Association between PM_{10} from vegetation fire events and hospital visits by children in upper northern Thailand

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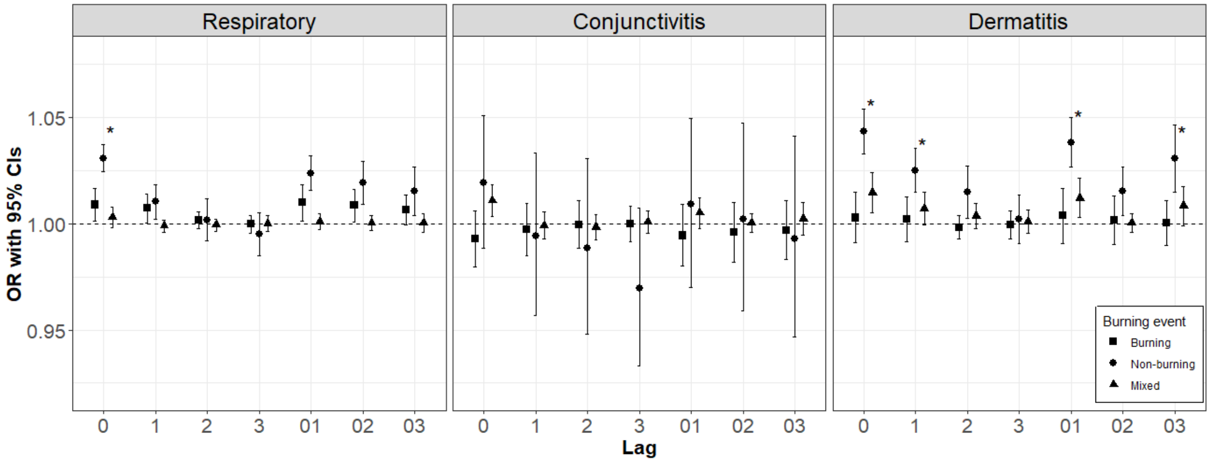
Abbreviations

UNT: Upper Northern Thailand, PM_{10}: Particulate Matter with aerodynamic diameter less than or equal to 10 micrometers, ICD: International Classification of Disease, NASA: National Aeronautics and Space Administration, MODIS: Moderate Resolution Imaging Spectroradiometer.

Highlights

- Effect of vegetation fire events on hospital visits for children was examined.
- Effect of PM_{10} between burning and non-burning day was compared.
- PM_{10} on burning days associated with hospital visits for respiratory diseases.
- Effect of PM_{10} on burning day was lower than non-burning day.

Graphic Abstract



Abstract

Few studies have focused on the effects of exposure to air pollutants from vegetation fire events (including forest fire and the burning of crop residues) among children. In this study we aimed to investigate the association between PM_{10} concentrations and hospital visits by children to address respiratory disease, conjunctivitis, and dermatitis. We examined and compared these associations by the presence of vegetation fire events on a given day (burning, non-burning, and mixed) across the upper northern region of Thailand from 2014 through 2018. A vegetation burning was defined when a fire hotspot (obtained from NASA-MODIS) exceeded the 90th percentile of the entire region and PM_{10} concentration was over 100 μg/m^3. To determine the association between hospital visits among children with PM_{10} concentrations on burning and non-burning days, we performed a time-stratified case-crossover analysis fitted with conditional logistic regression for each province. A random-effects meta-analysis was applied to pool province-specific effect estimates. The number of burning days ranged from 64 to 139 days across eight provinces. A 10 μg/m^3 increase in PM_{10} concentration on a burning day was associated with a respiratory disease-related hospital visit at lag 0 (OR = 1.01 (95% CIs: 1.00, 1.02)). This association was not observed for hospital visits related to conjunctivitis and dermatitis. A positive association was also observed between PM_{10} concentration on non-burning days and hospital visits

related to respiratory disease at lag 0 (OR = 1.03 (95% CIs: 1.02, 1.04). Hospital visits for conjunctivitis and dermatitis were significantly associated with PM_{10} concentration at lag 0 on both non-burning and mixed days.

Keywords: vegetative fire events, particulate matter, hospital visit, children, respiratory disease, remote sensing

1. Introduction

In Southeast Asia, vegetation fire events as an agricultural practice as well as from forest fires causes local and transboundary severe air pollution events, particularly during the dry season (Chen and Taylor 2018; Takami et al., 2020). According to WHO, vegetation fires was referred to the fire mostly caused by humans, including forest fire and also slash and burn activities which need the measures to mitigate smoke effects on population health and to control these events (World Health Organization, 1998). Vegetation burning can emit massive amounts of aerosols and trace gases into the atmosphere. The frequency of vegetation burning activity is highest over Southeast Asia (Streets et al., 2003). Seasonal haze from vegetation burning primarily affects human health of the people in Southeast Asian countries, and is particularly prominent in Brunei, Indonesia, Malaysia, , Singapore, and Thailand (Ho et al., 2014).

Smoke from vegetation burning in Thailand, particularly in upper northern Thailand (UNT), has been of concern as a seasonal severe air pollution event (Phairuang et al., 2019). Thailand is an agricultural country and generates large amounts of agricultural residue which is usually disposed of by burning in open areas (Phairuang et al., 2019). In addition to agricultural burning, forest fires also contribute significantly to air pollution from vegetation burning in UNT (Phairuang et al., 2019; Sukitpaneenit and Kim Oanh, 2014). The forest fire in the UNT are often set to collect non-timber forest product, e.g. mushroom and bamboo shoot (Forest Fire Control Office, 2005). The fire season typically lasts from February to April, when atmospheric conditions are dry and stagnant (Kim Oanh and

Leelasakultum, 2011). In 2013, the daily peak PM_{10} concentration in the area was reported to be 428 $\mu g/m^3$ during this period (Pollution Control Department, 2019). Topographical characteristics of UNT exacerbate the problem, as this area is primarily a mountain-valley, a feature that can enhance the amount of pollution trapped (Kim Oanh and Leelasakultum, 2011). Other miscellaneous sources of PM_{10} in the area include traffic, tobacco curing, and the brick-making industry (Kim Oanh and Leelasakultum, 2011). Coal power plants are also located in Lampang province.

Smoke events from vegetative burning are acknowledged as one of the reasons underlying the high exposure levels to air pollutants among residents in Asia (Chakrabarti et al., 2019; Zhuang et al. 2018). A better understanding of the health effects from air pollution derived from vegetation burning versus those from urban settings would provide helpful insight for source-specific policy-making that targets air pollution control. Several existing studies have consistently shown that particulate matter (PM) from wildfires is associated with health effects (Henderson et al., 2011; Reid et al., 2019; Stowell et al., 2019), while few studies have focused on the health effects of PM from agricultural burning (Gupta, 2019).

Children are more vulnerable to exposure to smoke from burning activities because of their underdeveloped respiratory system and higher breathing rate (Michael Lipsett and Barbara Materna, 2008), and respiratory disease among children is one of the major consequences of vegetation burning. Previous studies have suggested that smoke from vegetation burning may increase hospital admission and emergency room visits due to asthma and acute bronchitis in children (Chen et al., 2006; Paraiso and Gouveia 2015). However, such studies have not been conducted much in Asia (Gupta, 2019). Exposure to smoke from vegetation burning may also cause irritating symptoms in the eyes, nose, throat, and skin (Michael Lipsett and Barbara Materna, 2008). One study examined how respiratory and eye symptoms were associated with exposure to wildfire smoke in children (Künzli et al., 2006). Given that direct exposure to pollutants from smoke induces biological responses in both the eyes and skin, the burden of these symptoms is not negligible. Despite this, few studies have focused on eye and skin symptoms. Therefore, quantifying the health effects of exposure to air pollutants from vegetation burning is warranted to prevent these consequences, particularly among susceptible groups.

Assessing exposure to smoke from vegetation burning is challenging. The most common method is to use PM concentrations from air pollution monitoring (Martin et al., 2013; Morgan et al., 2010). However, assessing only PM concentrations may not necessarily yield an accurate level of exposure to vegetation burning. High PM concentrations may be caused not by vegetation burning but by unusual activities near the monitoring area such as traffic congestion during long holidays. While air pollution monitoring stations are most often located in urban areas, where traffic air pollution is the main source of pollution, burning activities tend to occur outside these areas, farther from monitoring stations. Satellite-derived fire hotspots have been used for exposure assessment of vegetation burning (Gupta, 2019), and involve the use of satellite data obtained from different temperatures on the ground (Chakrabarti et al., 2019). Combining the information from fire hotspots with PM concentrations might increase the accuracy of fire-related PM readings. Indeed, the occurrence of vegetation burning measured via fire hotspots was found to correlate with PM_{10} concentrations (Sukitpaneenit and Kim Oanh, 2014). The number of fire hotspots has been used as a proxy for air pollution in areas without air pollution monitoring stations (Chakrabarti et al., 2019). Moreover, fire hotspots not only identify burning events, but can also provide information on burning intensity, which reflects the heat emitted from fire at the burning area (Elliott et al., 2013).

The aim of this study was to evaluate the effects of smoke from vegetation fire events on health outcomes in children. Specifically, we evaluated the association between PM_{10} concentrations and the number of hospital visits to address respiratory, conjunctivitis, and dermatitis in children under age 15 years. We compared effect estimates on burning, non-burning, and mixed days across UNT, and used daily PM_{10} concentrations measured during 2014 through 2018 coupled with fire hotspot data from Moderate Resolution Imaging Spectroradiometer (MODIS) to identify burning days.

2. Materials and methods

2.1 Study area

The study area consisted of eight provinces in UNT, including Chiangmai, Chiangrai, Lamphun, Lampang, Mae Hong Son, Nan, Phayao, and Phrea, which are the provinces most affected by smoke from vegetation fire events (Phairuang et al., 2017; Pollution Control Department, 2019). Figure 1 shows the provincial boundaries and locations of the ambient air monitoring stations. The area of interest spans 93,690 km^2 and borders Myanmar and Laos.

2.2 Hospital visits data

We obtained hospital visit (outpatient visits) data for children under age 15 years except for new born less than 1 month old within the study area between January 2014 and December 2018, which were provided by the Ministry of Public Health (MOPH), Thailand. The data were collected from 1,274 public hospitals belong to MOPH covering eight provinces of UNT area. Data from each hospital visit included demographic information (age and sex), date of visit, and International Classification of Diseases version 10 (ICD10) codes for diagnosis. We included diagnoses of respiratory disease (J00-J99.8), conjunctivitis (H10-H10.9), and dermatitis (L20-L30). This study was officially exempted from ethics approval by the Ethics Committee of Kyoto University Graduate School of Engineering because it did not use personal data (No. 201904).

2.3 Air pollution and meteorological data

Hourly concentrations of PM_{10} ($\mu g/m^3$), carbon monoxide (CO), ozone (O_3), sulphur dioxide (SO_2), and nitrogen dioxide (NO_2) were obtained from 14 air monitoring stations (Fig. 1) from the Pollution Control Department, Thailand. Daily concentrations of each air pollutant were computed from hourly data. Data on meteorological variables (ambient temperature, relative humidity, wind speed, and rainfall) measured at 16 meteorological stations were obtained from Meteorological Department, Thailand. We averaged the value of PM_{10} and meteorological data from the stations within the province.

2.4 Burning day occurrence

In order to identify burning events, fire hotspot data (MCD14ML) (Giglio et al., 2018) were obtained from the National Aeronautics and Space Administration (NASA) Land, Atmosphere Near real-time Capability for EOS (LANCE) Fire Information for Resource Management System (FIRMS) (NASA 2018). Fire hotspot data were retrieved from satellite data obtained from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) onboard Terra and Aqua satellites. Hotspots are recorded at a resolution of 1 kilometer when both Terra and Aqua satellites overlap (occurring globally at 1:30 am, 10:30 am, 1:30 pm, and 10:30 pm) (Jordan et al., 2008). We mapped fire hotspots using QGIS 3.4 (QGIS Development Team 2014) and summed the number of fire hotspots by day and province. The detection of hotspots may be influenced by reflective surfaces or cloud cover. However, meteorological conditions during the burning season in UTN are dry with low wind speed and cloudiness (Kim Oanh and Leelasakultum, 2011). Hotspot data also included confidence values that indicate the quality of individual fire pixels determined from the geometric mean of the difference between background and brightness temperatures in each channel algorithm (Giglio et al., 2003). In this study, fire hotspots with a confidence value under 20% (low confidence) were excluded from the analysis.

As no study have been using fire hotspot data to be a criterion of a burning day, we defined a 'burning day' as a day when the number of fire hotspots exceeded the 90^{th} percentile of the daily distribution of the entire region (10 counts) and the daily PM_{10} concentration in each province was greater than 100 $\mu g/m^3$. A day without fire hotspot was defined as a 'non-burning day'. The remaining days were classified as 'mixed days'. For example, when the cumulative number of fire hotspots for the entire area region (sum up of eight provinces) was 35 counts, and PM_{10} was 120 $\mu g/m^3$ and 75 $\mu g/m^3$ in Chiangmai and Chiangrai, respectively, we defined this day as a 'burning day' in Chiangmai and as a 'mixed day' in Chiangrai. Hence, we assumed that increases in PM_{10} on a burning day was driven by vegetative fire events. The previous studies found that the major contributed ion in PM were ammonium and potassium which is a tracer of vegetation burning while sulfate emitted from fuel combustion also found in this area (Chantara et al., 2012; Pengchai et al., 2009). The cut-off PM_{10} concentration was based on published studies that found that health effects from haze days developed when PM_{10} concentrations were higher than 100 $\mu g/m^3$ (Sahani et al., 2014). Figure 2 shows fire hotspots on April 1, 2014 across eight provinces.

2.5 Study design and statistical analysis

We examined the relationship between vegetation burning-derived PM_{10} and hospital visits among children using a time-stratified case-crossover study design. This analysis is similar to that of a case-control study, except that each case serves as its own control (Maclure, 1991). In order to matched case and control, we assigned the day on which a hospital visits occurred as the case day and comparisons to a control days chosen on the same day of the week earlier and later in the same month in the same year (Janes et al., 2005). We used a conditional logistic regression model to estimate the odds ratio for exposure to PM_{10} on burning and non-burning days and hospital visits in all health endpoints. We included the natural splines of a 3-day moving average lag in temperature (Morgan et al., 2010), assuming 3 degrees of freedom (df). The model with the best fit was selected by the Akaike Information Criterion (AIC). Relative humidity, precipitation, and wind speed were also included. However, relative humidity did not influence the AIC value and was omitted from the final model. The analysis was conducted for burning, non-burning, and mixed days separately because we surmised that this association may vary by the type of day. We examined the association with single lag (lag 0 - lag 3) and average lag (lag 01- lag 03) for all health outcomes.

A random-effects meta-analysis was conducted to obtain pooled effect estimates of PM_{10} and hospital visits on burning, non-burning, and mixed days. We tested whether the effect estimates for burning days are significantly different from those for non-burning and mixed day by calculating the difference of effect estimate, 95% CIs, and P-value (Altman and Bland, 2003).

A stratified analysis was carried out to explore the effect modification by age using two age groups, i.e. 0-4 year olds (pre-school children) and 5-14 year olds (school children) at lag 0.

We also conducted sensitivity analyses using alternative criteria of a burning day. First, we compared the results among the different percentile cut-off point of the fire hotspot (i.e. 75^{th} (1 count), 90^{th} (10 counts), and 99^{th} (88 counts)). Next, we repeated the analysis using the different of PM_{10} concentration (100 $\mu g/m^3$ and 120 $\mu g/m^3$) with fixing the fire hotspot at 90^{th} percentile.

All statistical analyses were conducted using the package "survival" (Fox J, 2012) and "metafor" (Viechtbauer, 2010) of R (version 1.2.1335, The R Foundation for Statistical Computing, Vienna, Austria). Results are presented as odd ratios (ORs) with 95% confidence intervals (CIs) for 10 μg/m^3 increase in PM_{10}.

3. Results

Environmental data, including air pollution, temperature, relative humidity, wind speed, precipitation, and number of fire hotspots, were obtained from burning, non-burning, and mixed days (Table 1). Numbers of burning days ranged from 64 days in Lamphun to 139 days in Mae Hong Son over the five-year study period. Concentrations of PM_{10}, CO, NO_2, SO_2, and O_3 were higher on burning days than on mixed days or non-burning days in all provinces. Mean concentrations of PM_{10} on burning days ranged from 122.9 μg/m^3 in Phrae to 165.1 μg/m^3 in Chiangrai. The daily mean temperature was not significantly different between burning, non-burning, and mixed days.

In total, 5,641,107 hospital visits due to respiratory disease, conjunctivitis, and dermatitis among children aged <15 years were recorded during the study period (Table 2). Study participants included more pre-school children (age 0-4 years) than school-aged children (age 5-14 years). Among the three reported health conditions, respiratory disease was responsible for the most hospital visits among children.

PM_{10} was associated with hospital visits due to respiratory disease on both burning and non-burning days while its associations with conjunctivitis and dermatitis were found on non-burning and mixed days (Figure 3). Significantly positive associations between PM_{10} and hospital respiratory diseases on burning days were observed with lag 0, lag 1, lag 01, and lag 02. The pooled estimate was high on the day of exposure, with an OR of 1.01 (95% CIs: 1.00, 1.02) (Table S1). Positive associations between PM_{10} concentration and hospital visits due to respiratory disease in children were found in all provinces except Chiangrai (Table S1).

Positive associations were also found between hospital visits for all health outcomes and PM_{10}

concentrations on non-burning days. On mixed days, hospital visits for conjunctivitis and dermatitis were associated with PM_{10} concentrations. Pooled risks for non-burning days were 1.03 (95% CIs: 1.02, 1.04 (lag 0)) for respiratory disease, 1.04 (95% CIs: 1.03, 1.05 (lag 0)) for dermatitis, and 1.02 (95% CIs: 1.00, 1.03 (lag 02)) for conjunctivitis (Table S1). For mixed days, a high estimated risk was found with lag 0 for conjunctivitis (OR=1.01, 95% CIs: 1.00, 1.02) and dermatitis (OR=1.01, 95% CIs: 1.01, 1.02) (Table S1). The comparison of non-burning/mixed days with burning days showed that the estimated effect of PM_{10} on respiratory disease on burning days was slightly but significantly lower when compared with non-burning days at lag 0 (Figure 3).

We further examined the association at lag 0 stratified by two subgroups of the children (pre-school and school children) which is presented in the Figure 4. We found that ORs for school children (5-14 year olds) were slightly higher than pre-school children (0-4 year olds) on both burning and non-burning day although there was no significant difference in ORs between the two age groups.

Sensitivity analyses were performed by comparing the effect estimate of the different cut-off points for fire hotspot and PM_{10} concentration. Applying different cut-off point of fire hotspot (Figure 5) and PM_{10} concentration (Figure 6) generally showed similar effect estimates.

4. Discussion

This study investigated the association between hospital visits by children and exposure to PM_{10} on vegetation burning days. The study also compared the effect estimates on burning days with those on non-burning and mixed days. Across UNT, PM_{10} concentrations differed significantly between burning, non-burning, and mixed days. PM_{10} concentrations on burning days were generally higher than those on other days, with daily mean concentrations above the Thailand air quality standards for PM_{10} (120 $\mu g/m^3$). A significant association between PM_{10} and hospital visits due to respiratory disease were observed on both burning and non-burning days while its associations with conjunctivitis and dermatitis were found on non-burning and mixed days. The effect estimates were highest at lag 0 for those significant associations. These finding indicates an acute effect.

We found that PM_{10} concentrations on burning days significantly influenced the number of hospital visits for respiratory disease. This finding is consistent with previous vegetation-derived particulate studies (Henderson et al., 2011; Stowell et al., 2019). Specifically, various acute respiratory outcomes were observed in children during burning events and included asthma (Henderson et al., 2011; Stowell et al., 2019), upper respiratory inflammation (Künzli et al., 2006), lower respiratory inflammation (Mirabelli et al., 2009), and respiratory mortality (Sahani et al., 2014). However, we found an inverse association in Chiangrai province. This may be due to the effectiveness after burning ban policy has been implemented (Yabueng et al., 2020) or implementation of the preventive activities e.g. establishment of safety zone, and school closure in the province during burning day. This inverse association could also be by chance. Children are more susceptible to respiratory issues because their lungs are less developed and they have higher respiratory rates than adults. Thus, the effects of vegetation burning-derived PM are most evident in their respiratory system; in some cases, systemic damage in the lung may be sustained (World Health Organization, 2005). It is possible that the different patterns of activities and the duration of time spent in outdoor may contribute to variation in susceptibility to PM effects among different age groups. However, the effect estimates of preschool children and school children in this study were not different.

Although we found significant associations between vegetation burning-related PM and the number of hospital visits for respiratory disease, similar associations were not observed consistently for conjunctivitis and dermatitis. Few studies have focused on how vegetation-derived particulates influence conjunctivitis and dermatitis. One previous study found an increased likelihood of doctor visits to address eye irritation when wildfire-derived PM concentrations were high (Künzli et al., 2006). Another study reported clinical cases of eye complaints and dermatitis during a haze period in Singapore (Yeo et al., 2014). The discrepancy between our results and those of previous studies may be attributed to differences in the severity of the disease (e.g. complaint data, eye symptoms reported by school, or hospital visits data). In the present study, only a few of those who had symptoms may have visited the hospital during the burning period.

Vegetation burning-derived particles contained high levels of potassium, organic carbon, black carbon, and specific components such as methoxyphenol, Polycyclic Aromatic Hydrocarbons (PAHs), and levoglucosan (Naeher et al., 2007). We hypothesized that the effects of PM_{10} on burning days would be more prominent than those on non-burning and mixed days. However, we found a slightly higher effect estimate for respiratory diseases of non-burning day compared to burning day at the immediate lag. A previous study conducted in Australia estimated an increased risk of approximately 1% in the number of respiratory illness-related hospital admissions for every 10 $\mu g/m^3$ increase in bushfire and urban PM_{10} (Morgan et al., 2010). In another study, multi-exposure metrics for PM documented a similar increase in risk of respiratory illness-related hospitalization and PM from smoke and non-smoke days (Deflorio-Barker et al., 2019). Specifically, that study found a higher likelihood for asthma-related hospitalizations on smoke days. Our result was inconsistent with the previous studies. One potential reason can be attributed to difference in the toxicity of PM components derived from different sources. It is possible that PM during non-burning days may have contained more toxic components in this study. A toxicological study also found that vegetation-derived PM reduced cell viability and IL-8 induction, while urban-derived PM increased pro-inflammatory and mutagenic activity (Heuvel et al., 2018). These findings collectively suggest that both vegetation burning and urban sources can trigger respiratory incidents in children.

In addition, higher numbers of hospital visits for conjunctivitis and dermatitis were observed on non-burning and mixed days. In this study, burning day corresponded to a day when the number of fire hotspots exceeded the 90^{th} percentile of the daily distribution of the entire region and PM_{10} concentration in each province was greater than 100 $\mu g/m^3$, whereas a non-burning day was the day without fire hotspot detection. Main sources of PM on non-burning and mixed days include urban sources e.g. traffic and some burning activities such as waste burning. Associations between PM_{10} concentrations from urban sources (non-burning days) and hospital visits for dermatitis in children in the present study are similar to those reported in a previous study (Kim et al., 2017). Children are more susceptible to dermatitis given their immature skin barrier function, and thus are in a vulnerable developmental stage (Ahn, 2014). We also observed positive associations between the number of hospital visits for conjunctivitis and dermatitis and PM concentrations on mixed days, but not on burning days. This may be due to the fact that people likely spent more time outside on non-burning days; typically, they are cautioned to stay indoors on burning days (Moran et al., 2019). In California, for example, children are more likely to take preventive actions such as staying indoors during the wildfire season (Künzli et al., 2006).

Our study has several strengths. First, we conducted a multi-province analysis, which provides a representative overview of associations between various health outcomes and air pollution levels during a burning event in Southeast Asia. Second, we examined associations between the number of hospital visits and exposure to PM_{10}, specifically focusing on burning days using satellite data coupled with PM concentrations, whereas some previous studies used only PM concentrations (Martin et al., 2013) or limited the study period to burning seasons which might lead to misclassification of burning day (Gupta, 2019). Third, we compared effect estimates of PM_{10} on burning, non-burning, and mixed days in the same population, rather than in different populations. Finally, we examined the health effects of vegetation fire events among children, and was thus one of the first to address the question in this susceptible population (Gupta, 2019; Sahani et al., 2014).

A few limitations are worth noting. We used PM_{10} concentrations from ground monitoring to reflect exposure, which may have been subject to misclassification, and may not accurately represent an individual's exposure. While our results offer insight into the health effects of vegetation burning, generalizing these findings to other regions may require further research, since conditions relating to fuel type, meteorology, and topography can all influence the characteristics of PM (composition, size, and concentration) and impact health outcomes. An additional limitation might be misclassification of a burning day. First, smoldering fires sometimes cannot be detected from satellite observation even when they emit substantial smoke which can lead to high level of PM concentration. Second, valley topography of UNT might have affected the spatial distribution of PM_{10} and could cause misclassification of burning day.

5. Conclusion

We found that PM_{10} on burning days was significantly associated with the number of hospital visits among children due to respiratory disease, but not conjunctivitis or dermatitis. Effect estimates of PM_{10} on hospital visits for respiratory diseases was lower on burning than non-burning days. The associations observed were generally acute, occurring within the first two days.

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Author contribution

U Athicha collected data and designed the study. U Athicha conducted data analysis and drafted the manuscript as per discussion with U Kaya and O Kei., H Akiko and T Hirohisa evaluated the results and substantially provided scientific interpretation for improving the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics consideration

This study was approved as an exemption for ethical research since we applied secondary and aggregated data for the analysis by the Ethics Committee of Kyoto University Graduate School of

Engineering (No. 201904).

CRediT author statement

Athicha Uttajug: Conceptualization, Methodology, Software, Writing - Original Draft. Kayo Ueda: Supervision, Writing - Review & Editing. Kei Oyoshi: Writing - Review & Editing. Akiko Honda: Writing - Review & Editing. Hirohisa Takano: Writing - Review & Editing.

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Table 1. Daily average of environmental variables during 2014 – 2018 (values represent daily mean (standard deviation))

Variables	Chiangmai	Chiangrai	Lamphun	Lampang	Mae Hong Son	Nan	Phayao	Phrae
Days (count)								
Burning day	103	103	64	122	139	87	119	126
Non-burning day	950	950	950	950	950	950	950	950
Mixed day	773	773	812	754	737	789	757	750
*Air pollution**								
PM_{10} (μg/m^3)								
Burning day	132.7 (35.7)	165.1 (55.1)	128.4 (26.5)	125.3 (23.6)	160.3 (60.0)	132.2 (24.3)	135.8 (37.2)	122.9 (22.1)
Non-burning day	30.4 (10.6)	24.3 (9.3)	24.0 (12.9)	23.4 (10.6)	18.7 (9.9)	21.3 (9.9)	18.0 (12.0)	26.2 (12.5)
Mixed day	53.4 (20.7)	46.7 (19.6)	53.8 (22.5)	52.1 (24.6)	42.9 (26.4)	45.3 (22.1)	46.8 (22.9)	54.8 (24.4)
CO (ppm)								
Burning day	1.2 (0.3)	1.3 (0.7)	1.1 (0.4)	1.2 (0.3)	1.1 (0.5)	1.0 (0.2)	0.8 (0.3)	0.8 (0.4)
Non-burning day	0.7 (0.2)	0.6 (0.4)	0.4 (0.2)	0.6 (0.2)	0.5 (0.3)	0.4 (0.2)	0.3 (0.2)	0.3 (0.2)
Mixed day	0.8 (0.2)	0.7 (0. 3)	0.6 (0. 3)	0.7 (0.3)	0.6 (0.3)	0.5 (0.2)	0.5 (0.2)	0.4 (0.2)
O_3 (ppb)								
Burning day	39.6 (7.7)	38.6 (6.1)	39.6 (7.6)	47.4 (6.0)	41.9 (10.8)	40.9 (7.8)	49.8 (9.4)	41.6 (8.7)
Non-burning day	17.2 (7.1)	13.4 (5.8)	19.3 (8.4)	18.2 (5.3)	12.4 (7.0)	14.6 (6.3)	19.3 (7.3)	17.7 (6.9)
Mixed day	28.5 (9.4)	23.8 (10.3)	31.1 (11.2)	31.4 (11.4)	23.7 (12.2)	26.4 (11.3)	33.3 (12.9)	31.1 (13.1)
NO_2 (ppb)								
Burning day	25.5 (7.1)	NA	13.2 (4.0)	10.4 (2.5)	NA	7.8 (3.3)	12.3 (4.1)	16.1 (4.0)
Non-burning day	10.2(4.8)	NA	4.8(3.5)	3.4(1.5)	NA	2.1(1.5)	4.7(2.2)	5.3 (2.8)
Mixed day	15.3 (5.9)	NA	7.5 (3.9)	6.2 (2.2)	NA	4.3 (2.4)	7.4 (2.6)	9.6 (3.9)
SO_2 (ppb)								
Burning day	1.8 (0.9)	NA	2.6 (1.3)	1.7 (0.6)	NA	1.2 (0.9)	2.0 (1.4)	1.7 (1.6)
Non-burning day	1.0 (0.4)	NA	1.6 (1.3)	1.2 (0.3)	NA	0.8 (0.8)	1.0 (1.0)	1.2 (1.5)
Mixed day	1.1 (0.6)	NA	2.0 (1.6)	1.4 (0.5)	NA	1.1 (0.9	0.9 (0.9)	1.2 (1.3)
Meteorology								
Temperature (°C)								
Burning day	29.6 (2.2)	26.8 (2.1)	27.6 (3.1)	28.4 (3.0)	28.6 (2.4)	29.3 (2.1)	27.7 (2.5)	27.9 (2.8)
Non-burning day	27.1 (2.1)	26.0 (2.6)	27.0 (2.2)	27.1 (2.2)	26.7 (2.2)	27.2 (2.3)	25.9 (3.6)	27.2 (2.1)
Mixed day	26.6 (3.3)	24.3 (3.4)	26.6 (3.5)	26.7 (3.6)	25.6 (4.3)	26.1 (3.4)	24.6 (4.7)	26.9 (3.6)
Relative humidity (%)								
Burning day	51.0 (4.5)	61.8 (6.7)	53.7 (5.7)	56.0 (5.8)	54.5 (4.9)	61.0 (4.6)	60.0 (7.4)	61.4 (5.8)
Non-burning day	76.7 (7.0)	81.0 (5.7)	79.4 (7.2)	79.7 (6.7)	82.5 (5.9)	80.1 (11.0)	82.8 (10.0)	81.3 (6.0)
Mixed day	64.4 (8.3)	72.2 (7.1)	66.5 (10.6)	69.0 (9.0)	71.1 (10.5)	72.4 (7.3)	73.9 (12.3)	70.6 (8.5)
Wind speed (m/s)								
Burning day	19.3 (7.1)	17.6 (8.5)	13.8 (6.2)	13.5 (9.4)	18.0 (5.1)	16.6 (3.5)	12.9 (4.6)	13.5 (7.0)

Variables	Chiangmai	Chiangrai	Lamphun	Lampang	Mae Hong Son	Nan	Phayao	Phrae
Non-burning day	21.5 (10.0)	20.6 (8.3)	18.4 (6.9)	17.9 (9.8)	16.8 (5.6)	17.4 (3.3)	12.4 (4.2)	16.5 (8.5)
Mixed day	20.6 (11.2)	20.5 (10.4)	16.7 (6.8)	16.4 (11.3)	17.5 (6.8)	17.1 (3.9)	12.7 (5.7)	15.9 (9.0)
Precipitation (mm)								
Burning day	0.2 (0.2)	0.3 (0.3)	0.5 (0.3)	0.3 (0.3)	0.1 (0.1)	1.1 (0.4)	0.2 (0.2)	0.3 (0.2)
Non-burning day	5.0 (4.5)	8.1 (4.9)	5.1 (4.7)	5.0 (4.6)	5.4 (3.6)	5.2 (3.2)	5.1 (3.3)	5.3 (4.4)
Mixed day	1.3 (5.4)	2.3 (8.6)	1.5 (7.0)	1.6 (7.1)	1.0 (4.5)	1.5 (5.9)	1.3 (5.3)	1.5 (6.3)
No. hotspots								
Burning day	43.9 (40.0)	28.0 (22.3)	7.0 (4.75)	20.2 (17.8)	42.7 (42.6)	32.5 (31.3	7.9 (7.1)	12.6 (10.0)
Non-burning day	0	0	0	0	0	0	0	0
Mixed day	4.8 (1.4)	3.6 (2.0)	4.9 (1.7)	2.2 (1.6)	3.0 (2.6)	3.1 (3.0)	0.7 (0.6)	1.6 (1.2)

* One-way ANOVA was applied to compare the concentration of all air pollutants among burning, non-burning, and mixed days in each province and the results showed significantly different ($p < 0.01$) for all provinces.
NA: not assessed.

Table 2. Summary of hospital visits by children during 2014 - 2018

	Case count							
	Chiangmai	Chiangrai*	Lamphun	Lampang	Mae Hong Son	Nan	Phayao	Phrae
Total number	1680799	1173571	376871	600436	393262	576122	484132	355914
Daily number (%)								
Age (years)								
0 – 4	60.0	59.6	56.7	53.3	60.7	56.8	52.9	50.4
5 – 14	40.0	40.4	43.3	46.7	39.3	43.2	47.1	49.6
Sex								
Male	53.0	52.7	52.7	53.1	52.8	52.4	53.0	53.0
Female	47.0	47.3	47.3	46.9	47.2	47.6	47.0	47.0
Diagnosis (ICD-10)								
Conjunctivitis (H10-H19)	2.1	2.1	2.3	2.5	1.7	2.2	1.9	3.3
Dermatitis (L20-L30)	6.8	7.4	5.5	6.7	6.9	8.5	8.0	7.3
Respiratory (J00-J99)	91.0	90.5	92.2	90.8	91.4	89.3	90.0	89.4

*Available data are from October 2014 to December 2018

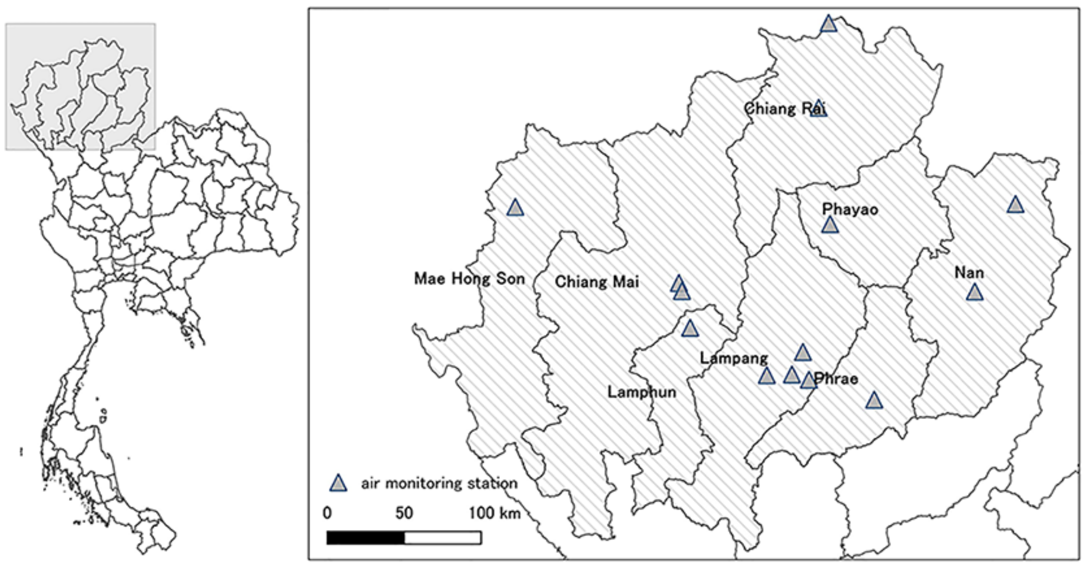

Figure 1: Study area and air monitoring stations.

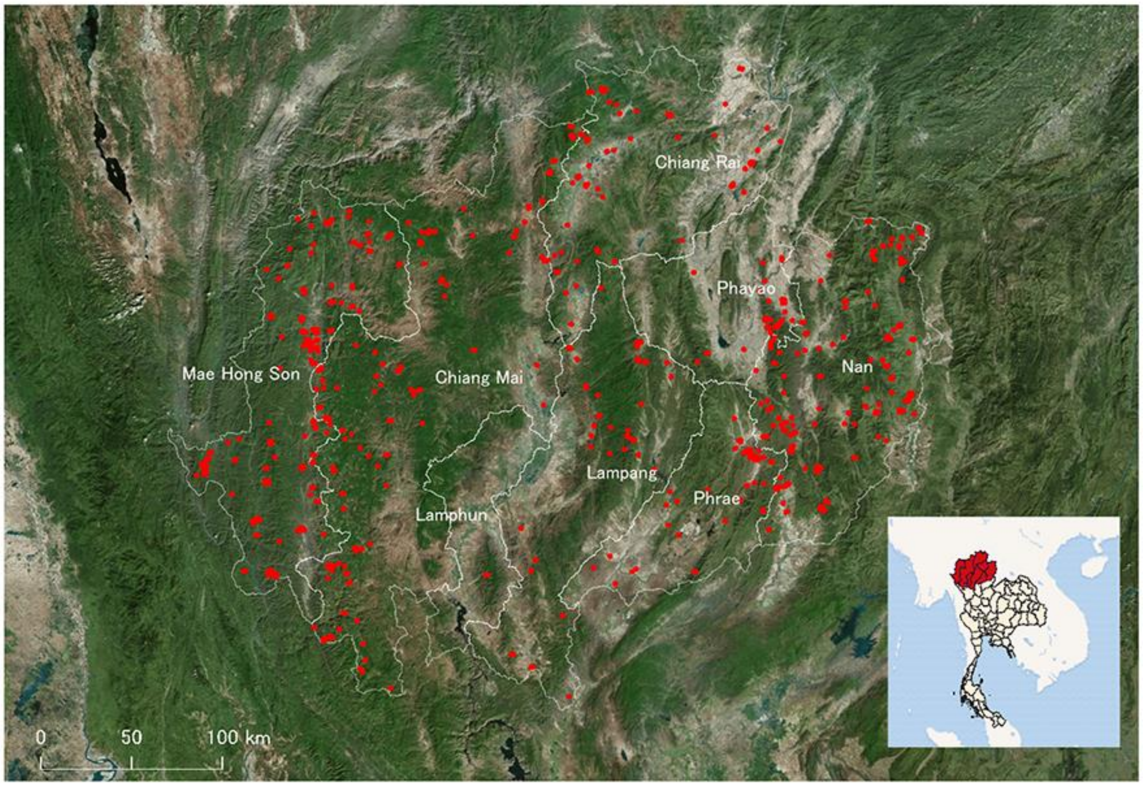

Figure 2: Fire hotspot detected (red dot) on April 1, 2014 over UNT.

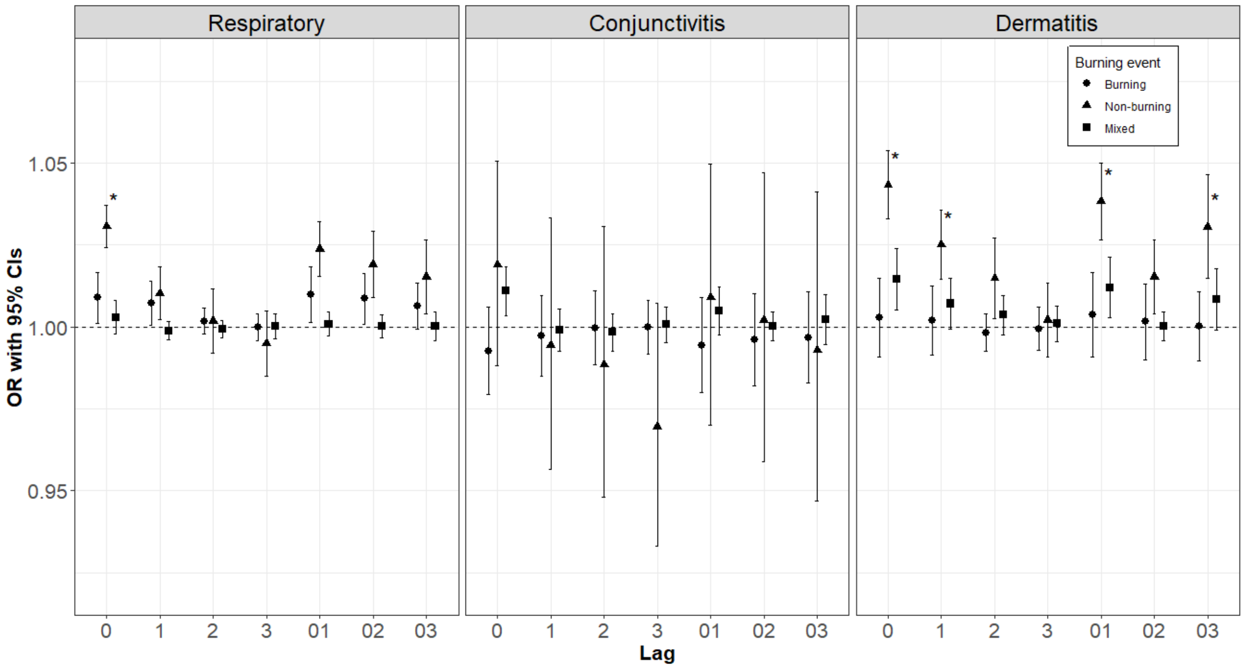

Figure 3: Odds ratio of hospital visits (pooled effect) as associated with a 10 μg/m^3 increase in PM_{10} concentration on burning, non-burning, and mixed days for single and average lag models. *Statistically significant difference at $p < 0.05$ compared to burning day.

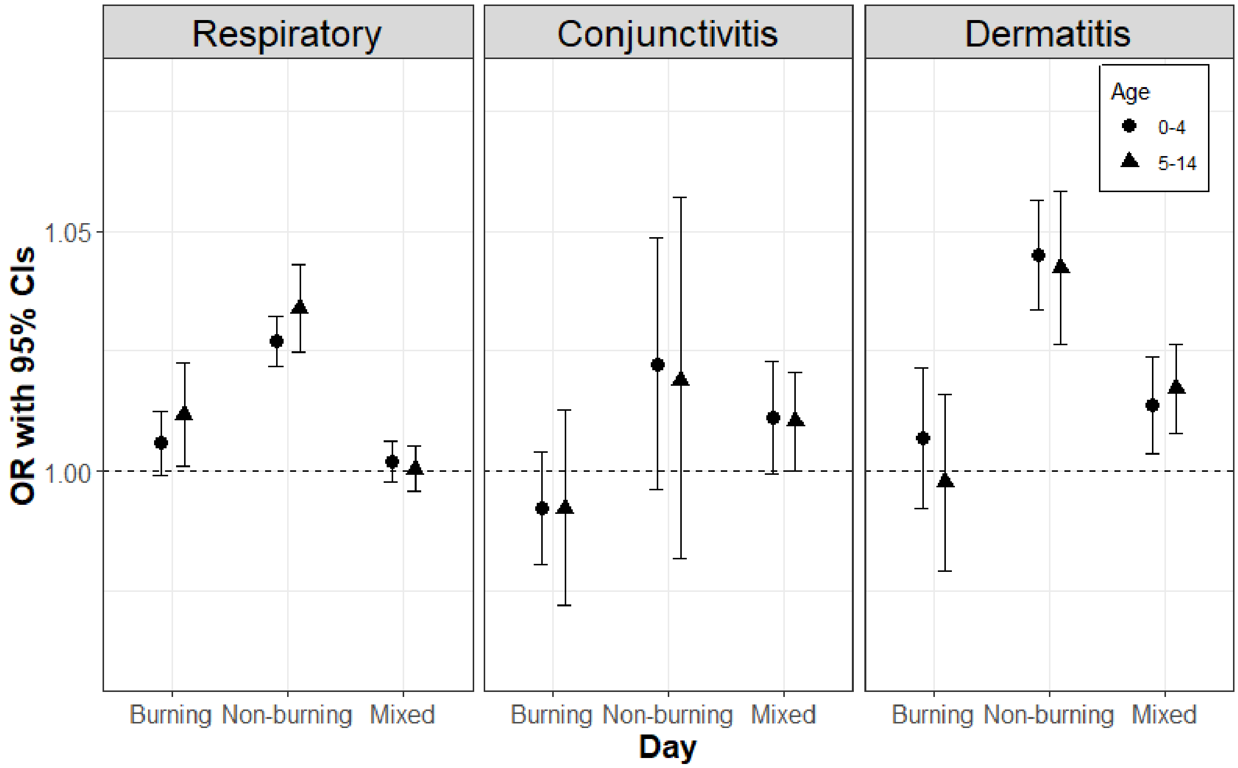

Figure 4: Odds ratio of hospital visits for stratified analysis of children age 0-4 and 5-14 years as associated with a 10 µg/m^3 increase in PM_{10} concentration on burning, non-burning, and mixed day at lag 0.

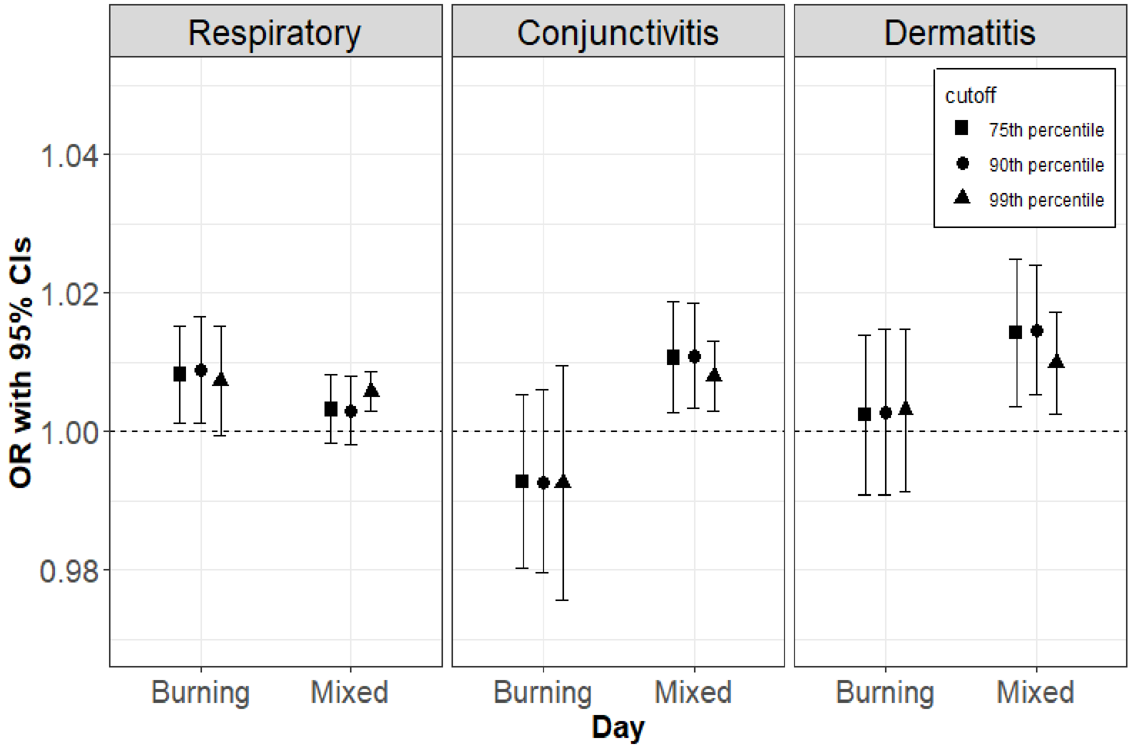

Figure 5: Odds ratio of hospital visits for respiratory diseases in children associated with a 10 μg/m^3 increase in PM_{10} concentration on burning and mixed days at lag 0 applying the different cut-off point of fire hotspot (75th, 90th, and 99th percentile). The results of non-burning days were not presented because changing the cut-off point does not affect them.

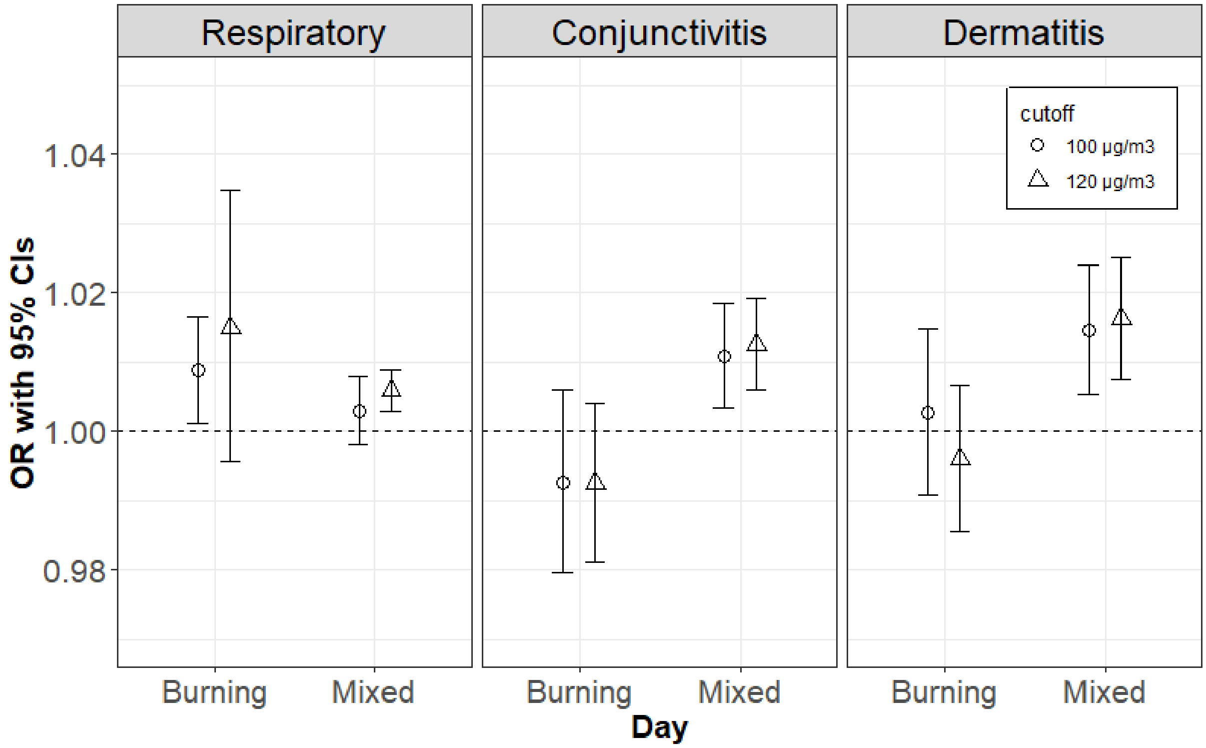

Figure 6: Odds ratio of hospital visits for respiratory diseases in children associated with a 10 µg/m^3 increase in PM_{10} concentration on burning and mixed day compared to the different cut-off point of PM_{10} (100 and 120 µg/m^3). The results of non-burning days were not presented because changing the cut-off point does not affect them.

Supplementary material

Association between PM_{10} from vegetation fire events and hospital visits by children in upper northern Thailand

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Table S1. Odd ratio and 95% confident interval of hospital visit and PM_{10} on burning, non-burning, and mixed day of each province

	Burning day		Non-burning day		Mixed day	
	Lag 0	Lag 01	Lag 0	Lag 01	Lag0	Lag 01
Respiratory disease						
Chiangmai	1.00 (1.00, 1.01)	1.00 (1.00, 1.01)	1.04 (1.03, 1.04)	1.03 (1.02, 1.04)	1.01 (0.99, 1.01)	1.00 (1.00, 1.00)
Chiangrai	0.99 (0.99, 0.99)	0.99 (0.99, 0.99)	1.03 (1.03, 1.04)	1.03 (1.03, 1.04)	1.01 (1.01, 1.01)	1.01 (1.00, 1.01)
Lamphun	1.01 (1.00, 1.02)	1.01 (1.00, 1.03)	1.04 (1.04, 1.05)	1.04 (1.03, 1.05)	1.00 (0.99, 1.00)	1.00 (0.99, 1.00)
Lampang	1.02 (1.01, 1.02)	1.02 (1.02, 1.03)	1.04 (1.03, 1.04)	1.03 (1.02, 1.04)	1.01 (1.00, 1.01)	1.01 (1.00, 1.01)
Mae Hong Son	1.00 (1.00, 1.01)	1.00 (1.00, 1.01)	1.04 (1.03, 1.05)	1.03 (1.02, 1.04)	1.00 (0.99, 1.00	1.00 (0.99, 1.00)
Nan	1.02 (1.01, 1.03)	1.02 (1.01, 1.03)	1.02 (1.01, 1.03)	1.01 (1.00, 1.02)	1.00 (1.00, 1.00)	1.00 (0.99, 1.00)
Phayao	1.02 (1.01, 1.02)	1.02 (1.01, 1.02)	1.02 (1.01, 1.03)	1.01 (1.00, 1.02)	1.01 (1.01, 1.01)	1.01 (1.00, 1.01)
Phrea	1.01 (1.00, 1.02)	1.01 (1.00, 1.02)	1.02 (1.01, 1.03)	1.01 (1.00, 1.02)	0.99 (0.99, 1.00)	1.00 (0.99, 1.00)
Pooled analysis	1.01 (1.00, 1.02)	1.01 (1.00, 1.02)	1.03 (1.02, 1.04)	1.02 (1.02, 1.03)	1.00 (0.99, 1.01)	1.00 (0.99, 1.00)
Conjunctivitis disease						
Chiangmai	0.99 (0.97, 1.02)	0.99 (0.96, 1.01)	1.04 (1.02, 1.06)	1.03 (1.00, 1.05)	1.02 (1.00, 1.03)	1.01 (0.99, 1.02)
Chiangrai	0.98 (0.97, 0.99)	0.98 (0.97, 0.99)	1.01 (0.98, 1.04)	1.01 (0.98, 1.04)	1.02 (1.00, 1.04)	1.01 (0.99, 1.02)
Lamphun	0.94 (0.87, 1.01)	0.94 (0.86, 1.03)	1.02 (0.97, 1.07)	1.01 (0.96, 1.06)	0.98 (0.95, 1.00)	0.97 (0.94, 1.00)
Lampang	1.01 (0.98, 1.05)	1.02 (0.99, 1.06)	1.03 (0.99, 1.07)	1.01 (0.97, 1.05)	1.02 (1.00, 1.04)	1.01 (0.99, 1.03)
Mae Hong Son	1.01 (0.98, 1.03)	1.01 (0.99, 1.04)	1.02 (0.95, 1.09)	1.05 (0.98, 1.12)	1.01 (0.98, 1.04)	1.00 (0.97, 1.03)
Nan	1.02 (0.97, 1.06)	1.02 (0.97, 1.06)	1.03 (0.99, 1.06)	1.01 (0.98, 1.05)	1.00 (0.98, 1.02)	1.00 (0.98, 1.03)
Phayao	0.98 (0.94, 1.01)	0.99 (0.95, 1.02)	1.09 (1.04, 1.14)	1.09 (1.03, 1.14)	1.02 (0.99, 1.04)	1.01 (0.99, 1.04)
Phrea	1.00 (0.95, 1.05)	1.00 (0.96, 1.05)	0.93 (0.89, 0.97)	0.89 (0.85, 0.93)	1.01 (0.98, 1.03)	1.01 (0.98, 1.03)
Pooled analysis	0.99 (0.98, 1.01)	0.99 (0.98, 1.01)	1.02 (0.99, 1.05	1.01 (0.97, 1.05	1.01 (1.00 ,1.02)	1.01 (0.99, 1.01)
Dermatitis disease						
Chiangmai	1.01 (1.00, 1.03)	1.02 (1.00, 1.03)	1.04 (1.03, 1.05)	1.03 (1.02, 1.05)	1.01 (1.00, 1.01)	1.00 (0.99, 1.01)
Chiangrai	0.98 (0.97, 0.99)	0.98(0.97, 0.99)	1.07 (1.05, 1.08)	1.07 (1.05, 1.08)	1.02 (1.01, 1.03)	1.01 (1.01, 1.02)
Lamphun	1.04 (0.99, 1.09)	1.04 (0.98, 1.09)	1.03 (0.99, 1.06)	1.02 (0.99, 1.05)	0.99 (0.97, 1.01)	0.99 (0.98, 1.01)
Lampang	1.02 (1.00, 1.05)	1.03 (1.00, 1.05)	1.04 (1.02, 1.07)	1.04 (1.01, 1.06)	1.01 (1.00, 1.03)	1.01 (1.00, 1.03)
Mae Hong Son	1.00 (0.99, 1.02)	1.00 (0.99, 1.01)	1.03 (1.00, 1.07)	1.03 (1.00, 1.06)	1.00 (0.98, 1.01)	1.00 (0.98, 1.01)
Nan	1.00 (0.98, 1.03)	0.99 (0.97, 1.02)	1.04 (1.02, 1.06)	1.03 (1.01, 1.06)	1.03 (1.02, 1.04)	1.03 (1.02, 1.04)
Phayao	1.00 (0.99, 1.02)	1.00 (0.98, 1.02)	1.04 (1.02, 1.07)	1.04 (1.02, 1.07)	1.03 (1.02, 1.04)	1.02 (1.01, 1.04)
Phrea	0.99 (0.96, 1.02)	1.00 (0.97, 1.03)	1.03 (1.00, 1.06)	1.02 (0.99, 1.05)	1.02 (1.00, 1.03)	1.02 (1.01, 1.04)
Pooled analysis	1.00 (0.99, 1.01)	1.00 (0.99, 1.02)	1.04 (1.03, 1.05)	1.04 (1.03, 1.05)	1.01 (1.01, 1.02)	1.01 (1.00, 1.02)