final responsibility for the content and quality of our article rests with us, the authors. Bing chat can be accessed at https://www.bing.com/chat.

Results

Descriptive results

During the study, we observed 210 960 respiratory and 178 952 cardiovascular hospital admissions, averaging 22.2 and 18.9 daily cases (Table 1). Children (49.9%), adults (33.8%) and the elderly (16.8%) were the primary groups for respiratory admissions, while for cardiovascular cases, the majority were adults (64.4%), followed by the elderly (33.1%) and children (2.5%). Males represented a higher percentage of cases in both categories (Supplementary Table S1, available as Supplementary data at *IJE* online). BB events occurred on 4868 days, nearly half the study period, with PM_{10} levels averaging 53.1 μg/m^3 on BB days vs 40.1 μg/m^3 on non-BB days. Alternative BB day definitions based on fixed (PM_{10} ≥100 μg/m^3) or percentile thresholds (PM_{10} ≥95th percentile) significantly reduced the BB day count to 1.9% and 5% (Table 2).

Association between PM exposures and hospital admissions

Table 3 presents the estimated risks of hospital admissions for exposure to source-specific PM_{10}. For respiratory admissions, exposure to BB PM_{10} was associated with 0.44% (95% CI: 0.06%, 0.80%) higher for cumulative lag 0–1 days. We did not find any associations for non-BB PM_{10} on BB days. On normal days, the estimated risk increase for exposure to non-BB PM_{10} was larger and more delayed up to lag 0–4 days (%IR = 3.14%; 95% CI: 2.13%, 4.15%). For cardiovascular admissions, we did not find any significant risk increases, except for exposure to non-BB PM_{10} on BB days where risk decreases were observed for lag 0–2 and 0–3. The location-specific risk estimates appeared homogeneous for both admission causes (all *P-values for* Q >0.05).

We also examined possible effect modification by age and gender subgroups. Figure 2 shows the results stratified by age and gender subgroups. Exposure to BB PM_{10} was associated with increased respiratory admissions in the adult and female subgroups with %IR of 0.76% (95% CI: 0.09%, 1.43%) and 0.57% (95% CI: 0.39%, 0.75%), respectively. On normal

Table 2. Summary of biomass burning occurrences and the corresponding daily PM_{10} concentration in the five study locations in Peninsular Malaysia

Location[a]	Total days	Days with biomass burning[b]						Normal days (no biomass burning)					
		No. of days identified, *n* (%)	PM_{10} concentration (μg/m^3)					No. of days identified, *n* (%)	PM_{10} concentration (μg/m^3)				
			Mean (SD)	Min	P25	P75	Max		Mean (SD)	Min	P25	P75	Max
Kinta	2922	1244 (42.6)	50.1 (18.2)	21.7	38.2	57.2	205.5	1678 (57.4)	37.9 (8.5)	13.3	32.0	42.8	85.6
Kuantan	1095	518 (47.3)	40.7 (11.8)	14.7	32.6	46.9	108.4	577 (52.7)	31.3 (7.6)	12.8	26.2	36.1	66.9
Kuala Lumpur	2191	1112 (50.8)	56.3 (28.6)	18.3	42.5	62.7	465.4	1079 (49.3)	41.7 (11.4)	13.1	34.0	48.5	130.2
Klang	1096	530 (48.4)	71.1 (26.4)	21.5	54.5	82.2	194.0	566 (51.6)	55.7 (15.5)	19.3	46.3	63.8	157.1
Johor Bahru	2556	1467 (57.4)	51.1 (25.9)	18.7	37.1	56.9	348.6	1089 (42.6)	38.5 (11.2)	12.4	31.0	44.4	99.6
Overall	9860	4868 (49.4)	53.1 (24.9)	14.7	38.8	60.3	465.4	4992 (50.6)	40.1 (12.4)	12.4	32.0	46.1	157.1

[a] Ordered by latitude, north to south.
[b] Days with biomass burning are defined by the presence of Moderate Resolution Imaging Spectroradiometer (MODIS) satellite fire hotpots and supported by the Hybrid Single Particle Lagrangian Integrated Trajectory (HYSPLIT) Model wind trajectory.
P25, 25th percentile; P75, 75th percentile; PM, particulate matter; SD, standard deviation.

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Table 3. Estimated percent increase in risk (IR) (95% CI) for respiratory and cardiovascular hospital admissions associated with biomass burning PM_{10} and non-biomass burning PM_{10} during biomass burning days[a] and non-biomass burning PM_{10} during normal days

Hospital admission	Lag days	BB PM_{10}[a]				Non-BB PM_{10} during BB day[a]				Non-BB PM_{10} during normal day[a]			
		% IR (95% CI)[b]	I^2 (%)	τ^2	Q P	% IR (95% CI)[b]	I^2 (%)	τ^2	Q P	% IR (95% CI)[b]	I^2 (%)	τ^2	Q P
Respiratory	0–1	0.44 (0.06, 0.80)*	7	<0.01	0.37	−0.04 (−0.73, 0.65)	0	0	0.82	0.86 (0.31, 1.41)*	0	0	0.88
	0–2	0.39 (−0.18, 0.97)	37	<0.01	0.18	0.25 (−0.83, 1.33)	0	<0.01	0.41	1.34 (0.25, 2.44)*	0	0	0.57
	0–3	0.32 (−0.37, 1.02)	49	<0.01	0.10	0.33 (−1.20, 1.87)	47	<0.01	0.11	2.35 (1.44, 3.25)*	0	0	0.85
	0–4	0.29 (−0.54, 1.13)	55	<0.01	0.07	0.3 (−1.11, 1.72)	38	<0.01	0.17	3.14 (2.13, 4.15)*	0	0	0.87
Cardiovascular	0–1	0.05 (−0.50, 0.60)	40	<0.01	0.16	−0.49 (−1.75, 0.79)	17	<0.01	0.31	0.10 (−1.10, 1.30)	40	<0.01	0.15
	0–2	−0.02 (−0.70, 0.70)	46	<0.01	0.12	−0.86 (−1.61, −0.11)	0	0	0.72	0.07 (−1.60, 1.80)	47	<0.01	0.11
	0–3	−0.10 (−0.88, 0.68)	45	<0.01	0.12	−0.64 (−1.19, −0.09)	0	0	0.89	0.13 (−1.78, 2.08)	39	<0.01	0.16
	0–4	−0.20 (−1.06, 0.68)	51	<0.01	0.09	−0.71 (−1.43, 0.02)	0	0	0.77	0.69 (−1.20, 2.62)	21	<0.01	0.28

[a] The estimates for non-biomass burning and biomass burning PM_{10} were estimated from three-sources model adjusted for the other PM source in turn, and with interaction of biomass burning days with non-biomass burning PM_{10}.
[b] Percent increase in risk (% IR) per 10 $\mu g/m^3$ increase in exposure.
* $P < 0.05$.
BB, biomass burning; CI, confidence interval; PM, particulate matter; I^2, heterogeneity among location-specific estimates; τ^2, variance of the true effect sizes; Q P value, Cochran's Q Test.

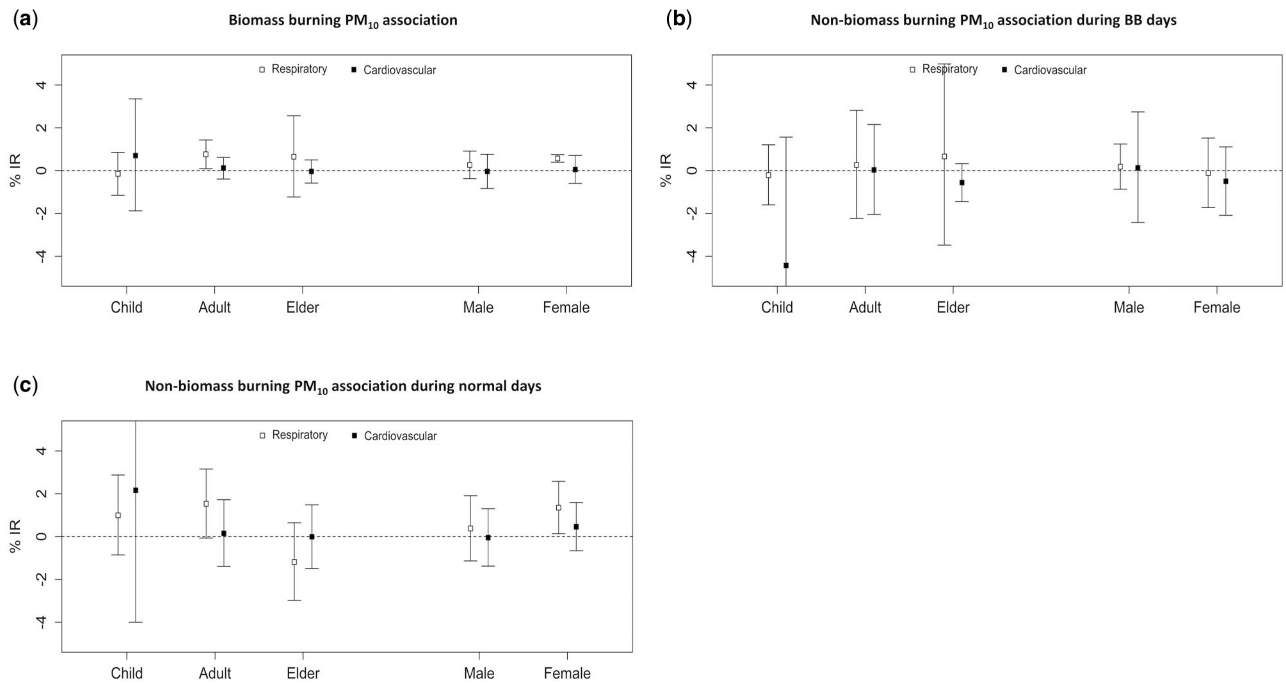

Figure 2. Estimated percent increase in risk (IR) (95% CI) of respiratory admissions (white symbol) and cardiovascular admissions (black symbol) associated with 10 µg/m3 increase in biomass burning PM_{10} (a), non-biomass burning PM_{10} during biomass burning days (b), and non-biomass burning PM_{10} during normal days (c) for lag 0–1 days, stratified by age and gender

days, respiratory admissions showed a positive association with exposure to non-BB PM_{10} amongst the females at %IR of 1.35% (95% CI: 0.13%, 2.58%). This association was not observed during BB days. For cardiovascular admissions, we did not find any associations across the different subgroups.

Our study found that different degrees of freedom didn't significantly affect quasi-AIC values (Supplementary Table S3, available as Supplementary data at *IJE* online), and buffer size changes mostly yielded consistent results, except for non-BB PM_{10} on BB days which varied by admission cause (Supplementary Figures S2 and S3, available as Supplementary data at *IJE* online). Larger buffers increased respiratory risks but not cardiovascular ones. Additional adjustments for gases and humidity had minimal impact (Supplementary Figures S4 and S5, available as Supplementary data at *IJE* online). Different methods for defining BB days, like fixed or percentile thresholds, altered results compared to the HYSPLIT-MODIS method, with fixed thresholds indicating increased risks for BB and non-BB PM_{10} (Supplementary Figures S6 and S7, available as Supplementary data at *IJE* online).

Discussion

In this study, we examined the associations between PM_{10} attributable to BB and hospital admissions in Peninsular Malaysia. We used a novel exposure definition that allowed us to disentangle the associations between PM_{10} and hospital admissions attributable to BB and non-BB sources during BB days and normal days. We found that respiratory admissions were associated with BB PM_{10} and non-BB PM_{10} during normal days. The lag time was relatively shorter for BB PM_{10} (0–1 days) and longer for non-BB PM_{10} during normal days

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(0–4 days). Subgroup analysis showed evidence of associations in adults aged 15–64 years old and females. We did not observe consistent associations for cardiovascular disease admissions.

Our results suggest that both BB PM_{10} and non-BB PM_{10} can have an adverse effect on respiratory admissions, with BB PM_{10} having a more immediate impact while non-BB PM_{10} has a longer lag association. The difference in the size of the estimated effects and the lag structure between BB PM_{10} and non-BB PM_{10} may be related to the BB/haze warning systems implemented in Malaysia. The Department of Environment and mass media provide alerts for BB/haze days in Malaysia by updates its website with API and BB/haze warnings[35] and news highlights during a BB/haze day. These BB/haze warning systems could lead to changes in behavior, such as staying indoors and reducing exposure, during BB/haze days. However, even though API calculations from monitoring stations are published daily, PM_{10} concentrations during normal days may be neglected due to media focus on BB/haze days, resulting in delayed associations in our models. Another possible explanation for the associations with respiratory admissions could be the toxicity of source specific PM_{10}. A study by de Oliveira Alves *et al.* (2017) also suggests that exposure to PM_{10} which is also abundant during non-bb days can cause significant damage to human lung cells.[36]

We did not find a consistent association between PM_{10} exposure and cardiovascular disease admissions. Negative associations were observed for lag 0–2 and 0–3 with non-BB PM_{10} during BB days. One possible reason for the association is that people who have existing risk factors for CVD (i.e. hypertension, high cholesterol) may have other underlying conditions and are aware of their risks thus reducing their time outside even more. The National Health and Morbidity Survey 2019 in Malaysia showed that approximately 1.7 million (8.1%) people currently live with three major risk factors (High cholesterol, Hypertension and Diabetes) and approximately 3.4 million (16%) live with two major risk factors.[37] Compared to respiratory disease, the results for cardiovascular disease admissions were inconsistent when we used different buffer sizes in the sensitivity analysis to identify BB days. Previous studies have also reported inconsistent results regarding the association between BB events or PM_{10} exposure and cardiovascular outcomes.[13,38–40] This lack of association between cardiovascular hospital admissions and PM_{10} exposure could be due to the immediate onset of cardiovascular diseases. The association between PM_{10} and cardiovascular outcomes might be better reflected using emergency room visitation data rather than hospital admission data as the severity of a cardiovascular disease onset might cause it to be treated immediately by emergency personnel,[41–43] with only severe cases being admitted to the hospital.

Our subgroup analysis found a significantly positive association between BB PM_{10} and the adult subgroup. The Department of Statistics Malaysia, (2010) recorded that the highest percentage of occupations for adults in Malaysia are in service and sales (19.3%), elementary occupations (12.2%) and plant and machine operation (11.7%).[18] These occupations often involve outdoor labour, travel, construction or manual labour and have higher effect estimates of air pollutants compared to white-collar jobs.[44] This prolonged outdoor exposure, and pre-existing medical conditions may increase the risk of disease. We also found significantly positive risk estimates among females, which is consistent with some literature that found higher risks for respiratory/asthma diseases in females.[40,42,45,46] This may be due to hormonal factors unique to females,[47] such as the pre-menstrual or menstrual phase of their monthly cycle which could increase the breathing rate,[48] exacerbate asthma symptoms,[49] and reduce lung function.[50]

Our study has several strengths. Firstly, we used a multi-criteria method to improve the identification of BB days. This process is computationally intensive as it involves calculating many back trajectories to provide daily coordinates for detecting fire hotspots at three different altitudes. Secondly, to our knowledge, this is the first study in Malaysia to distinguish the effects of source specific PM_{10} from BB and examine their short-term associations with respiratory and cardiovascular hospital admissions. Our results suggest that the effects of BB PM_{10} and non-BB PM_{10} were consistent across Peninsular Malaysia and that the pooled results can be used to represent the region. Our study also has several limitations. Firstly, the definition of BB PM_{10} we used is an adaptation from desert dust definitions by Escudero *et al.*[51] and Tobías and Stafoggia,[24] and there is no existing knowledge on how to assess $PM_{10\%}$iles using chemical source apportionment data during BB events in Southeast Asia. Secondly, we used ground monitor PM_{10} concentrations to reflect exposure, but we cannot accurately determine if patients were exposed to the same daily PM_{10} concentration throughout the study period. Thirdly, we were unable to control for pre-existing health conditions in our model due to a lack of data. Fourthly, while we filtered for 'presumed vegetation fires', some non-vegetation fires may have been included in our analysis. Finally, our results should not be generalized to other locations with different topographical, meteorological and fire sources.

Conclusion

Our study suggests that exposure to PM_{10} from BB is associated with increased respiratory hospital admissions in Peninsular Malaysia, especially among adults and females. The effect of BB PM_{10} is more immediate than that of non-BB PM_{10}, which has a longer lag association. We did not find consistent associations between PM_{10} exposure and cardiovascular hospital admissions. Our findings have implications for public health policy and intervention, as they highlight the need to monitor and reduce the exposure to PM_{10} from BB, especially during BB events, and to raise the awareness of the health risks of PM_{10} from non-BB sources during normal days. Future research could include using Chemical Transport Model to identify and measure BB PM_{10} more accurately, as well as the potential interactions with other air pollutants or risk factors.

Ethics approval

This study was registered with the National Medical Research Register (NMRR-21–71-57986) and received approval from the Ministry of Health Research Ethics Committee (KKM/NIHSEC/P21-229(2)) prior to data collection.

Data availability

Restrictions apply to the availability of the health and air pollution data where access requires permission from the Ministry of Health Malaysia and the Department of

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Environment Malaysia of the Ministry of Natural Resources while the NASA—FIRMS MODIS fire archive is available from the following website: http://firms.modaps.eosdis.nasa.gov/download/. The NOAA—ARL HYSPLIT wind trajectory is available from the following website: https://www.ready.noaa.gov/HYSPLIT.php.

Supplementary data

Supplementary data are available at *IJE* online.

Author contributions

M.A.B.A.T. contributed to data management, drafted the manuscript and final revision. M.A.B.A.T. and C.F.S.N. contributed to the study design, data analysis and manuscript writing. S.T. wrote the algorithm in Python to automatically identify biomass burning days. L.M., X.S., M.S., A.T., M.T. L., K.M, M.F.I., W.R.W.M. and M.H. contributed to the refinement of the protocol and provided edits to the manuscript for intellectual content.

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Conflict of interest

None declared.

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