Health impacts of particulate matter from vegetation fire events and regulatory intervention for smoke haze control in Upper Northern Thailand

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ABSTRACT

Vegetation fire event was referred to the fire mostly caused by anthropogenic activities, including forest fire and slash and burn in the agricultural practices. High level of particulate matter (PM) has been seasonally reported in eight provinces across Upper Northern Thailand (Chiangmai, Chiangrai, Lamphun, Lampang, Nan, Mae Hong Son, Phayao, and Phrae). There has been a concern about the association of PM emitted from vegetation fire burning with adverse health effects. Several epidemiological evidences have been documented various health effects from exposure to fire-related PM ranging from mild to severe effects such as irritating symptoms, hospital/clinic visits, emergency visits, hospital admission, and premature death. The haze control by regulatory measures is an important intervention that might alleviate the health impacts attributable to air pollution from vegetation fire events. This thesis aimed to investigate the health impacts from exposure to PM emitted from vegetation fire events in view of risk estimation, effect of the burning ban policy, and health burden estimation.

The first study (*Study I*) investigated association between PM_{10} and hospital visits for respiratory, conjunctivitis, and dermatitis in children on burning, non-burning, and mixed day in UNT. Pooled estimated showed that there were significant increased hospital visits for respiratory diseases on burning days [Odd Ratio (OR): 1.01 (95% confidence interval (CI): 1.00, 1.02)]. The effect estimates of hospital visits for respiratory diseases on non-burning day was higher than burning day with the OR of 1.03 (95% CI: 1.02, 1.04). The effects of hospital visits for conjunctivitis and dermatitis were observed on non-burning and mixed days, but not on the burning days.

The second study (*Study II*) evaluated the effect of the burning ban enforced in May 2016 on hospital visits for respiratory diseases. The ban led to both decreases of the number of fire hotspot and PM_{10} concentration across UNT ranging from 14.3 to 81.5% and 5.3% to 34.3%, respectively. The pooled effect estimates of hospital visits for respiratory diseases decreased by 8.7% (95% CIs: 4.3, 12.9), whereas null association was observed for gastrointestinal diseases, a negative control disease.

The third study (*Study III*) assessed number of hospital visits for respiratory diseases attributable to VFS and the impacts of the burning ban policy. During five-years period, 75,380 and 34,399 cases of hospital visits for respiratory diseases among people of all ages and children under 15 years were estimated from exposure to PM_{10} emitted from vegetation fire events. A decline of the cases attributable to VFS-PM_{10} were observed after the burning ban has enforced in 2016 from 64,061 (before the ban enforcement) to 11,319 (after the ban enforcement) cases.

In brief, this thesis concluded that PM from vegetation fire events poses health impacts in UNT. In addition, the regulation measure by prohibition burning events implemented in 2016 was effective to decrease PM_{10} concentration and consequently reduced the prevalence of respiratory morbidity in UNT.

DEDICATION

This thesis is dedicated to
my family,
and my teachers

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I would not have made it to the end of the doctoral degree, and to the end of this thesis, without the help and support of a number of individuals. Here I would like to give some recognition for their effort on my behalf.

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LIST OF SYMBOLS AND ABBREVIATIONS

SYMBOLS

℃	Degree Celsius
µm	Micrometer
%	Percent
m/s	Meter per second
mm	Millimeters
$\mu g/m^3$	Microgram per cubic meter

ABBREVIATIONS

AIC	Akaike Information Criteria
ANOVA	Analysis of variance
AOD	Aerosol Optical Depth
AP-HRA	Health Risk Assessment of Air pollution
ASEAN	Association of Southeast Asian Nations
CI	Confidence interval
CLRD	Chronic lower respiratory diseases
CO	Carbon monoxide
CRF	Concentration response function
FIRM	Fire Information for Resource Management System
GLM	Generalized linear model
HIA	Health impact assessment
HV	Hospital visits
I^2	Amount of heterogeneity (I-squared)

ICD-10	International Statistical Classification of Diseases and Related Health Problem version.10
ITS	Interrupted time series
LANCE	Land, Atmosphere Near Real-time Capability for Earth Observing System
MODIS	Moderate Resolution Imaging Spectroradiometer
MOPH	Ministry of Public Health
MSEA	Mainland Southeast Asia
NA	Not applicable
NASA	National Aeronautics and Space Administration
NO_2	Nitrogen Dioxide
O_3	Ozone
OR	Odds ratio
PAHs	Polycyclic Aromatic Hydrocarbon
PM	Particulate matter
PM_{10}	Particulate matter with aerodynamic diameter less than 10 µm
$PM_{2.5}$	Particulate matter with aerodynamic diameter less than 2.5 µm
RH	Relative humidity
RR	Relative risk
SEA	Southeast Asia
SO_2	Sulfur Dioxide
UNT	Upper Northern Thailand
VFS-PM_{10}	Vegetation fire smoke-related PM_{10}
WHO	World Health Organization
df	Degree of freedom

ppb	Part per billion
ppm	Part per million

EXECUTIVE SUMMARY

Vegetation fire events are getting more attention on public health issues. Exposure to air pollution emitted from vegetation fire events poses health effects ranging from irritating symptoms to premature deaths. Moreover, the effect of exposure to air pollution emitted from vegetation fire events for vulnerable groups, such as children, elderly, and pre-existing respiratory patients, is a further concern.

This thesis illustrated the health impacts of vegetation fire related particles, covering the description of the historical situations, its sources, health risk and the exposure assessments, as well as regulatory measures for vegetation fire to reduce air pollution in UNT. Furthermore, this thesis introduced an interrupted time series study design, which has been increasingly used for the evaluation of public health intervention. The content also included the process of health burden estimation (HBE) attributable to vegetation fire-related air pollution, and the existing studies of HBE in Southeast Asian region.

The purposes of this thesis were to investigate health impacts of particulate matter from vegetation fire events and the burning ban policy in Upper Northern Thailand (UNT) in view of health risk estimation, the effect of a prohibition of vegetation fire on health, and estimation of the health burden attributable to vegetation fire smoke.

The first study examined the risk on hospital visits for respiratory diseases, conjunctivitis, and dermatitis among children from exposure to PM_{10} on different classified days (burning, non-burning, and mixed day) in UNT. The assumption of this study was that exposure to PM_{10} on burning, non-burning, and mixed day may lead to different health effects due to the different components of PM on each day. The burning day occurrence was identified by PM_{10} concentration (> 100 μg/m^3) and fire hotpots count (> 90th percentile of the daily distribution of the entire data; 10 counts). A time stratified case-crossover analysis fitted with conditional logistic regression was used for examining the association of each occurrence day (burning, non-burning, and mixed day) for each province separately. A random-effects meta-analysis was applied in the second stage to pool the province-specific effect estimates. Number of burning days across eight provinces in UNT ranged from 64 to 139 days. I found a positive association between PM_{10} on burning day and hospital visits for respiratory diseases at lag 0 (OR = 1.01 (95% CIs: 1.00, 1.02) per a 10 μg/m^3 increase in PM_{10}concentration). The association between PM_{10} on non-burning day with hospital visits for respiratory diseases was also observed, with the effect estimates higher than burning day (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. This study concluded that increase of hospital visits for respiratory diseases among children was associated with PM_{10} on burning day and non-burning day. The effect on burning days was lower than non-burning days.

The second study evaluated the effect of the burning ban policy enforced in May 2016 on hospital visits for respiratory diseases. This study responds to answer the research question whether the respiratory morbidity rate decreased as a result of a decline in PM_{10} concentration and fire hotpots in the years after the burning ban policy was implemented in UNT. In this study, I analyzed the data between January to April of 2014-2016 (before ban enforcement) and between January to April of 2017-2018 (after ban enforcement). PM_{10} concentrations, numbers of satellite fire hotspots, and age-standardized rates of hospital visits for respiratory diseases before and after the ban enforcement were compared. For each province, the effect of the ban on hospital visits for respiratory diseases was evaluated using a controlled interrupted time series analysis adjusting for season-specific temporal trends, day of week, public holiday, temperature, relative humidity, number of hospitals, and offset population, with gastrointestinal diseases as a negative control. A random-effects meta-analysis was performed to pool province-specific effect estimates. The daily average PM_{10} concentration and the number of fire hotspots decreased after the ban enforcement in all provinces in UNT, with percent changes ranging from 5.3 to 34.3% and 14.3 to 81.5%, respectively. The pooled effect estimates of hospital visits for respiratory diseases decreased by 8.7% (95% CI: 4.3, 12.9), whereas null association was observed for gastrointestinal diseases. The second study concluded that the 2016 burning ban led to a decrease in average PM_{10} concentration and the hospital visits for respiratory diseases in UNT.

The third study estimated the number of hospital visits from respiratory diseases attributable to PM_{10} emitted from vegetation fire smoke (VFS-PM_{10}) and the health impact of the burning ban policy in UNT. This study can help to consider the priority for controlling air pollution emitted from vegetation fire events, relative to other interventions that improve public health to minimize the impact from exposure to air pollution from vegetation fire events. Exposure estimation was applied from the first study. VFS-PM_{10} was derived after conducting population-weighted and classifying the burning occurrence day. The number of hospital visits due to respiratory diseases attributable to VFS-PM_{10} was estimated during 2014 to 2018 for all age groups and children aged below 15 years by using the population weighted VFS-PM_{10}, population data, and concentration-response function derived from the first study. The attributable cases were then compared between before and after 2016 when the burning ban was implemented. Daily average VFS-PM_{10} during the study period across UNT was 133.5 $\mu g/m^3$. The estimated 75,380 and 34,399 cases of hospital visits due to respiratory diseases for all ages and children were attributed to the VFS-PM_{10} during 2014 to 2018. The estimated total cases were accounted for approximately 1% during the study periods and 12% during the burning days. There was a decline in the cases attributable to VFS-PM_{10} from 64,061 before the ban enforcement to 11,319 after the ban enforcement cases. This study suggests that PM_{10} emitted from vegetation fire events affected hospital visits for respiratory diseases across UNT and the burning ban policy decreased the number of hospital visits attributable to VFS-PM_{10}.

In conclusion, exposure to vegetation fire related PM_{10} has effect on respiratory morbidity across UNT. Information of risk estimation and estimated cases may be useful for further policy decision on haze control. Additionally, the finding of this study suggests that the regulatory actions on vegetation fire event control had a positive impact on both air pollution levels and rates of hospital visits for respiratory diseases in UNT.

CHAPTER 1: INTRODUCTION

1.1 Situation of vegetation fire events

Southeast Asian (SEA) region has seasonally affected from smoke haze caused from vegetation fire events and peat fires more than two decades (Nichol, 1997). The events have occurred from intensive burning for several purposes such as agricultural practices, land clearing, and plantation (Jones, 2006). Vegetation fires terminology was given by WHO and referred to the fires mostly caused by anthropogenic activities, including forest fire and slash and burn (World Health Organization, 1998). As SEA is located in the equatorial Pacific Ocean, smoke haze episodes were worsened by El Nino some year (Fuller and Murphy, 2006; Khan et al., 2020). EI Nino phenomenon has driven more drought conditions occurring from the interaction between high air pressure and sea surface temperature among tropical central and eastern Pacific Ocean. A previous study had also documented that the severe disastrous smoke haze was associated with the El Nino event in 1997 (Sastry, 2002). The earlier smoke haze events were frequently observed in the Equatorial SEA countries (Indonesia, Malaysia and Singapore) which is usually occurring during the monsoon season (June-September) (Jones, 2006).

Recently, Mainland Southeast Asian (MSEA) has also faced with local and transboundary air pollution from vegetation fire smoke across the region (Yin et al., 2019). MSEA is located in a half of a mountainous area, including Vietnam, Laos, Cambodia, Myanmar, and Upper Northern Thailand. Figure 1.1 shows the monthly occurrence of vegetation fire events in SEA for year 2019 by satellite-fire hotspot data, with a different burning period between the Equatorial SEA and MSEA. The period of haze in MSEA occur during January to April (Figure 1.1, upper row), which differs from the Equatorial SEA countries.

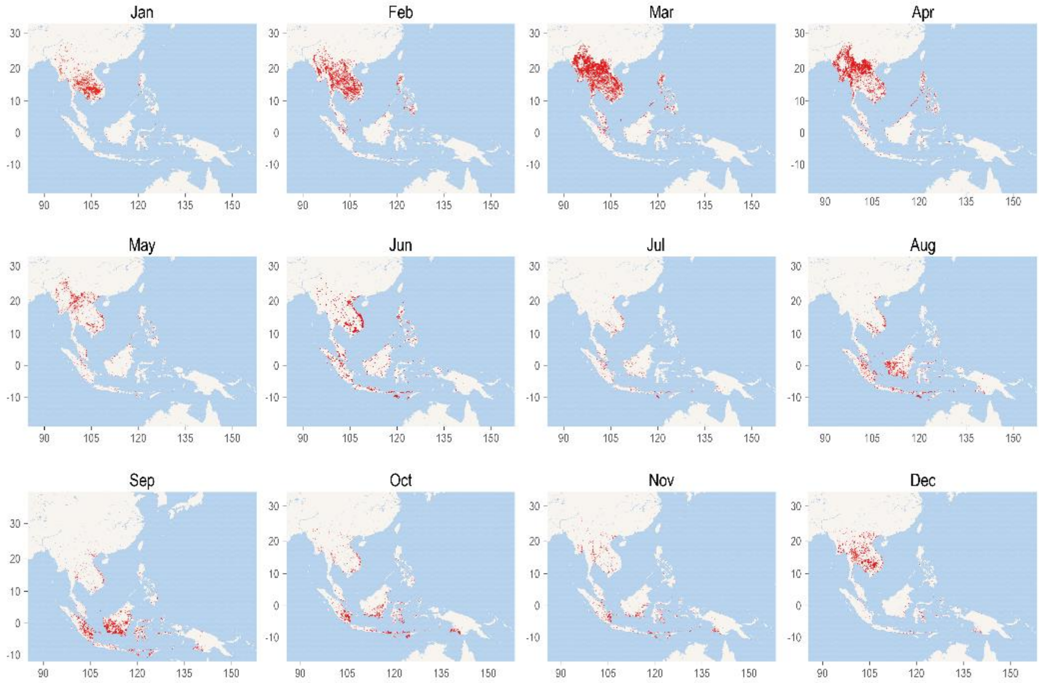

Figure 1.1. MODIS-fire hotspot detected (red dot) in SEA countries during January to December of 2019 (Data was retrieved on 19 April 2020 from FIRM-NASA MODIS website).

In Thailand, it is reported that seasonal characteristics of air pollution from vegetation fire events differs between northern and southern regions. Figure 1.2 presents the smoke haze situation in Thailand with the fire hotspot and wind directions. During the dry season, the air quality in northern area was affected by VFS from the local burning sources within the areas and from the neighbor areas (Figure 1.2, upper row). On the other hand, the smoke detected in southern region is mainly from transboundary-Equatorial Asia-smoke, which was transported by the prevailing winds of Southwest Monsoon during September to November (Figure 1.2, lower row).

Smoke in UNT has occurred as a seasonal air pollution event across the region (Phairuang et al., 2017). The two dominant sources of the vegetation burning in this area are agricultural debris practice and forest fire (Phairuang et al., 2017). As Thailand is the agricultural country, a huge amount of agricultural residues are usually disposed by burning in the open areas. Furthermore, forest fires have also manifested as the crucial contributor of air pollution in the UNT. The man-made forest fires in this area have often occurred from non-timber forest product picking, e.g., mushroom, and bamboo shoot (Forest Fire Control Office, 2005). Among the vegetation fire events setting, forest was reported as the predominant burnt area in the UNT (Geo-Information and Space Technology Development Agency, 2019). Moreover, a previous study conducting air pollution inventory from vegetation fire events found that the largest amount of burning occurred in the deciduous forest areas of UNT (Boonman et al., 2014). The fires typically originate in the mountainous areas with dry and stagnant atmospheric conditions during January to April (Kim Oanh and Leelasakultum, 2011). High concentration of daily PM_{10}, particulate matter with a diameter of 10 μm, was also reported at 428 μg/m^3 in this area (Pollution Control Department, 2019). Other sources of non-fire PM_{10} include traffic, tobacco curing, and the brick-making industry (Kim Oanh and Leelasakultum, 2011).

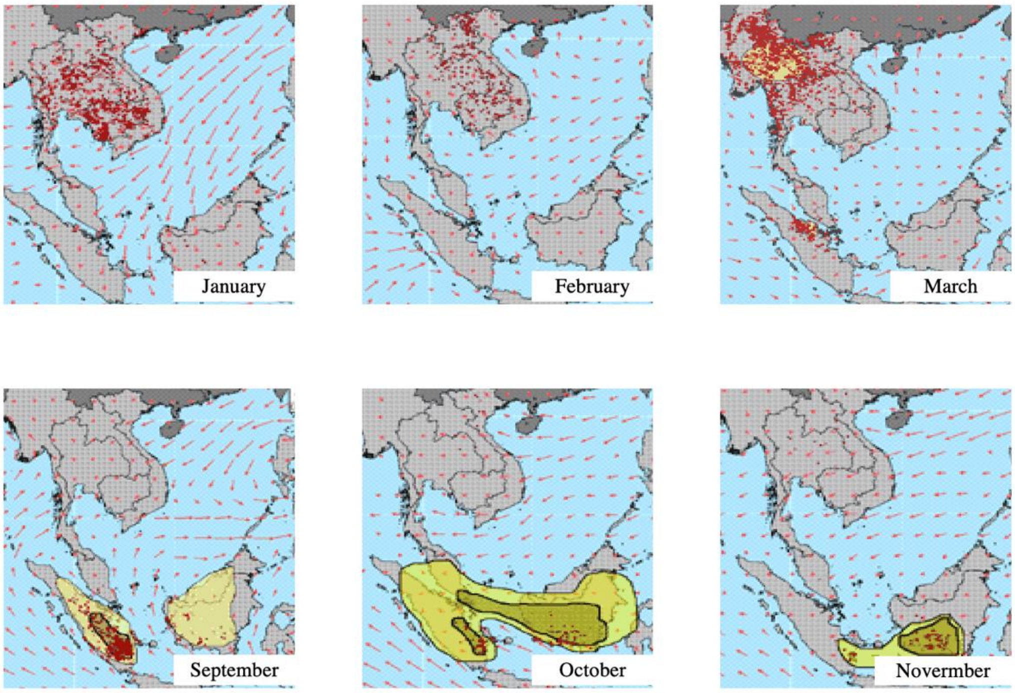

Figure 1.2 Smoke haze situation in Thailand from January to March (upper row) and from September to November (lower row). Red points indicate fire hotspot, yellow areas indicate transboundary smoke haze, and red arrows presents wind direction at 762 meters. Source: International workshop on the "Haze and biomass burning in Asia", Bandung, Indonesia, October 2018.

1.2 Air pollution from vegetation fire smoke and health effects

Vegetation fire smoke (VFS) emits various health-relevant pollutants, including gaseous and particles such as oxides of nitrogen, sulfur dioxide, carbon monoxide and particulate matter (PM) (World Health Organization, 1998). PM is the most considered of all pollutants from vegetation because it has potentially detrimental health effects. The differences of PM compositions between vegetation fires and urban sources have documented in the previous study (Naeher et al., 2007). Vegetation fires-derived particle comprised toxic components such as Polycyclic Aromatic Hydrocarbon (PAHs) and Leveglucosan (Naeher et al., 2007).

Many epidemiological studies found the consistent relationship between exposure to air pollution from VFS-PM and increased respiratory health outcomes. The previous studies have manifested that smoke from vegetation burning may increase hospital admissions and hospital visits for respiratory diseases (Chen et al., 2006; Henderson et al., 2011; Morgan et al., 2010; Naeher et al., 2007). An increase in hospitalization for asthma has also been documented during the burning periods (Jacobs et al., 1997) Several studies also indicated the association between vegetation burning smoke exposure and emergency department visits (Alman et al., 2016; Hutchinson et al., 2018). Some evidence revealed the physical and psychological symptoms of fires-haze exposure (Ho et al., 2014). In contrast, the evidence of relationship between fires-haze exposure and cardiovascular health outcomes is inconsistent. A study found the association of exposure to fires-related haze with cardiovascular health outcomes (Haikerwal et al., 2015) while others did not (Alman et al., 2016; Henderson et al., 2011).

Considering susceptibility to the health effects of exposure to vegetation burning is also necessary. Children are more vulnerable to fire-haze exposure because of their underdeveloped respiratory system and higher breathing rate (Lipsett and Materna, 2008). The recent studies have suggested that smoke from vegetation burning may increase hospital admission and emergency room visits due to asthma and acute bronchitis in children in Australia (Chen et al., 2006) and Brazil (Paraiso and Gouveia, 2015). However, such studies have not been conducted much in Asian region (Gupta, 2019). Moreover, the physical symptoms were also associated with exposure to fire-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.

1.3 Exposure assessment of particulate matter from vegetation fire events

The most common method for estimating air pollution is to use recorded data from air pollution monitoring (Martin et al., 2013; Moran et al., 2019). However, only the monitoring PM data may not be yielded the precise level of exposure to fire-specific PM. In developing countries, air pollution monitoring station are commonly located in the urban area with high population density because of limited resources. On some occasions, high PM concentration may be caused by unusual activities such as traffic congestion from holiday events, rather than the burning activities. Satellite-derived fire hotspots have been used for exposure assessment of vegetation burning (Chakrabarti et al., 2019). Combining the information from fire hotspots with PM concentrations is expected to increase the accuracy of fire-PM. The previous study also found the correlation between satellite fire hotspot and PM_{10} concentration (Sukitpaneenit and Kim Oanh, 2014).

Alternatively, simulated VFS-PM from air pollution modelling is another metric for exposure assessment of VFS-PM. The air pollution inventory from vegetation fire events using satellite data such as MODIS products (burnt area and fire radiative power: FRP) is a useful input data for VFS-PM simulation (Boonman et al., 2014; Kollanus et al., 2017). The previous epidemiological study using different exposure metrics (monitoring and modelling) found the consistence results of the VFS-PM exposure on health outcomes (Deflorio-Barker et al., 2019).

1.4 Control measures of smoke haze from vegetation fire events

Vegetation fire events are now common in MSEA which can has negative effects on economy, security, and health (Vadrevu et al., 2019). VFS is a substantial source of local and transboundary air pollutions (Kim Oanh et al., 2018; Vongruang and Pimonsree, 2020; Yin et al., 2019). In 2015, the Association Asian Nations (ASEAN) committees proposed a framework to response the prevalent of vegetation fires by achieving "Transboundary Haze-free ASEAN" by 2020, and strict laws and policies were enforced to control vegetation fire events and haze smoke (ASEAN, 2018). In UNT, the government proactively introduced the National Haze Action Plan in 2004 (Figure 1.3) and several haze controls measures have been implemented since then (e.g., preparation of firebreaks to prevent intensifying forest fires, promotion of the "villages free from burning" campaign, enhancement of public relations to raise awareness, and expanded cooperation with neighboring countries to mitigate transboundary haze). "Zero-burning" campaign was also implemented and introduced in the area during dry seasons (January to April) in 2013. However, due to lack of strict prohibition measures, the occurrence of seasonal smoke haze from vegetation fire events have still affected the region. Later on, the measure that relies on regulation for burning prohibition with strong penalties has been strictly implemented since May 2016. This law was enforced under the National Reserved Forest Act and was amended to impose strict penalties and sanctions—ranging from fines to criminal charges—for violations (The Office of the Council of State, 2016). The number of fire hotspots detected by satellite, as well as PM concentrations, reportedly decreased after the enactment of the law (Yabueng et al., 2020).

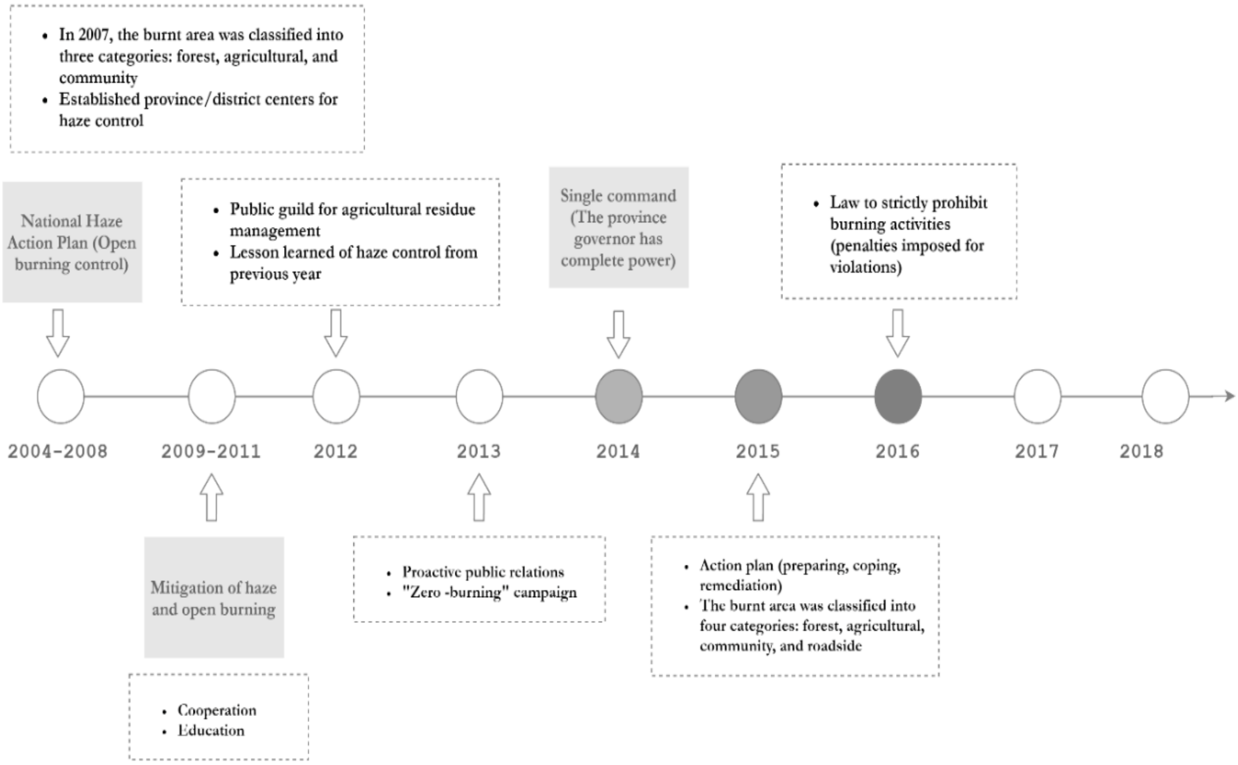

Figure 1.3. Haze control measures in the UNT.

1.5 Interrupted time series study

Recently, the evidence of the relationship between respiratory morbidity and vegetation smoke exposure have increased in MSEA (Johnston et al., 2019; Pothirat et al., 2019; Uttajug et al., 2020). Mitigation policy aiming to reduce the level of air pollution as an intervention for the burning ban, is expected to reduce the prevalence of respiratory morbidity. To examine the effect of the interventions on health outcomes, interrupted time series (ITS) study design has been used in the previous accountability studies in different settings such as industry and traffic (Friedman et al., 2001; Hasunuma et al., 2014; Yorifuji et al., 2016, 2011). ITS has increasingly being used for evaluation of health intervention, which is a comparison between the effect from interrupted (underlying trend at a known point in time) and the counterfactual scenario (the expected trend without the intervention) (Bernal et al., 2019, 2017). This counterfactual scenario can provide a comparison for examining any change occurring after intervention (Figure 1.4).

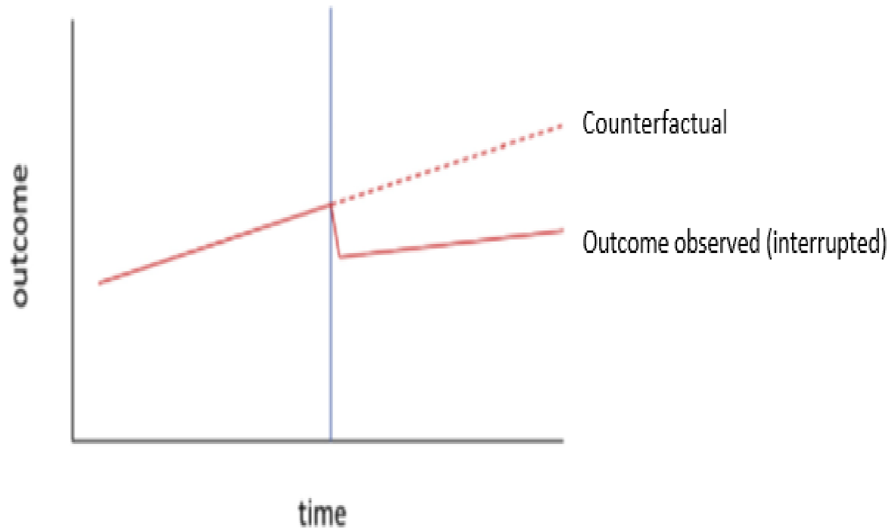

Figure 1.4. Interrupted time series. Blue vertical line indicates an intervention. The red continuous line indicates an example in which the intervention was effective while the red dashed line indicated the effect without intervention.

However, the basic ITS design cannot exclude co-interventions or other events during the time of the intervention. Using the control series as a comparison group can be the one approach to minimize the confounding from co-intervention or other simultaneous events of the study. The recent published study has documented the range of control series such as location-based, characteristic based, behaviors based, historical cohort, or control time periods

(Lopez Bernal et al., 2018). For instant, the study evaluated the effect of diesel emission control on mortality also performed an ITS with comparing the target population with the reference population (Yorifuji et al., 2016). Moreover, a negative control which is a health outcome presumably unrelated to the policy can be used when no appropriate control groups are available (Boogaard et al., 2017).

1.6 Health burden estimation of vegetation fire smoke

Air pollution from vegetation fire events is defined as a source of risk to human health and well-being. Estimation of the health burden attributable to VFS is useful for public health communication and policy decision. In this study, I used the term "health burden estimation (HBE)" as estimating the potential adverse health outcomes resulting from VFS and the health impacts of a regulatory intervention on vegetation fire events ban.

The estimation of health burden follows the guideline "Health Risk Assessment of Air Pollution (AP-HRA)" involves several steps including inputting data, such as the level of air pollution, the exposed population, and the health outcome affected. It is also necessary to build valid concentration-response functions (CRF) connecting the air pollution and the health outcomes (WHO Regional Office for Europe, 2016) (the details are described in Chapter 4). Most of the studies in SEA estimated mortality attributable to fire-related PM using simulated data obtained from air pollution modellings and some combined with the Satellite-Aerosol Optical Depth (AOD) for exposure estimation (Crippa et al., 2016; Johnston et al., 2012; Kiely et al., 2020; Koplitz et al., 2016; Uda et al., 2019). CFR is typically based on Relative Risks (RRs) expressed as the proportional increase in the health outcomes associated with a given increase in pollutant concentration, which is derived from epidemiological studies. Because this thesis focuses on morbidity rather than mortality, I summarized the epidemiological studies examining the health effects of exposure to vegetation fire events-related air pollution on morbidity in Table 1.1. Four epidemiological studies conducted in the U.S. where wildfire was the important sources of VFS (Alman et al. (2016); Deflorio Barker et et. (2019); Hutchinson et al. (2018); and Reid et al. (2016)) while two studies were conducted in Thailand (Mueller et al. (2020); Pothirat et al. (2019). All of the studies examined health effects from short-term exposure to PM emitted from burning events.

Table 1.1 Epidemiological studies used for CRF of morbidity from exposure vegetation fire events-related air pollution.

Author (year)	Study period	Study area	Sources	Air pollutants	Health outcomes	Short/long term effect	Risk Unit	Effect estimates (per 10 $\mu g/m^3$ increase)
Alman et al. (2016)	2012	Colorado, U.S.	Wildfire	$PM_{2.5}$	Emergency department visits	Short-term	OR	1.02 (1.01, 1.03)
Deflorio Barker et et. (2019)	2008-2010	U.S.	Wildfire	$PM_{2.5}$	Respiratory hospitalization	Short-term	RR	2.08 (1.28, 2.89)
Hutchinson et al. (2018)	2007	California, U.S.	Wildfire	$PM_{2.5}$	Hospital visits for respiratory diseases	Short-term	RR	1.07 (1.02, 1.14)
Mueller et al. (2020)	2014-2017	Thailand	Vegetation fire events	PM_{10}	Hospital visits for CLRD	Short-term	RR	1.02 (1.01, 1.03)
Pothirat et al. (2019)	2016-2017	Thailand	Vegetation fire event	PM_{10}, $PM_{2.5}$	Respiratory hospitalization	Short-term	RR	PM_{10}: 1.05 (1.02, 1.09) $PM_{2.5}$: 1.06 (1.01, 1.10)
Reid et al. (2016)	2008	California, U.S.	wildfire	$PM_{2.5}$	Respiratory health	Short-term	RR	1.07 (1.05, 1.10)*

CLRD is chronic lower respiratory diseases

*Effect estimates per 5 $\mu g/m^3$ increase in $PM_{2.5}$

There are several challenges in HBE from exposure to vegetation fire events. The scarce epidemiological evidence on the health risk of exposure to air pollution emitted from vegetation fire events is one of the most important challenges. In most of the polluted areas across Southeast Asia, particularly MSEA, there is a severe lack of epidemiological evidence on both short-term and long-term effects of exposure to VFS. Such studies are urgently needed in these areas, because the health response per units change in air pollution at such high levels may diff from other countries with low pollution levels. In case of limited or no evidence from epidemiological studies, information from studies in other countries may be used to conduct HBE (Crippa et al., 2016; Marlier et al., 2019; Uda et al., 2019). However, using the extrapolated information may not accurately describe the concentration response relationship in the area to be assessed, leading to high uncertainties in the results.

Another challenge is the distribution of exposure estimation. PM was commonly chosen as a principal pollutant when considering health impact from vegetation fire smoke. Most of the studies conducted HBE of VFS by using simulated fire-PM data derived from air modelling (Crippa et al., 2016; Johnston et al., 2012; Kiely et al., 2020; Koplitz et al., 2016; Marlier et al., 2019, 2013; Uda et al., 2019). The strength of using air modelling data is that it allows full geographical coverage and is useful for estimates of future exposure based on predicted change in air pollution as a result of new policies. However, the simulated data are based on a set of assumptions, it is not possible to obtain the certain estimated exposure in a given location. Moreover, such data is scares in some countries, particularly in MSEA. Using data from monitoring station coupled with satellite-fire hotspot might be useful for exposure estimation of VFS-PM_{10} for HBE study.

Up to date, there are few studies estimating the health impacts attributable to VFS. Globally, more than 300,000 premature deaths were estimated from exposure to PM emitted from vegetation fire events, with the biggest death accounted in sub-Saharan Africa and SEA (Johnston et al., 2012). Most of HBE studies in SEA mainly assessed the health impacts among the Equatorial region, which the sources of VFS are rather different from MSEA (Crippa et al., 2016; Johnston et al., 2012; Kiely et al., 2020; Koplitz et al., 2016; Marlier et al., 2019, 2013; Uda et al., 2019). There is no study estimating the health burden from VFS in the MSEA.

1.7 Rational

As seasonal air pollution emitted from vegetation fire events has been recently common in MSEA. Health impacts from exposure to VFS is necessary to consider for public health prevention and environmental policy decisions at the local, national and international level. While there is increasing epidemiological evidence on health effects of PM from burning events in other regions of the world, the sources of burning and the background of health outcomes in MESA is distinctively different from those regions. Thus, the evidence examining the health effects of exposure to air pollution from VFS on respiratory health is needed in this area, particularly for susceptible groups such as children. Prohibition of vegetation fire events by regulatory measures is an important key for haze control. The ASEAN committee meeting for coping the haze problems in SEA also emphasized this. The achievement of the ban is indicated by a decrease of number of fire hotspot, air pollution concentration, as well as respiratory-related health outcomes. Evaluation of the effect of the burning ban policy on respiratory health outcomes may provide evidence for haze management in UNT. Moreover, estimation of health burden from exposure to PM released from vegetation fire events might be useful for the public health communication, and the future environmental policy decision for smoke haze abatement and control.

1.8 Objective

General objective

This thesis aims to comprehensively investigate the health impacts of exposure to PM from vegetation fire events and the implementation of burning ban in view of risk estimation and the effect from the burning ban policy, as well as estimation of morbidity burden attributable to VFS in the area.

Specific objectives

1. To investigate the association between PM_{10} concentrations and the number of hospital visits to address respiratory, conjunctivitis, and dermatitis in children under age 15 years. *(Study I)*
2. To evaluate the effect of a burning ban in May 2016 on hospital visits for respiratory diseases. *(Study II)*
3. To estimate the number of hospital visits for respiratory diseases attributable to VFS-PM_{10} and implementation of strict ban. *(Study III)*

The study diagram of health impact from exposure VFS in UNT is presented in Figure 1.5. *Study II* was examined the effect of the ban on respiratory morbidity after the association of hospital visits for respiratory diseases and VFS was found in *Study I*. *Study III* utilized the CRF derived from *study I* and evaluated the attributable cases from the effect of the burning ban which was observed in *Study II*.

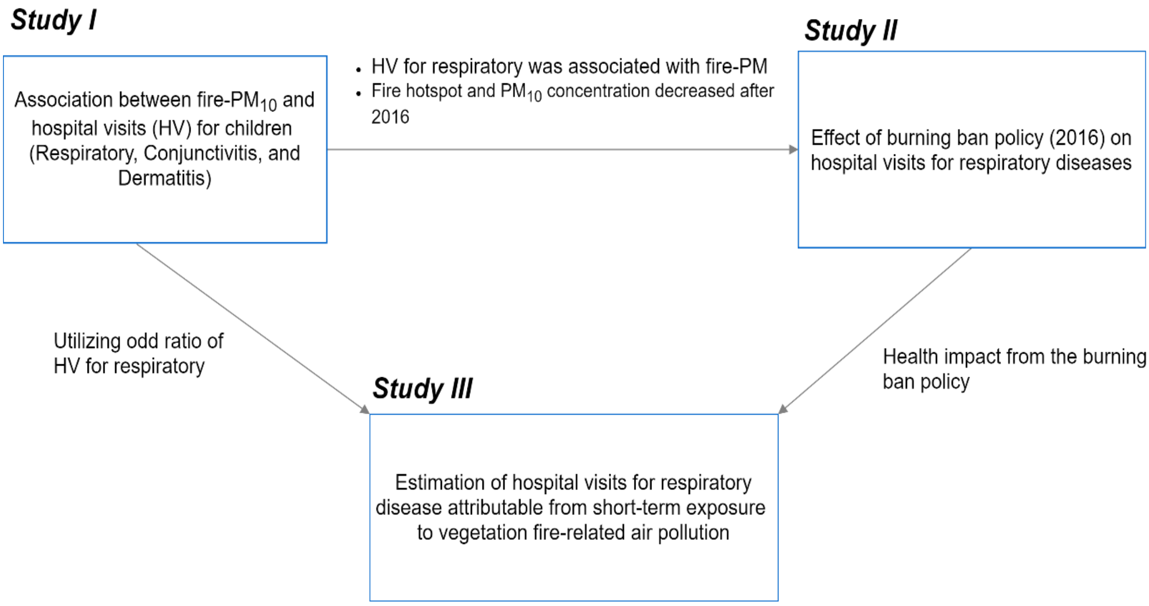

Figure 1.5. Study diagram of health impacts from VFS in UNT

CHAPTER 2: Study I (Association between PM_{10} from vegetation fire events and hospital visits by children in upper northern Thailand)

This chapter discussed the first study investigating the effects of exposure to PM_{10} from vegetation fire events on hospital visits for children as the morbidity health indicator. Specifically, the objective of the first study was to examine the association between PM_{10} concentrations and hospital visits to address respiratory, conjunctivitis, and dermatitis in children aged under 15 years across the UNT.

In chapter I, I briefly explained that the difference in the components of PM originated from vegetation fire events and other sources may lead to different outcomes/magnitude of the effects. In this study, I examined and compared the effect estimates of PM on respiratory morbidity among burning, non-burning, and mixed days. As this study emphasized the health effect of PM from vegetation fire smoke, I classified each day into above categories based on the level of PM_{10} concentration coupled with the satellite-fire hotspot data retrieved from Moderate Resolution Imaging Spectroradiometer (MODIS)-NASA information.

2.1 Methodology

Study area

The study area comprised of eight provinces in the UNT, including Chiangmai, Chiangrai, Lamphun, Lampang, Mae Hong Son, Nan, Phayao, and Phrea. These provinces are the most affected by smoke from vegetation fire events (Phairuang et al., 2017; Pollution Control Department, 2019). Figure 2.1 presents the provincial boundaries and locations of the ambient monitoring stations.

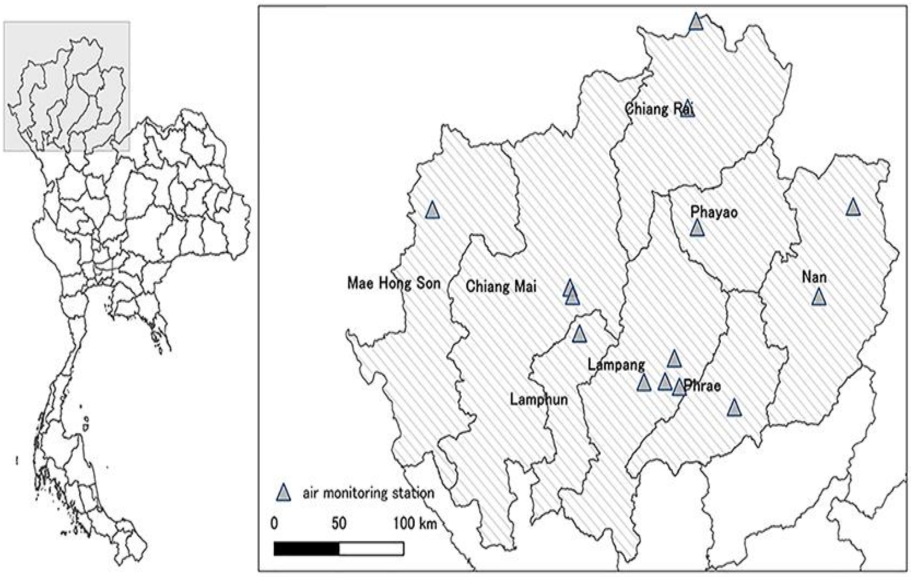

Figure 2.1. Study area and air monitoring stations.

Hospital visits data

Daily hospital visits data (outpatient visits) for children aged under 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.

The data contained the information on sex, age, date of visit, and International Classification of Diseases version 10 (ICD10) codes for diagnosis. The hospital visit data included for respiratory disease (J00-J99.8), conjunctivitis (H10-H10.9), and dermatitis (L20-L30).

Air pollution and metrological 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 (Figure 2.1) from the Pollution Control Department, Thailand. Daily concentrations of each air pollutant were computed from hourly data. Metrological data were obtained from Meteorological Department, Thailand, which included ambient temperature, relative humidity, wind speed, and rainfall. The value of PM_{10} and meteorological data were averaged from the stations within the province.

Burning day occurrence

Satellite-fire hotspot and PM_{10} concentration were used to identify the burning events. Fire hotspot data (MCD14ML) (Giglio et al., 2018) were obtained from 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. The resolution of fire-hotspots is 1 kilometer as recorded 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). Fire hotspot were provincially mapped and summed by QGIS 3.4 (QGIS Development Team 2014). Numbers of fire hotspots of this study are compared with the data of GISTDA, Thailand (Table A-1). 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, which was classified into three categories i.e., low (0-30%), medium (30-80%), and high (80-100%) (Giglio and Justice, 2003). In this study, fire hotspots with a confidence value under 20% (low confidence) were excluded from the analysis (Figure A-2).

As no study have been using fire hotspot data to be a criterion of a burning day, I defined a 'burning day' as a day when the number of fire hotspots exceeded the 90th percentile of the daily distribution of the entire region (10 counts) (Figure A-3) and the daily PM_{10} concentration in each province was greater than 100 μg/m^3. The correlation of PM_{10} and fire hotspot is presented in Figure A-1. A day without fire hotspot was defined as a ‘non-burning day’. The remaining days were classified as ‘mixed days. For example, at day1, when the cumulative number of fire hotspots for the entire area region (sum up of eight provinces) was 45 counts, and PM_{10} was 23 μg/m^3 and 260 μg/m^3 in Chiangmai and Chiangrai, respectively, I defined this day as a ‘burning day’ in Chiangrai and as a ‘mixed day’ in Chiangmai (Figure 2.2). Hence, I assumed that increases in PM_{10} on a burning day was driven by vegetative fire events. 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 μg/m^3 (Sahani et al., 2014).

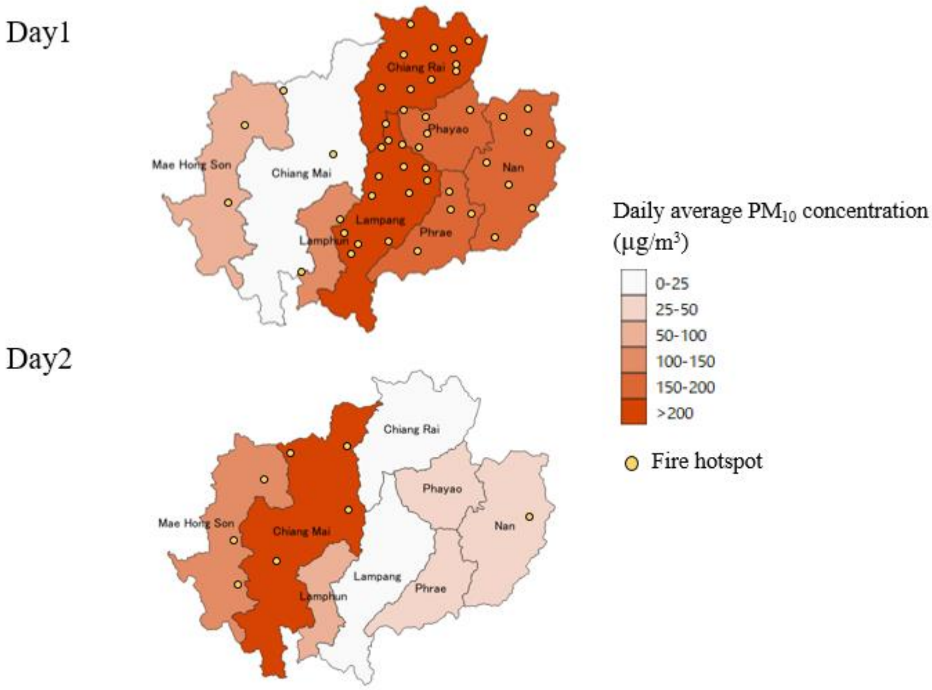

Figure 2.2. Examples of classification of the burning day occurrence. Upper figure (Day 1) shows Chiang Rai and Lampang was classified as “burning day” because the total fire hotpots (indicated as yellow dots) within these provinces were more than 10 counts (>90th percentile

of the daily distribution of the entire region) and PM_{10} concentration exceeded 100 $\mu g/m^3$;

Lower figure (Day 2) shows that all provinces were classified as "mixed day".

Study design and statistical analysis

The association 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). The hospital visits occurred were assigned as the case day and comparisons to 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). A conditional logistic regression model was used to estimate the odds ratio for exposure to PM_{10} on burning/ non-burning/mixed days and hospital visits in all health endpoints. The model 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). Some environmental variables were also adjusted in the model such as relative humidity, precipitation, and wind speed. However, relative humidity did not influence the AIC value and was omitted from the final model. The analyses were separately conducted for burning, non-burning, and mixed days because the association may vary by the type of day. Lagged effects were examined as single (lag 0 - lag 3) and average (lag 01- lag 03) lag 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. I also 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). The modification effect was explored as a stratified analysis by age groups, i.e., 0–4 year-olds (pre-school children) and 5–14 year-olds (school children) at lag 0.

Sensitivity analyses were performed using the alternative criteria of a burning day. First, I 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, I repeated the analysis using the different of PM_{10} concentration (100 μg/m^3 and 120 μg/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}.

Ethical review

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).

2.2 Results

Table 2.1 presents the summary statistics for the environmental variables, including air pollution, temperature, relative humidity, wind speed, precipitation, and number of fire hotspots, for burning, non-burning, and mixed days. 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. Daily average PM_{10} concentration ranged from 122.9 μg/m^3 to 165.1 μg/m^3 in the UNT. There was no significant difference of daily mean temperature between burning, non-burning, and mixed days.

During the study period, 5,641,107 hospital visits due to respiratory disease, conjunctivitis, and dermatitis among children aged <15 years were recorded during the study period (Table 2.2). Study subjects included more pre-school children (age 0-4 years) than school-aged children (age 5-14 years). Hospital visits for respiratory diseases was the most responsible among three reported smoke related health conditions.

Table 2.1. Daily average of environmental variables during 2014 – 2018 (values represent daily mean (standard deviation)).

Variables	Chiangmai	Chiangrai	Lamphun	Lampang	Maehongson	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)

Variables	Chiangmai	Chiangrai	Lamphun	Lampang	Maehongson	Nan	Phayao	Phrae
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)
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 2.2. Summary of hospital visits for children during 2014 – 2018.

	Case count							
	Chiangmai	Chiangrai*	Lamphun	Lampang	Maehongson	Nan	Phayao	Phrae
Total number	1,680,799	1,173,571	376,871	600,436	393,262	576,122	484,132	355,914
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

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 2.3). Significantly positive associations between PM_{10} and hospital respiratory diseases on burning days were observed in the immediate lag (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) (Figure 2.3). Positive associations between PM_{10} concentration and hospital visits due to respiratory disease in children were found in all provinces except Chiangrai (Figure A-4). The effect estimates of each provinces and diseases are presented in Figure A-4 to A-11.

The positive relationships 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 (Figure 2.3). For mixed days, an elevated 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) (Figure 2.3). 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 2.3).

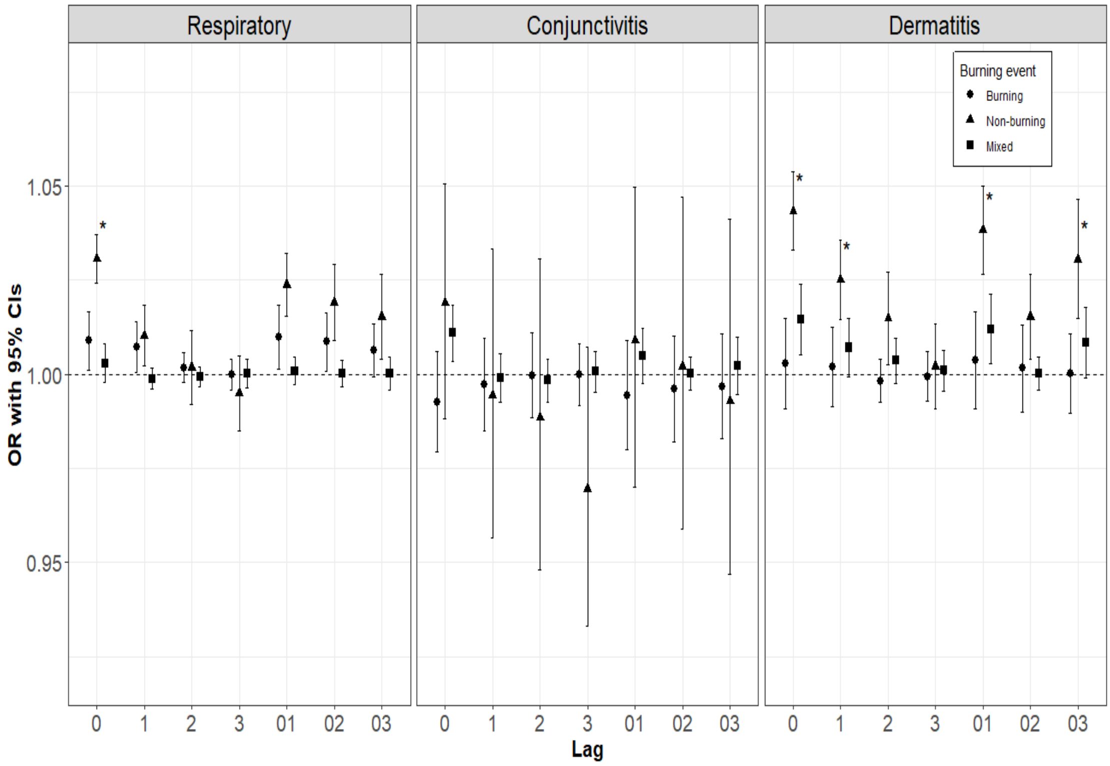

Figure 2.3. Odds ratio of hospital visits (pooled effect) as associated with a 10 μg/m^3 increase in PM_{10} concentration on burning, non-burning, and mixed days for single and average lag models. *Statistically significant difference at $p < 0.05$ compared to burning day.

The results of stratified analysis are presented in Figure 2.4. I 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.

Figures 2.5 and 2.6 present the sensitivity analyses by comparing the effect estimate of different cut-off points for fire hotspot and PM_{10} concentration, respectively. Applying different cut-off point of fire hotspot and PM_{10} concentration generally showed similar effect estimates

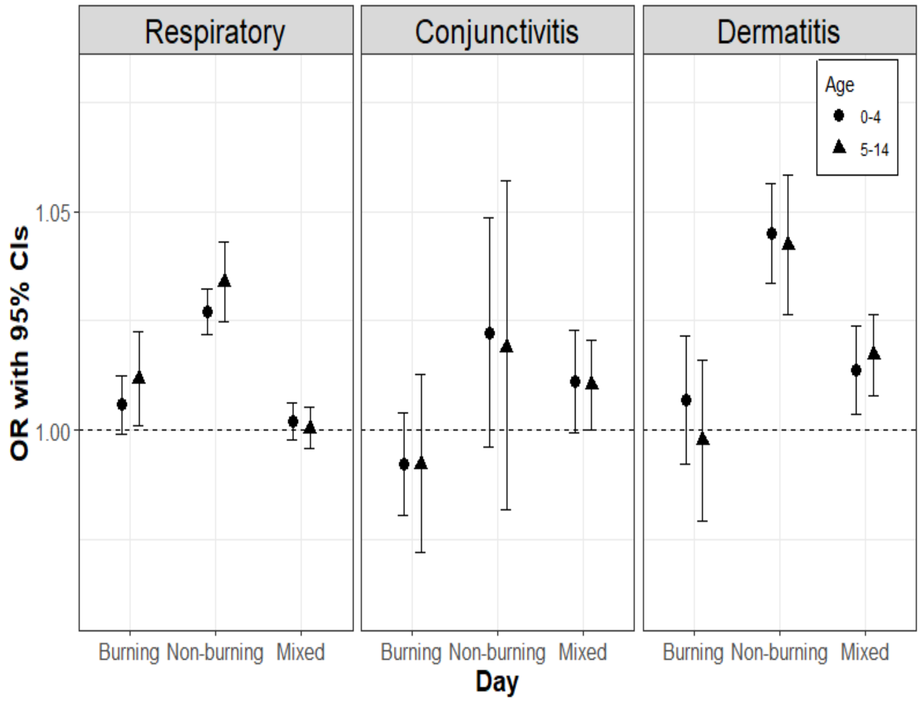

Figure 2.4. Odds ratio of hospital visits for stratified analysis of children age 0-4 and 5-14 years as associated with a 10 μg/m^3 increase in PM_{10} concentration on burning, non-burning, and mixed day at lag 0.

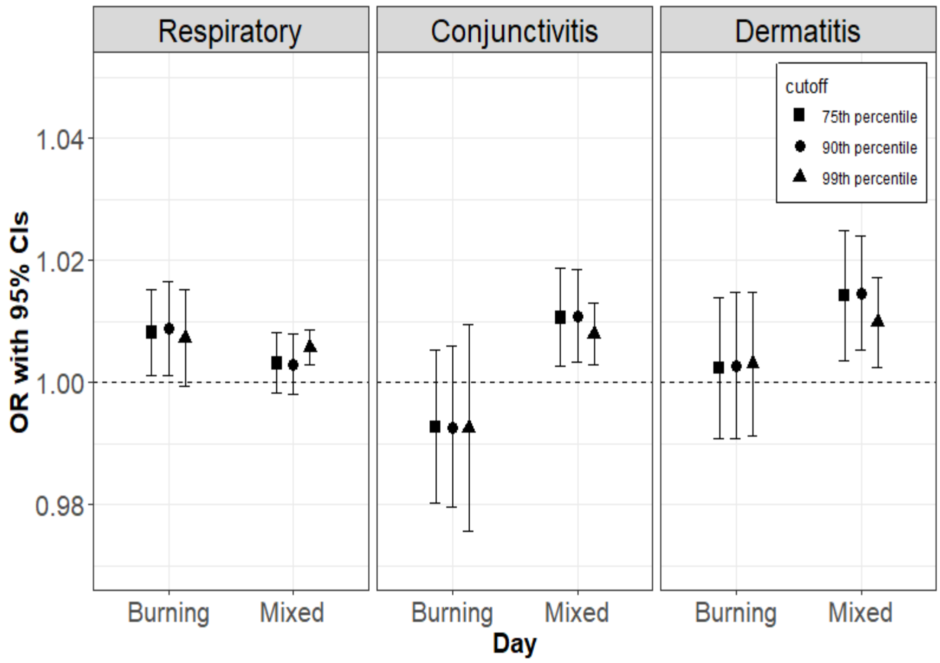

Figure 2.5 Odds ratio of hospital visits for respiratory diseases in children associated with a 10 μg/m^3 increase in PM_{10} concentration on burning and mixed days at lag 0 applying the

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.

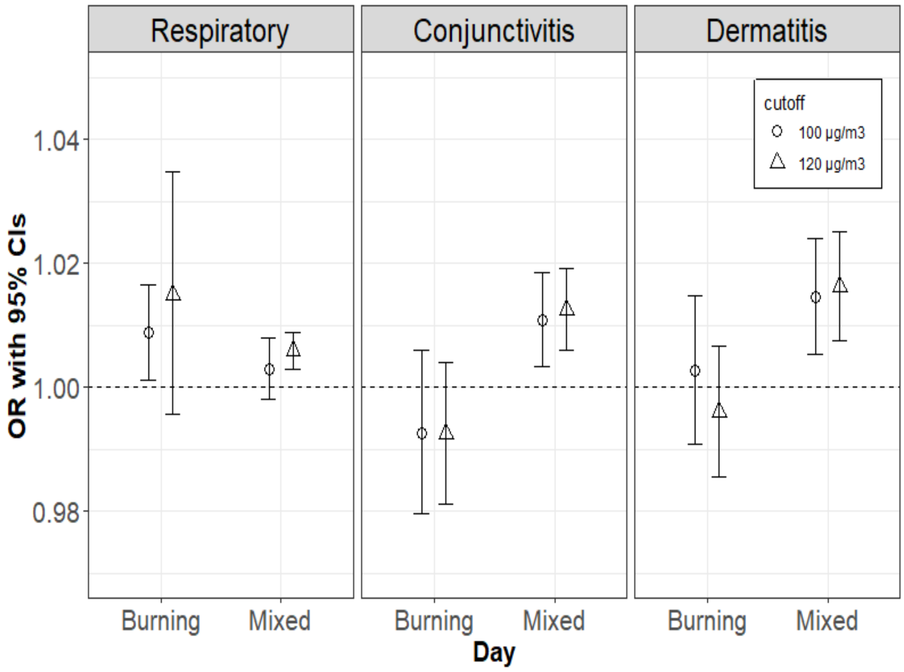

Figure 2.6 Odds ratio of hospital visits for respiratory diseases in children associated with a 10 µg/m^3 increase in PM_{10} concentration on burning and mixed day compared to the different cut-off point of PM_{10} (100 and 120 µg/m^3). The results of non-burning days were not presented because changing the cut-off point does not affect them.

2.3 Discussion

The main finding from this study is that 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 effects were highest in the immediate lag, especially at lag 0, which indicates an acute effect of PM_{10}.

Previous studies have also demonstrated the consistent evidence that exposure to PM_{10} on burning days significantly influenced the number of hospital visits for respiratory disease

(Henderson et al., 2011; Stowell et al., 2019). Specifically, various health outcomes of respiratory diseases were observed in children during burning events such as 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, the negative association were found in Chaingrai province. This may suggest the effectiveness of burning ban policy 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 vulnerable 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.

In contrast, the associations between vegetation burning-related PM and hospital visits for conjunctivitis and dermatitis were not observed. The 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.

As the different components of PM of each setting, the prior hypothesis is that the effects of PM_{10} on burning days would be more prominent than those on non-burning and mixed days. However, I found a slightly higher effect estimate for respiratory diseases of non-burning day compared to burning day at the immediate lag. This result was inconsistent with the previous study which found that the similar increase in risk of respiratory illness-related hospitalization and PM from smoke and non-smoke days (Deflorio-Barker et al., 2019). 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 the markers of vegetation-derived PM (encompassing levoglucosan, mannosan, and galactosan) 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, hospital visits for conjunctivitis and dermatitis were associated with PM_{10} on non-burning and mixed days. The main sources of PM on non-burning and mixed days include urban sources e.g., traffic and some burning activities such as waste burning. The finding of risk on hospital visits for dermatitis was consistent 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). I 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).

Strengths

This study has several strengths. First, this study 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, this study 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, this study compared effect estimates of PM_{10} on burning, non-burning, and mixed days in the same population, rather than in different populations. Finally, I 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).

Limitations

There were some limitations for this study. This study 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. Another 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 and might contain toxic substances from insufficient burning such as PAHs. Second, valley topography of UNT might have affected the spatial distribution of PM_{10} and could cause misclassification of burning day.

2.4 Conclusion

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.

CHAPTER 3: Study II (Effect of vegetation fire events ban on hospital visits for respiratory diseases in Upper Northern Thailand)

This chapter discussed the second study on evaluating the effects of the burning ban policy on hospital visits for respiratory diseases. In *study I*, the association between VFS-PM_{10} and hospital visits for respiratory diseases was observed in the UNT area. As mentioned in the *Chapter I*, the burning ban policy was amended and enforced on May 2016. Number fire hotspots and PM_{10} concentrations have set as the crucial indicators for evaluating the effectiveness of the vegetation haze control by the government. The decline of both indicators was documented after policy implementation by the previous study (Yabueng et al., 2020). This raised the hypothesis that hospital visit for respiratory diseases may consequently decrease after observing the decrease of PM_{10} and fire hotspot from the ban. In this chapter, I evaluated the effect of vegetation fire events ban on hospital visits for respiratory diseases in the UNT.

3.1 Methodology

Study area

This study included the data from eight provinces of the UNT which were described in the *study I*. The population of year 2016 in each province is presented in the Table 3.1 while the population trend is presented in Figure 3.1.

Study design

The study periods were defined into two specific time, as follows: 1) January to April of 2014-2016 (before ban enforcement) and 2) January to April of 2017-2018 (after ban enforcement). The data during the burning season (January through April) were analyzed, since these months represent the time when the region is most affected by intense fire events. Also, high concentrations of PM, which is predominantly emitted from vegetation fires, have been noted in the region during the dry season. I also utilized the data during the non-burning season (May through December) to compare the difference of PM_{10} concentration and the rate of hospital visits from the burning season. The study period was set to 5 years spanning 2014 - 2018 to cover both periods before and after ban enforcement.

Table 3.1. Population of each province in the UNT (National Statistical Office of Thailand, 2016).

Province	Population
Chiangmai	1,735,762
Chiangrai	1,282,544
Lamphun	748,850
Lampang	405,999
Maehongson	275,884
Nan	479,916
Phayao	479,188
Phrae	449,810

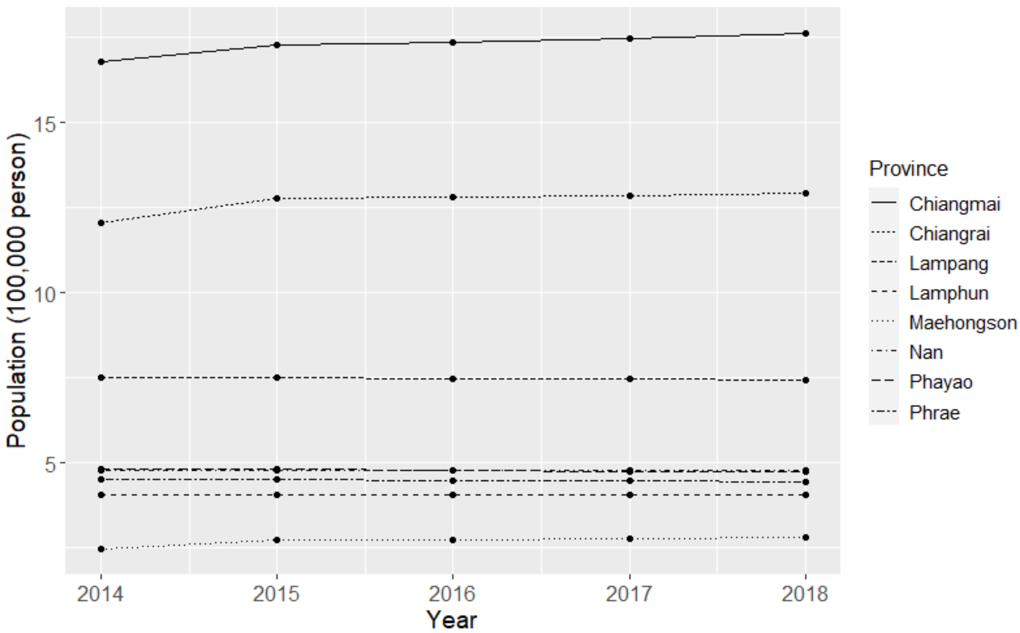

Figure 3.1 Population trend of each province in the UNT during 2014-2018

Hospital visits data

The hospital visits data of each province of the UNT during 2014 to 2018 were derived from Ministry of Public Health, Thailand. Data of Chiangrai province were available only from January 1 2015 to December 31 2018. The data included demographic information (age and sex), date of visit, and code of International Classification of Diseases version 10 (ICD10). In this study, I focused on hospital visits for respiratory diseases (J00-J99), since I expected that reduced PM_{10} concentrations due to ban enforcement would consequently lead to a reduced prevalence of respiratory diseases. On the other hand, assuming that the effect of the ban on the prevalence of gastrointestinal diseases would be minimal, if any, I also collected data for gastrointestinal diseases (K00-K99) as negative controls according to a previous study (Boogaard et al., 2017).

Daily age-standardized morbidity rates

Daily age-standardized rates of hospital visits for respiratory and gastrointestinal diseases were calculated to compare between before and after the ban intervention. I adjusted for population changes by calculating age-standardized rates of hospital visits for both respiratory diseases and gastrointestinal diseases. Daily morbidity rates were determined by age group (5-year intervals up to 85 years and >85 years) for each province by dividing the daily number of hospital visits by daily population (estimated by linear-interpolation of age-specific census population counts in 2014-2018 provided by the National Statistical Office of Thailand). Age-standardized rate of hospital visits was obtained by dividing the total number of daily expected cases for each age group by the standard population. Daily expected cases were calculated by multiplying the daily morbidity rate by the standard population of that same age group (2016 census population in each province). Morbidity rates were expressed per 100,000 person-days.

Environmental data

Hourly average PM_{10} concentrations from 14 stations across UNT were provided by the Pollution Control Department of Thailand. Daily average PM_{10} concentrations were estimated from hourly data within each province. I obtained daily meteorological data, including ambient temperature (in degrees Celsius; °C), relative humidity (in percent; %), wind speed (in meter per second; m/s), and rainfall (in millimeters; mm) from the Department of Meteorology of Thailand. I averaged PM_{10} concentrations and meteorological data from all stations in each province.

Data on fire hotspots representing possible fires or burning activities were retrieved from satellite data obtained from NASA's MODIS onboard Terra and Aqua satellites. Daily fire hotspots were summed by province using QGIS 3.4 (QGIS Development Team 2014).

Statistical analyses

In the first stage, the analysis was separately performed by each province. T-test was used to compare PM_{10} concentrations and age-standardized rates of hospital visits for respiratory diseases and gastrointestinal diseases before and after ban enforcement, and the Man-Whitney U test was used to analyze differences in the number of fire hotspots.

Controlled interrupted time-series (CITS) analysis was applied to assess the effect of the burning ban on hospital visits for respiratory diseases with a generalized linear model (GLM) based on a Poisson distribution for burning periods. Adjustments for season-specific temporal trends were performed by using a natural cubic spline of day of the season with 1 degree of freedom (df) (Bhaskaran et al., 2013). Adjustments were also performed for offset population (log of the population under the study period), number of hospitals (province/year) (Figure B-1), day of week, and public holidays as dummy variables, a 3-day moving average lag in temperature, and relative humidity using a smoothing function with 3 df. I changed the df of temperature ranging from 3-5 to check for robustness. The best fitted model was selected by the Akaike Information Criterion (AIC). Because initial analyses manifested an overdispersion, a quasi-Poisson models was used for all latter analyses. In this study, I only examined step changes in the model based on the hypothesis that the impact of the ban might be an abrupt effect on health outcomes. The same analysis was also applied to hospital visits for gastrointestinal diseases as the negative control, to verify whether the changes in the hospital visits for respiratory disease are truly attributable to the burning ban.

In second stage, a random-effect meta-analysis was performed to pool multi-province effect estimates. The heterogeneity was performed using I^2 statistic, while the significance of heterogeneity was tested by Cochran's Q statistic.

Sensitivity analyses were performed for temporal control by changing df from 1 to 5 for both respiratory and gastrointestinal diseases. I found narrower confidence intervals for hospital visit rates when df =1, whereas wider confidence intervals were observed with increasing df (Figure 3.2). The effect estimates were not significantly different for all df in both respiratory and gastrointestinal diseases. Moreover, lower heterogeneities in both diseases were consistently observed when df = 1. It is thus reasonable to believe that the use of df = 1 for the temporal control is suitable in examining the change of hospital visits after burning ban implementation. I also conducted sensitivity analyses by varying the cut-point year of burning ban instead of a year 2016 by year 2015 and 2017. I thus compared effects between three cut point-years (cut-point year 2015: 2014-2015 versus 2016-2018, cut-point year 2016: 2014-2016 versus 2017-2018, and cut-point year 2017: 2014-2017 versus 2018).

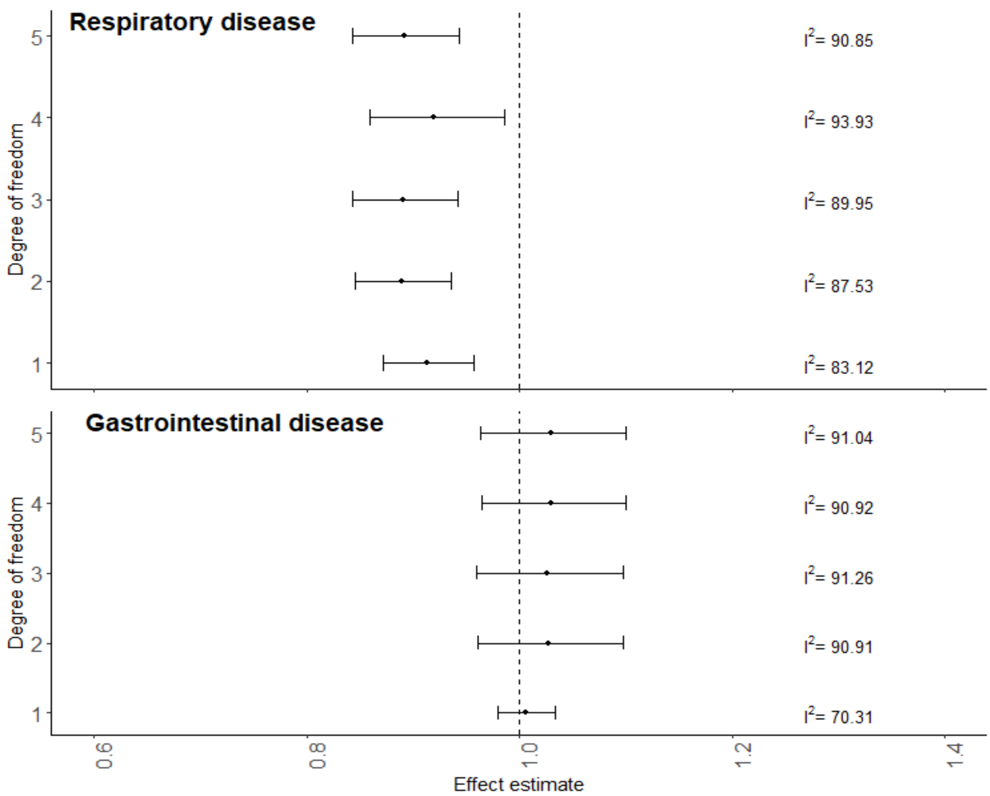

Figure 3.2. Sensitivity analyses by changing degree of freedom (ranged from 1 to 5) of day of season. Heterogeneity of each df of the pooled-effect estimate is represented as I^2.

All statistical analyses were conducted in R (version 3.5.1, The R Foundation for Statistical Computing, Vienna, Austria) utilizing the R package *tsModel* and *metafor* (Viechtbauer, 2010). All results were presented as percent change with 95% confidence intervals (CIs).

3.2 Results

The trends of PM_{10} and the number of fire hotspot during burning seasons decreased after the ban implementation in most of the provinces in the UNT while PM_{10} concentration levels and fire hotspot counts during non-burning seasons did not differ between before and after burning ban implementation (Figure 3.3 and 3.4). The decline of daily average PM_{10} concentration and fire hotspot ranged from 5.3 to 34.3 % and 14.3 to 81.5 %, respectively (Figure 3.5 and Table 3.2). The largest decreases in PM_{10} concentration and the number of fire hotspots were noted in Chiangrai province (Figure 3.5).

Age-standardized rates of hospital visits for respiratory diseases were higher in the burning season compared to the non-burning season and were slightly lower after ban enforcement compared to before in some provinces (Figure 3.6). On the other hand, age-standardized rates of hospital visits for gastrointestinal diseases did not differ between burning and non-burning seasons, while an increasing trend was observed over the course of the study period (Figure 3.7). The comparison of age-standardized rates of hospital visits for respiratory diseases before and after ban enforcement revealed a decrease by 6.5-18.8% in 5 provinces (Chiangmai, Chiangrai, Lampang, Phayao, and Phrae), whereas the rates for gastrointestinal diseases increased in all provinces by 5.7-64.6% (Table 3.3).

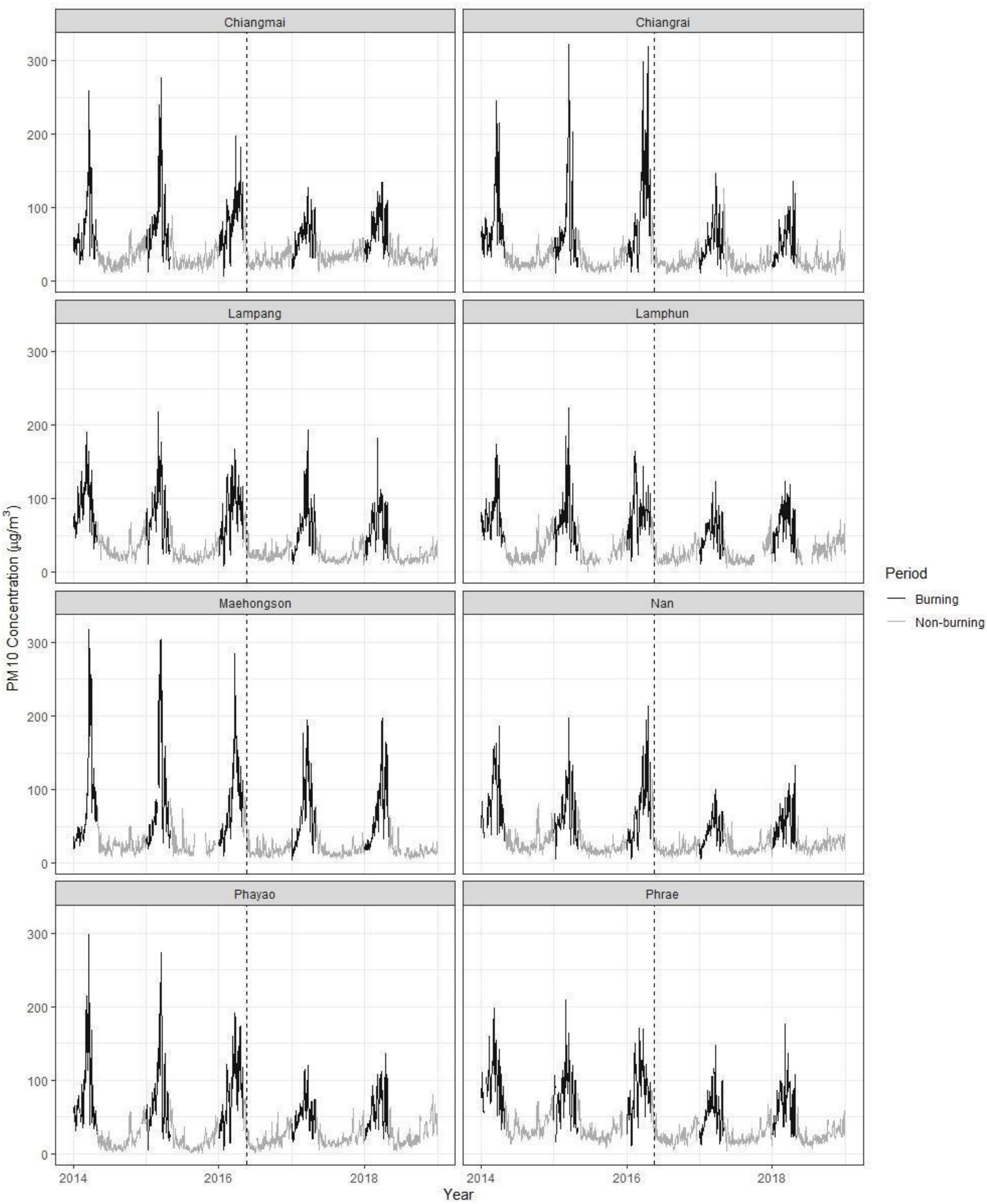

Figure 3.3. Daily average PM_{10} concentration by eight provinces during burning (January to April) and non-burning periods (May to December).

The vertical break line indicates 19 May 2016 when the ban came into force.

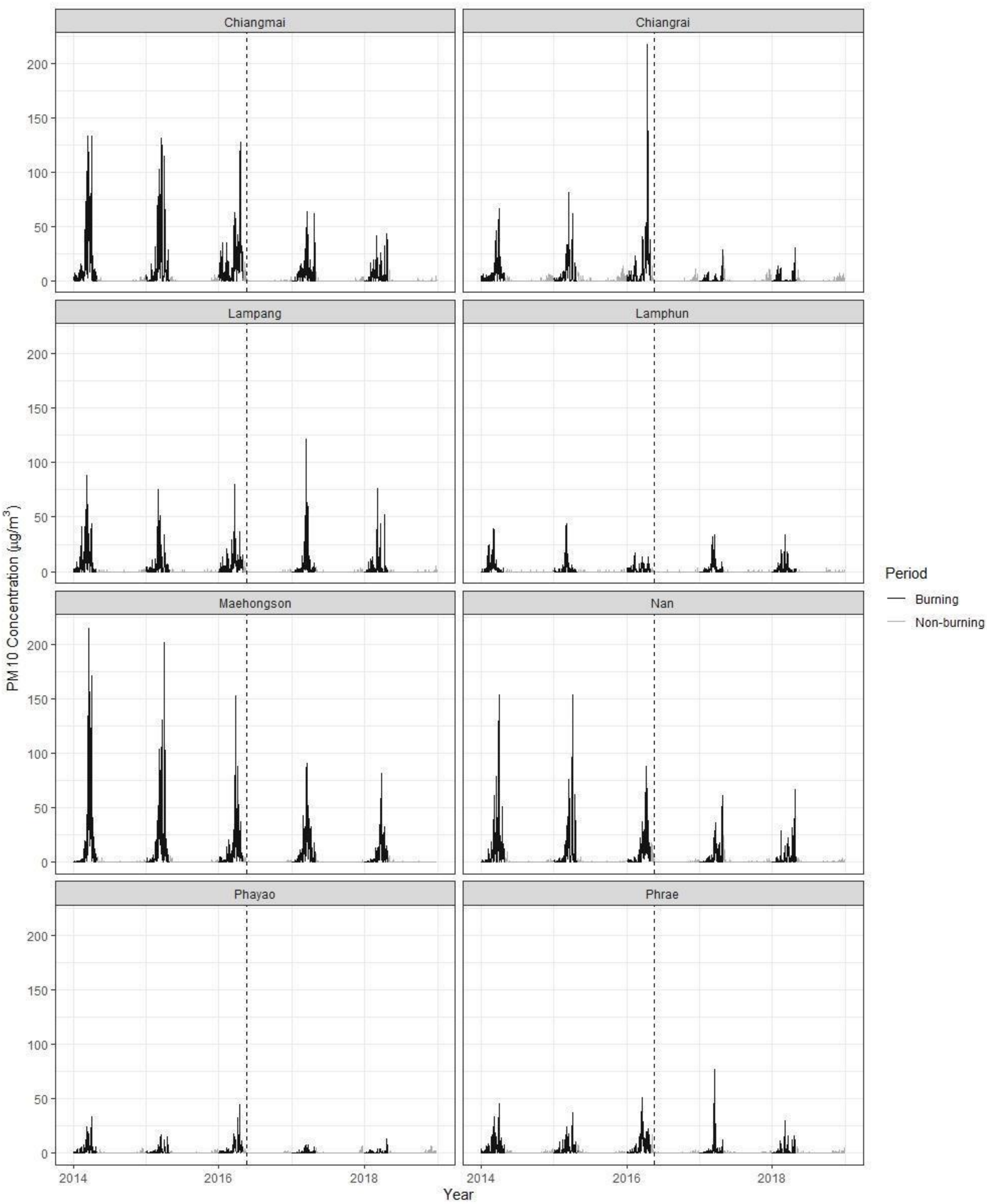

Figure 3.4. Daily sum of fire hotspot by eight provinces during burning (January to April) and non-burning periods (May to December).

The vertical break line indicates 19 May 2016 when the ban came into force.

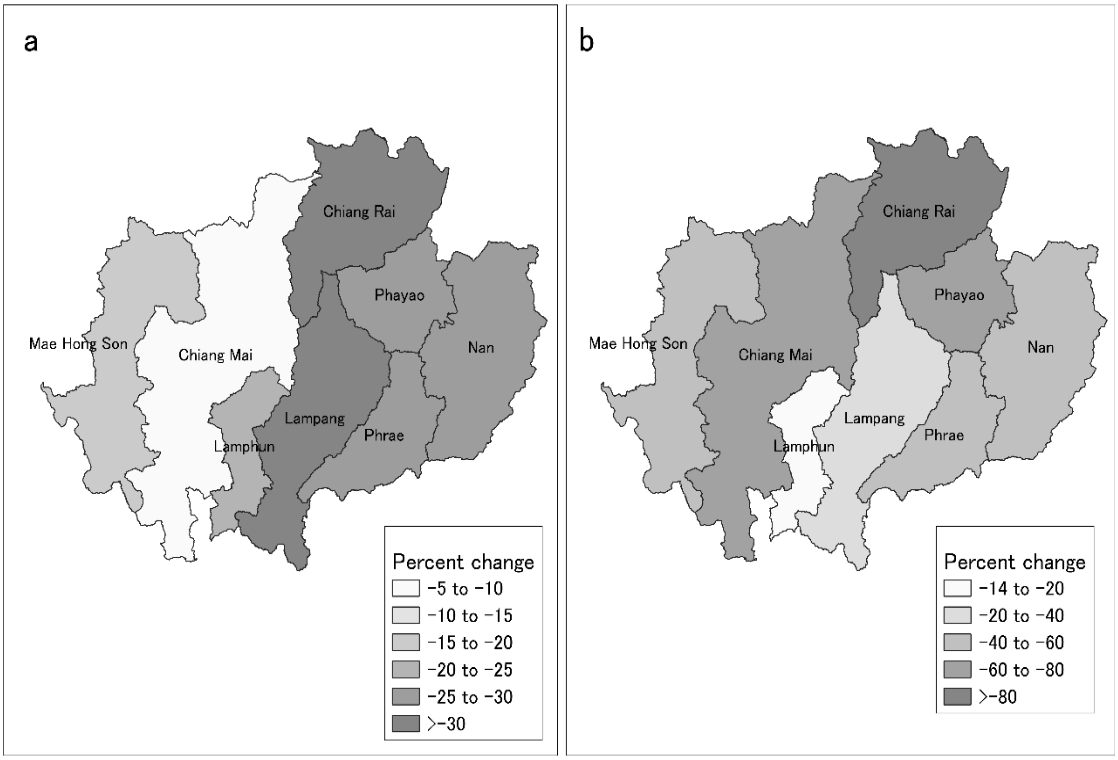

Figure 3.5. Change of (a) Daily average PM_{10} ($\mu g/m^3$) and (b) Daily mean of fire hotspots after implementation of burning ban in the UNT.

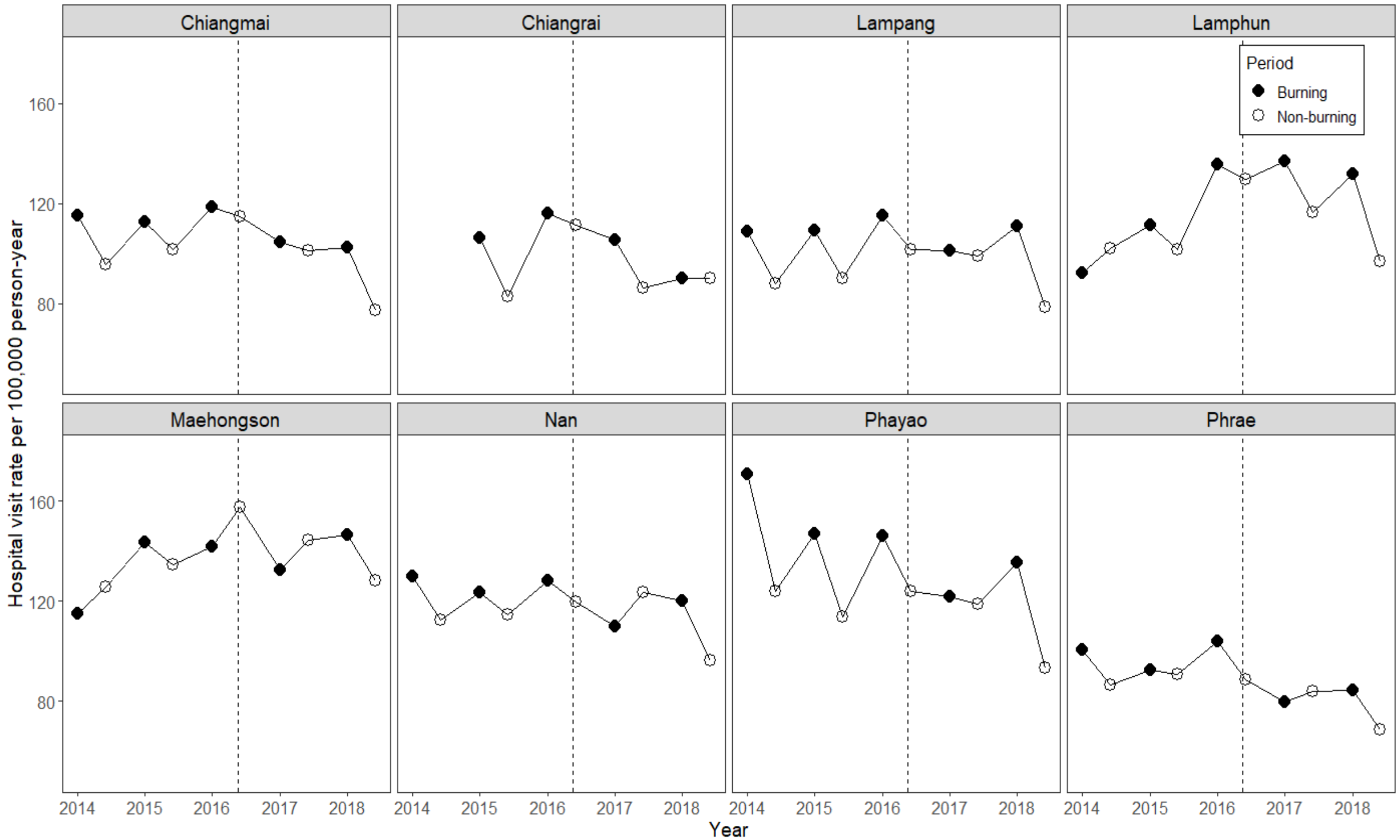

Figure 3.6. Period mean of standardized rates of hospital visit for respiratory disease during 2014-2018 in each province. Noted that the data in Chaingrai province is not available in year 2014.

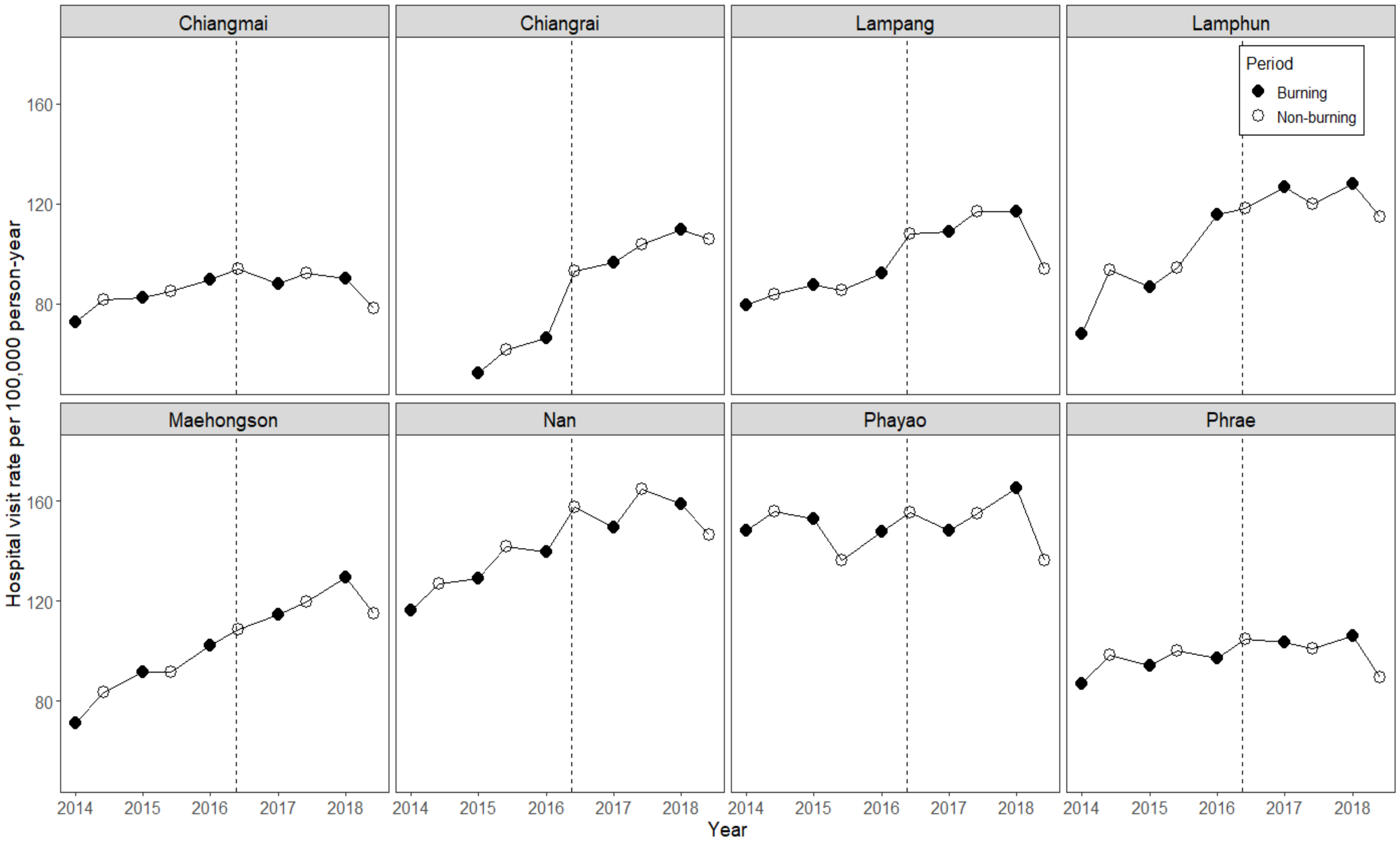

Figure 3.7. Period mean of standardized rates of hospital visit for gastrointestinal disease during 2014-2018 in each province. Noted that the data in Chaingrai province is not available in year 2014

Table 3.2. A comparison of daily average PM_{10} concentration and fire hotspot before and after burning ban in UNT, by province.

Province	Period	PM_{10} (µg/m^3)			Fire hotspot			
		Mean	Change from baseline period	p-value	Total count	Mean	Change (mean) from baseline period	p-value
Chiangmai	2014-2016	76.4	-5.3	0.10	6347	17.6	-64.8	< 0.01
	2017-2018	72.4			1499	6.2		
Chiangrai	2014-2016	79.9	-34.3	< 0.01	2925	8.1	-81.5	< 0.01
	2017-2018	52.5			351	1.5		
Lampang	2014-2016	77.5	-31.3	< 0.01	2618	7.3	-39.7	< 0.01
	2017-2018	53.2			1066	4.4		
Lamphun	2014-2016	75.7	-21.7	< 0.01	1018	2.8	-14.3	0.22
	2017-2018	59.3			583	2.4		
Maehongson	2014-2016	83.4	-18.3	< 0.01	5924	16.4	-48.8	< 0.01
	2017-2018	68.2			2024	8.4		
Nan	2014-2016	75.3	-26.0	< 0.01	3882	10.8	-59.3	< 0.01
	2017-2018	55.7			1063	4.4		
Phayao	2014-2016	80.3	-29.7	< 0.01	1029	2.9	-75.9	< 0.01
	2017-2018	56.5			178	0.7		
Phrae	2014-2016	86.9	-28.8	< 0.01	1637	4.5	-53.3	< 0.01
	2017-2018	61.9			516	2.1		

Table 3.3 Age-standardized rate of hospital visits for respiratory and gastrointestinal diseases before and after burning ban implementation in the UNT, by province

Province	Total hospital visits for respiratory diseases (n)	Total hospital visits for gastrointestinal diseases (n)	Period	Respiratory diseases			Gastrointestinal diseases		
				Age-standardized rate (per 100,000 person-day	Change from pre-intervention	p-value	Age-standardized rate (per 100,000 person-day)	Change from pre-intervention	p-value
Chiangmai	595,724	43,833	2014-2016	116.0	-12.5	<0.01	60.0	8.8	0.284
			2017-2018	101.6			65.2		
Chiangrai	340,769	17,693	2015-2016	114.1	-11.9	<0.01	45.9	64.6	<0.01
			2017-2018	100.5			75.6		
Lampang	313,931	20,597	2014-2016	113.8	-6.5	0.12	63.3	28.6	<0.01
			2017-2018	106.4			81.4		
Lamphun	184,430	10,683	2014-2016	112.7	15.4	<0.01	65.2	42.3	<0.01
			2017-2018	130.0			92.7		
Maehongson	109,930	7,610	2014-2016	146.5	0.4	0.90	69.7	33.1	<0.01
			2017-2018	147.0			92.8		
Nan	199,258	8,890	2014-2016	50.5	0.3	0.94	64.2	20.0	<0.01
			2017-2018	50.6			77.0		
Phayao	311,244	14,032	2014-2016	154.3	-18.0	<0.01	106.7	5.7	0.284
			2017-2018	126.4			112.8		
Phrae	196,330	12,176	2014-2016	103.6	-18.8	<0.01	69.1	13.6	<0.05
			2017-2018	84.1			78.6		
Total	3,448,659	2,251,616	2014-2016	114.0	-4.7	<0.01	94.4	22.8	<0.01
			2017-2018	109.3			117.2		

The controlled ITS analysis revealed that the enforcement of the ban was associated with a decrease in hospital visits for respiratory diseases in all provinces except for Lampang province, after adjusting for potential confounders (Table 3.4). The effect estimates for respiratory diseases decreased in seven provinces (-1.2% (95% CI: -8.0, 6.2) to -15.7% (95% CI: -21.2, -9.8)). The pooled estimate of the effect of ban enforcement was -8.7% (95% CI: -12.9, -4.3) for respiratory diseases, whereas that for gastrointestinal diseases was 1.0% (95% CI: -2.1, 3.4). The test for heterogeneity of pooled effect estimates revealed I^2 values of 83.1% (P < 0.01) and 70.3% (P < 0.01) for respiratory diseases and gastrointestinal diseases, respectively.

Table 3.4. Effect estimates of the burning ban implementation on respiratory and gastrointestinal diseases in the UNT.

Province	% Change (95% CI)	
	Respiratory diseases	Gastrointestinal diseases
Chiangmai	-10.3 (-13.6, -6.9)	-2.4 (-10.0, 5.8)
Chiangrai	-1.2 (-8.0, 6.2)	-3.5 (-26.9, 19.8)
Lampang	4.4 (-2.2, 11.5)	-8.2 (-2.8, 19.2)
Lamphun	-11.7 (-16.0, -7.3)	-3.5 (-6.3, 13.3)
Maehongson	-15.7 (-21.2, -9.8)	-1.1(-8.5, 6.4)
Nan	-10.0 (-14.7, 4.9)	0.2 (-5.5, 5.9)
Phayao	-8.8 (-12.8, -4.5)	-0.7 (-5.8, 7.2)
Phrae	-13.6 (-18.9, -7.9)	0.9 (-5.2, 7.0)
UNT*	-8.7 (-12.9, -4.3)[a]	1.0 (-2.1, 3.4)[b]

* Pooled effect by meta-analysis

[a]Test for heterogeneity: I^2 = 83.1%, df = 7 (P <0.01)

[b]Test for heterogeneity: I^2 = 70.3%, df = 7 (P <0.01)

The sensitivity analyses using 2015 and 2017 as cut-point years revealed that the decreases in rates of hospital visits for respiratory diseases disappeared with changing cut-point years earlier (2015) from the original cut-point (Table 3.5). However, small increases in the rates of hospital visits for respiratory diseases were observed for the 2017 cut-point year.

Table 3.5. Sensitivity analyses by adjusting the cut-point year of the ban.

Province	Change of respiratory diseases (Percentage (%) with 95 CI)		
	2014-2015 vs. 2016-2018	2014-2016 vs. 2017-2018	2014-2017 vs. 2018
Chiangmai	15.6 (11.6, 19.9)	-10.3 (-13.6, -6.9)	-4.4 (-7.4, -1.4)
Chiangrai	7.2 (3.3, 11.2)	-1.2 (-8.0, 6.2)	0.9 (-2.7, 4.7)
Lamphun	31.7 (23.9, 39.9)	4.4 (-2.2, 11.5)	-18.2 (-21.9, -14.3)
Lampang	5.6 (0.6, 10.8)	-11.7 (-16.0, -7.3)	7.4 (3.5, 11.4)
Meahongson	-3.4, (-8.0, 1.5)	-15.7 (-21.2, -9.8)	-1.2 (-5.6, 3.4)
Nan	1.1 (-3.9, -8.1)	-10.0 (-14.7, 4.9)	6.0 (2.0, 10.1)
Phayao	4.0 (-0.7, 8.9)	-8.8 (-12.8, -4.5)	2.2 (1.6, 2.5)
Phrae	24.9 (18.7, 31.4)	-13.6 (-18.9, -7.9)	2.8 (-1.9, 7.9)
UNT	11.2 (4.4, 18.6)	-8.7 (-12.9, -4.3)	1.2 (-6.2, 9.2)

3.3 Discussion

This study found that the burning ban policy in 2016 led to reduce in both average PM_{10} concentration and number of fire hotspot counts during burning periods in all provinces of UNT ranging from 5%-34% and 14%-81% respectively. the enforcement of the ban was associated with a decrease in the rate of hospital visits for respiratory diseases (-8.7% (95% CI: -12.9, -4.3)). On the other hand, the rate of hospital visits for gastrointestinal diseases increased, albeit non-significantly, by 1.0% (95%CI: -2.1, 3.4)) during the same period.

The decline of PM_{10} concentration and fire hotspot in this study were consistent with the previous study (Yabueng et al., 2020). In addition, I found the constant trend of PM_{10} concentration during non-burning periods. Thus, suggesting that the burning ban is effective in reducing PM_{10} from vegetation fire events.

In the controlled ITS analyses, the meta-analysis results revealed the reduction of the hospital visits rates for respiratory diseases for entire the UNT. As a potential factor, decreased PM_{10} concentrations due to ban enforcement across the region might have led to a reduced prevalence of respiratory diseases. The decrease of respiratory visits might be attributable to the burning ban when burning activities was prohibited (decrease of fire hotspot counts) and the level of PM_{10} concentration consequently decreased after the ban enforcement in 2016. The heterogeneity of the pooled effect estimates was high, possibly due to differences in settings (e.g., urban, rural, mixed area) and the rigidity of the policy enforcement by each province. Indeed, I found a non-significant increase of hospital visits in Lampang province after burning ban enforcement contrast to the rest of the provinces. This might be due to the variability in law enforcement among the provinces as I observed a smaller decline of daily fire hotspot and PM_{10} concentration after burning ban enforcement in 2016 in Lampang.

Second factor is that the secular change might have led to reduce the rates of hospital visits for respiratory diseases as Thailand has been facing low birth rates for several decades, and a decline in birth rates was also noted across UNT during the study period. However, age-standardized rates of hospital visits for gastrointestinal diseases showed an increasing trend in all provinces in UNT. In 2002, Thailand implemented the universal health coverage (UHC) insurance, which supported financial assessment for medical services (Tangcharoensathien et al., 2018). The UHC also extended beneficial services to hard-to-reach areas in 2014 (Tangcharoensathien et al., 2018). Moreover, the UHC reportedly increased the rate of outpatient visits by 13% (Ghislandi et al., 2014). This may explain the increase in hospital visits for gastrointestinal diseases across UNT, but not for respiratory diseases.

Different cut-point year of implementation was adopted in the sensitivity analyses. I found that no reduction in the rate of hospital visits for respiratory diseases when the cut-point was moved to earlier years. However, the effect was slightly increased when the cut-point year was changed to 2017 (2014-2017 vs. 2018). The strict penalties imposed for violations may not be sustained after enforcement in the later years. In order to overcome haze/smoke crises, not only regulation measures but also other preventive mechanisms will be needed to reduce burning practices, such as educating and providing information to villagers regarding the health effects of haze exposure, facilitating land allocation to optimize use for different purposes, and encouraging and supporting modern farming methods (Moran et al., 2019; Quah and Johnston, 2001).

Strengths

There were several strengths of this study. First, this study is initiate applying an interrupted time series as a powerful quasi-experimental design for revealing the effect of burning control measures and morbidity, which might be useful for evaluating the policy implementation. Second, this study is performed multi-city of controlled ITS to clarify the effect of burning control measures on morbidity. Another strength is that data on gastrointestinal diseases, which are unrelated to air pollution, were included in the analyses as a negative control, and comparisons with respiratory diseases were performed using the same model. This allowed us to control for the same potential confounders that affect both respiratory and gastrointestinal diseases in the area (e.g., health care education, health insurance system).

Limitations

There were potential limitations of this study. First, I compared PM_{10} concentrations before and after ban enforcement by using the average from few stations in the area. Increased PM concentrations may not only be due to emissions from burning activities, as PM can also be released from other sources such as traffic. However, a previous study found vegetation fire events to be the dominant source of PM during the year 2012-2018 (Yabueng et al., 2020).

Second, I did not control for the effect of other environmental policies which could have impacted PM concentrations and affected the hospital visits for respiratory diseases in UNT. Third, I did not perform external validation in this study. According to Cochrane Effective Practice and Organization of Care Review Group (Cochrane EPOC), eligible control sites should be comparable to the implementation affected areas (EPOC, 2008). A previous accountability study compared the effect of vehicle-related air pollution on health outcomes between regulation-affected and non-regulation-affected populations by selecting similar urbanization areas (Yorifuji et al., 2016). However, there was no appropriate reference population for our study, because vegetation fires in UNT uniquely affect forest areas in the mountainous landscape. Moreover, the particular topography of UNT may account for high PM_{10} concentrations during the burning season compared to 'flat' areas, such as Bangkok Metropolitan Region (Narita et al., 2019).

3.4 Conclusion

Implementation of the burning ban to control vegetation fire events in UNT led to a decrease in PM_{10} concentrations and the number of satellite fire hotpots in the area. After adjusting for several confounders, a reduction in the rate of hospital visits for respiratory diseases was observed across UNT, which could be attributed to the effect of the burning ban.

CHAPTER 4: Study III (Estimation of hospital visits for respiratory diseases attributable to vegetation fire smoke-PM_{10} and health impacts from regulatory intervention of a vegetation fire event ban in Upper Northern Thailand)

In the *Study I and II*, I examined the health effects from exposure to VFS-PM_{10}. The results revealed that short-term exposure to PM_{10} on the burning day is associated with hospital visits for respiratory diseases. *Study II* further evaluated the effect of the smoke haze control using regulatory measures in 2016, and I found the beneficial effect of the ban on both PM_{10} concentration and hospital visits for respiratory diseases.

In this chapter, I estimated the number of hospital visits for respiratory diseases attributable to VFS for all-age and children groups during 2014 to 2018. This study also compared the estimates cases before and after the burning ban implementation.

4.1 Methodology

Studying the HBE from VFS need several inputs for calculation. In this study, I estimated the number of respiratory disease-related hospital visits attributable to VFS-PM_{10} in eight provinces in UNT (same as *Study I* and *II*). I used the population weighted VFS-PM_{10}, population data, and concentration-response function derived from *Study I*. The inputs and data sources used for each step is presented in Figure 4.1.

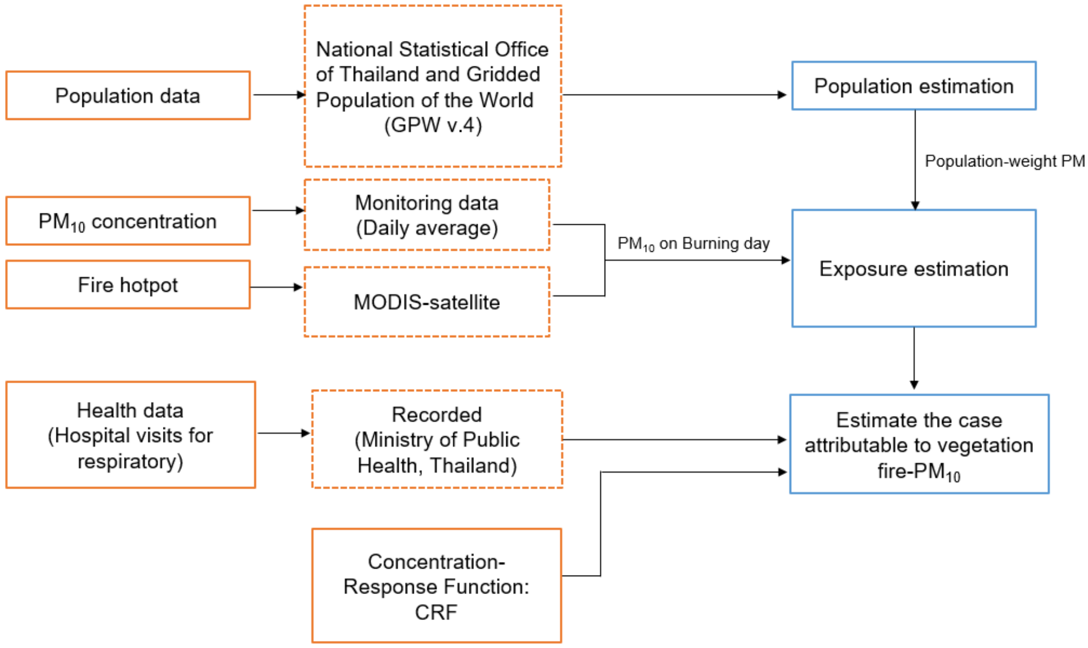

Figure 4.1 Overview of HBE process used in this study

4.1.1 Exposure estimation

Daily average PM_{10} concentrations were obtained from 14 monitoring stations provided by the Pollution Control Department Thailand. Data of VFS-PM_{10} concentrations were used to conduct the analyses after performing population weighted and classifying the burning days. First, I calculated population weighted PM_{10} concentration for more refined exposure estimation as,

$$\text{Population weighted } PM_{10} = \sum \frac{C_i \times P_i}{P_{tot}}$$

where C_i is the PM_{10} concentration and P_i is the population of district i (in each province), and P_{tot} is the total population of each province (Chapter 3 (Table 3.1)). The population data of each district was retrieved from Gridded Population of the World, version 4 (GPW v.4) (Center for International Earth Science Information Network and NASA Socioeconomic Data and Applications Center, 2016).

Next, population weighted VFS-PM_{10} concentrations were obtained after classifying the burning occurrence day which was applied the method from the *Study I* in each province.

4.1.2 Concentration-Response Function and morbidity impact assessment

In this study, I focused on the health impact of short-term exposure to VFS-PM_{10} on respiratory outcomes. I followed the methodology in the previous studies (Kollanus et al., 2017). First, risk of hospital visits for respiratory diseases caused by VFS-PM_{10} in each province and day of year was calculated as

$$RR = exp\ (\beta \times (\text{pop-weighted VFS-PM}_{10}))$$

where RR is the relative risk of daily averaged concentration of population weighted VFS-PM_{10} on burning day for each province. The coefficient β was derived from Study *I*. Specifically, we estimated the odd ratio of hospital visits for respiratory diseases as 1.009 (95% CI: 1.001 to 1.016) per 10 μg/m^3 in VFS-PM_{10}, which approximate to relative risk per unit increase. Therefore, β is calculated as $\ln(1.009)$ per 10 μg/m^3 in VFS-PM_{10}.

Next, the population attributable fraction (PAF) of hospital visits for respiratory diseases attributable to VFS-PM_{10}, was calculated for each province and day as

$$PAF = (RR - 1)/\ RR$$

Last, the number of daily respiratory visits attributable to the VFS-PM_{10} in each province and day was calculated as

$$Number\ of\ attributable\ cases = HV\ \times PAF$$

where HV is the daily number of hospital visits for respiratory diseases for total ages and children under age 15 years, which was derived from Ministry of Public Health Thailand for 2014-2018 of eights provinces in UNT. Finally, the number of attributable cases were summed over all days of the year and regional-or provincial-specific boundaries.

4.1.3 Sensitivity analyses

The sensitivity analyses were performed to address the uncertainty from several sources of the inputs in the HBE process. In the principal analysis, I used CFR from the *Study I*, which was the risk function of the children group. Then, the risk function from the previous studies were applied to estimate the attributable cases same as the principal analyses (Muller et al., 2020; Pothirat et al., 2016). I also tested the sensitivity analysis by changing the cut-point to determine the burning occurrence day using PM_{10} concentration from 100 μg/m^3 to 50 μg/m^3 (WHO guideline for daily PM_{10} concentration).

4.2 Results

Daily average of population weighted VFS-PM_{10} concentration ranged from 120.9 to 149.2 μg/m^3 across the region (mean = 133.5 μg/m^3) and the number of the burning ranged from 64 to 139 days (Figure 4.2). The average of VFS-PM_{10} and the number of burning days in each year are presented in Table 4.1.

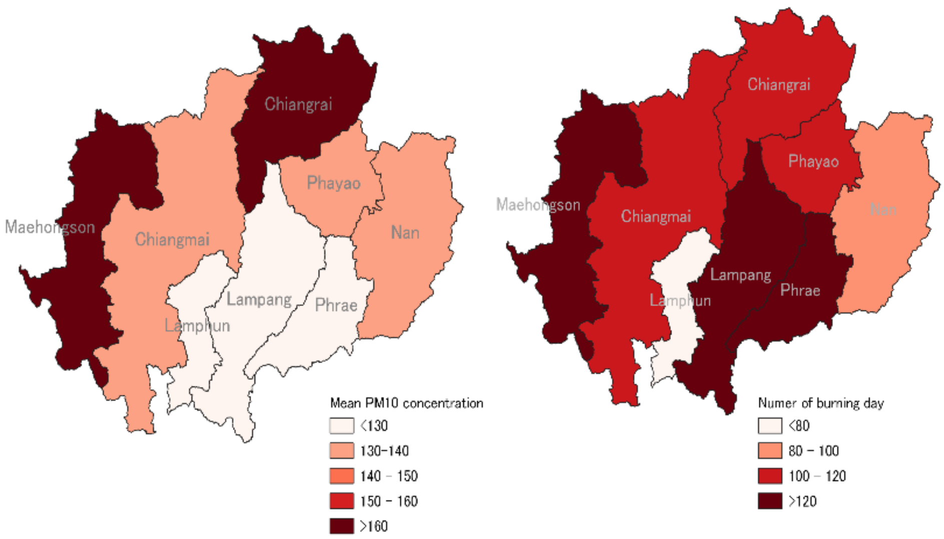

Figure 4.2. Mean of VFS-PM_{10} concentration (µg/m^3) and total number of burning days during 2014 to 2018 by province.

The estimate for cases of hospital visits for respiratory diseases attributable to VFS-PM_{10} for total ages and children groups throughout the study period were 75,380 and 34,399 cases, respectively (Table 4.1). The estimation of total attributable cases accounted for approximately 1% of the total hospital visits for respiratory diseases of five years and 12% during the burning days. Number of attributable cases in each province for total age and children by province-year is shown in Figure 4.3 and 4.4. The attributable cases of both total ages and children decreased after the burning ban was implemented in 2016, from 64,061 to 11,319 and 29,553 to 4,845 cases, respectively. The estimated cases of each province and year are presented in Table C-1.

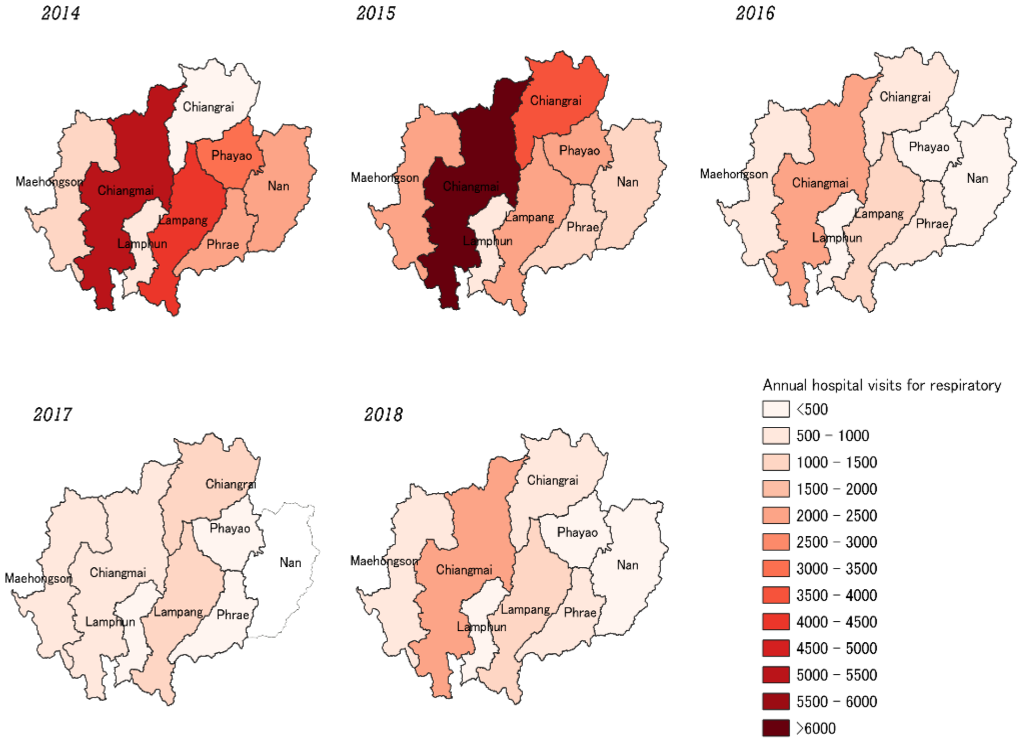

Figure 4.3. The estimation of each annual total cases of hospital visits due to respiratory diseases attributable to VFS-PM_{10} during 2014 to 2018.

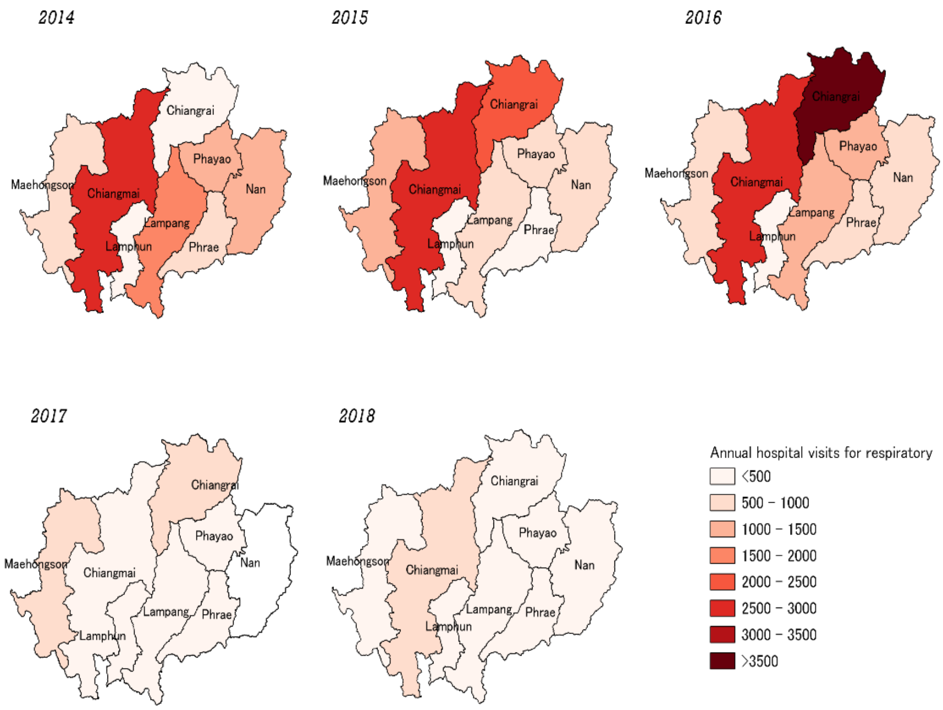

Figure 4.4 The estimation of each annual children cases of hospital visits due to respiratory diseases attributable to VFS-PM_{10} during 2014 to 2018.

Table 4.2 presents the results of the sensitivity analyses. The proportion of the estimated cases by applying CFR derived from previous studies were higher 4.3 times (Pothirat et al. 2016) and 2.1 times (Muller et al. 2020) compared to the principal analysis. Moreover, the attributable cases after changing the cut-point year by using the value from WHO guideline was also higher than using cut-point from the *Study I*. Number of the cases attributable to VFS-PM10 for the sensitivity analyses are presented in Table C-2.

Table 4.1. Summary of number of burning days, daily average VFS-PM_{10} concentration, and cases of hospital visits due to respiratory diseases attributable to VFS-PM_{10}.

Year	Number of burning days[a]	VFS-PM_{10}($\mu g/m^3$)		Annual case of respiratory visits			
		Average VFS-PM_{10}	Population weighted VFS-PM_{10}	Total	Children	% attributable[b]	
						Whole period	Burning day
2014-2018	863[a]	141.5	133.5	75,380 (11,062-132,744)	34,399 (5,052-60,529)	0.7	11.6
2014	244	143.5	140.5	19,842 (2,906-35,005)	8,720 (1,277-15,381)	1.2	11.4
2015	197	150.3	151.4	20,586 (3,049-35,936)	9,452 (1,401-16,486)	1.0	13.0
2016	259	144.1	137.7	23,633 (3,463-41,673)	11,381 (1,670-20,041)	1.0	11.4
2017	78	136.6	122.2	5,222 (759-9,282)	2,302 (334-4,093)	0.2	10.1
2018	85	132.9	121.0	6,097 (885-10,848)	2,543 (369-4,528)	0.3	9.8

[a]Total number of the days among eight provinces for 2014 to 2018 was 14,600 days

[b]Percentage of attributable cases were calculated from the total cases throughout study period (10,161,191 cases) and the burning days (651,121 cases)

Table 4.2. Results of sensitivity analyses.

Source of uncertainty	Case estimate proportion (75,380 cases)	Reference
Concentration response function		
1.01 (1.00, 1.02)*	1	Uttajug et al., 2020 (*Study I*)
1.05 (1.02, 1.09)	4.3	Pothirat et al., 2016
1.02 (1.01, 1.03)	2.1	Muller et al., 2020
Cut-off of PM_{10} concentration		
100 µg/m^3*	1	Uttajug et al., 2020 (*Study I*)
50 µg/m^3	2.1	WHO guideline

* Data used in the principal analysis

4.3 Discussion

The population-weighted daily average VFS-PM_{10} concentration across UNT for 2014 to 2018 were 133.5 µg/m^3 (ranged from 121.0 to 140.5 µg/m^3). In general, the distribution of VFS-PM_{10} concentrations were lower after the burning ban policy implementation in year 2016.

Although air pollution from vegetation fire events has more concerned, their far-reaching health effects are often ignored. This study suggests that exposure to particles emitted from vegetation fire events can poses the health effects of respiratory morbidity throughout UNT, with approximately 75,000 cases of all ages and the half were accounted for children group. Number of the attributable cases of respiratory visits decreased after the burning ban enforcement.

There are few studies conducted health impacts from exposure to air pollution from vegetation fire events, particularly on morbidity. Previously published HBE studies have mainly addressed mortality globally or Equatorial Asia (Johnston et al., 2012; Kiely et al., 2020; Kollanus et al., 2017; Koplitz et al., 2016; Marlier et al., 2019, 2013; Uda et al., 2019).

Some studies used morbidity as a health outcome such as hospitalization for cardiovascular and asthma in Australia (Borchers-Arriagada et al., 2020) and respiratory diseases in the United States (Fann et al., 2019). However, no study estimated the morbidity impacts from short-term exposure to particles emitted from vegetation fire events in MSEA, particularly in Thailand. Only the impact of long-term exposure to particles from all sources was conducted in Thailand (Mueller et al., 2020). As it was mentioned in Chapter I that most of HBE studies were conducted in the Equation Asia, health burden attributable to VFS-PM_{10} is needed in MSEA because the impacts may vary due to the difference in other environmental factors, pollution-temperature conditions, population-age distributions, background health conditions, socioeconomic statuses, and health-care systems.

There were uncertainties involved in the analyses. The validity of HBE is dependent on CRF used in risk assessment. Since there was no risk estimation for respiratory morbidity from exposure to VFS-PM_{10}, I used the OR from *Study I* as an approximation of RR and estimated the PAF and the number of hospital visits for respiratory diseases attributable to VFS-PM_{10} for all-age group. However, the estimates cases might be overestimated because the estimates risk was obtained from children who are more susceptible to exposure to VFS.

After applying the RR from other epidemiological studies, I observed greater estimates cases than the principal results. The reason is that this RRs were obtained from different exposure assessment methods. RR from Pothirat et al. (2016) was obtained from ambient PM data which was not specific to VFS source while Muller et al. (2020) used the 90^{th} and 95^{th} percentiles of PM_{10} concentrations to determine days of exposure to PM predominantly from vegetation burning. Moreover, RRs from the previous studies were derived from using more specific respiratory diseases which may lead to different effect estimates (e.g., chronic lower respiratory diseases (Muller et al., 2020) and chronic obstructive pulmonary diseases (Pothirat et al., 2016)).

Another source of uncertainty was the cutoff level above which the risk of hospital visits increases. The concentration of daily PM_{10} level was guided not to be exceeded 50 μg/m^3 by WHO. However, the guideline was set based on ambient air particles. In this study as considering the effects from VFS, I assumed that hospital visits for respiratory diseases increase when PM_{10} concentration exceeds 100 μg/m^3, the cut-off level of fire-related particles in UNT based on *Study I*.

Quantifying the health burden associated with exposure to air pollution emitted from vegetation burning may be useful for policy-making. In this study, I also observed a decline of attributable cases after the year 2016, when the strict burning ban was implemented. The results are consistent with the *Study II*, which found a decrease the prevalence of respiratory morbidity after the ban implementation in UNT. However, in order to minimize the health effects from exposure to VFS, not only the regulatory measures, but also other sustained measures will be needed to cope the smoke haze emission as mention in the discussion part of *Study II*.

4.4 Conclusion

This study suggests that PM_{10} emitted from vegetation fire events poses impacts on hospital visit for respiratory diseases across the UNT, with total estimates of approximately 75,000 cases. Number of hospital visits for respiratory decreased after a prohibited of vegetation fire events has implemented in year 2016. Adverse effects of VFS air pollution on overall health outcomes should be taken into consideration in the future when worsen air pollution from vegetation fire events are growing concern from climate change with increasing of population.

CHAPTER 5: CONCLUSION

Overall summary

From the finding of this thesis, vegetation fire events are an important contributor of PM_{10}, which increased respiratory morbidity in UNT. Exposure to PM_{10} during the burning days was associated with increased hospital visits due to respiratory diseases among children. This thesis also found that the policy of burning ban reduced both PM_{10} concentration and the prevalence of respiratory morbidity in UNT. Importantly, the estimated cases of respiratory visits attributable to PM_{10} emitted from vegetation fire events were accounted 1% of the total cases throughout five-years (2014 to 2018) and 12% during the burning days.

Implications of findings

Study I

- The findings support the causal link between PM_{10} during burning days and hospital visits for respiratory diseases for children. The effect estimates of hospital visits for respiratory diseases from exposure to PM_{10} on burning days is applicable to build the risk function for HBE study estimating the health burden caused by vegetation fire in this area. However, it is important for other areas' study to use this risk function with considering about the characteristic of the health outcomes and the different components of the PM emitted from different burning sources.

Study II

- I presented that the implementation of burning ban reduced the hospital visits for respiratory diseases and quantified the extent of its health effect. This would be beneficial for future implementation of burning ban in other areas of Asia. A prohibition of burning with strict regulatory measures is one effective measure that can minimize health effects from VFS. However, this measure may not be sustainable because it is difficult to observe the real-time burning events and need more manpower to observe the violations in the vast areas. In order to overcome VFS in this area, high participation of people living in both urban and rural area will be needed to reduce burning activities with other smoke haze control measures such as converting the method of agricultural debris disposal from conventional burning to modern method.

Study III

- I quantified the number of hospital visits from respiratory diseases during the study area using the frame of HBE. I also explored the sources and the extent of uncertainty in the estimates. The finding from this study can be further used to evaluate costs-benefits of the policy on haze control with careful consideration of the uncertainties of the results.

CHAPTER 6: FUTURE STUDIES

➢ *To investigate health effects of other air pollutants from vegetation fire events*

Vegetation fire events is an important contributor of particle air pollutants, and toxic gaseous. PM is the principal pollutants of concern from exposure to VFS. Other pollutants of concern during smoke events are carbon monoxide (CO), ozone (O_3), and formaldehyde. Exposure to CO can lead to more severe symptom by the people who have heart diseases while other gaseous can pose respiratory irritants or potentially exacerbate asthma. Moreover, toxic recondensed organic vapors are also emitted from vegetation fire events such as PAHs. Most of the studies of PAHs focused on benzo[a] pyrene (B[a]P) which is a physiologically active substance that can contribute to the development of cancer in humans. However, the study of health effects from exposure to other gaseous and chemicals emitted from VFS is still limited in SEA. Investigating health effects of the other air pollutants from vegetation fire events may be useful for the future HBE study.

➢ *To investigate health effects of air pollution from vegetation fire events by considering the burning duration, intensity, and phases.*

Indeed, exposure to air pollution from catastrophic haze from intensive burning is continuous over time (e.g., some extreme burning events emitted smoke from few days to weeks). Furthermore, burning phases (smoldering and flaming) significantly release different level of PM concentration and its components. Considering duration (number of consecutive days of burning day), intensity (level of air pollution concentration), and burning phase is challenge for the study examined health effects from exposure to VFS. These may provide insightful information for future policy decisions on smoke haze.

➢ *To differentiate health effects of local and transboundary air pollution from vegetation* *fire events*

In response to regional haze smoke, health effects from both local and transboundary of VFS is needed for seeking appropriate control measures to minimize the impacts. Thus. differentiating the health effects from local and transboundary sources of air pollution should be performed in the further study. In local scale, most of the previous studies used only PM concentration exposure assessment of VFS. However, these finding might not be clearly elucidated the actual sources of VFS which may be difficult for haze management in the policy circumstance. In this study, I examined health effects from air pollution emitted from VFS by utilizing PM concentration with the information of fire hotspot (representing the burning in the study area). For transboundary-VFS, the information such as fire hotpots and wind direction may be helpful for exposure assessment of the future study.

- *To predict health impacts of exposure to air pollution from vegetation fire events-driven by a climate change*

Up to date, few studies have estimated future health impacts attributable to VFS due to climate change, despite several evidence have been linked climate change and higher intensive vegetation burning in the future (Calheiros et al., 2021; Flannigan et al., 2009). Additionally, further studies are needed to investigate effective measures for reducing population exposure in the future such as land management practices, housing-air filters, and clean air-shelter.

- *To estimate health costs from vegetation fire smoke*

As health impact of air pollution from VFS may carry many significant financial and economic implications in term of the hospital and public budgets and also included for the society cost of mortality and morbidity. Thus, the further studies from health impact assessment are required to evaluate the economic burden arising from adverse health effects of VFS in order to obtain adequate consideration in policy decision process.

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APPENDIX

The Appendices used to depict the supporting information in addition to what have been inserted in the main chapter.

Appendix A: Providing the additional information for Chapter 2

Appendix B: Providing the additional information for Chapter 3

Appendix C: Providing the additional information for Chapter 4

Appendix A

This section provides the additional information of Chapter 2 (*study 1*).

Table A-1 Comparison of fire hotspot of this study and GISTDA during 2014 -2018

Province	Number of fire hotspot			
	This study	GISTDA*	% comparison	difference
Chaingmai	8,082	8,144	99.2	-0.8
Chaingrai	3,789	3,665	103.4	3.4
Lamphun	1,660	1,653	100.4	0.4
Lampang	3,800	3,775	100.7	0.7
Mae Hong Son	8,058	8,260	97.6	-2.4
Nan	5,210	5,313	98.1	-1.9
Phrae	2,404	2,333	103.0	3.0
Phayao	1,374	1,308	105.0	5.0
Total	34,377	34,451	99.8	-0.2

*Geo-Information and Space Technology Development Agency, Thailand

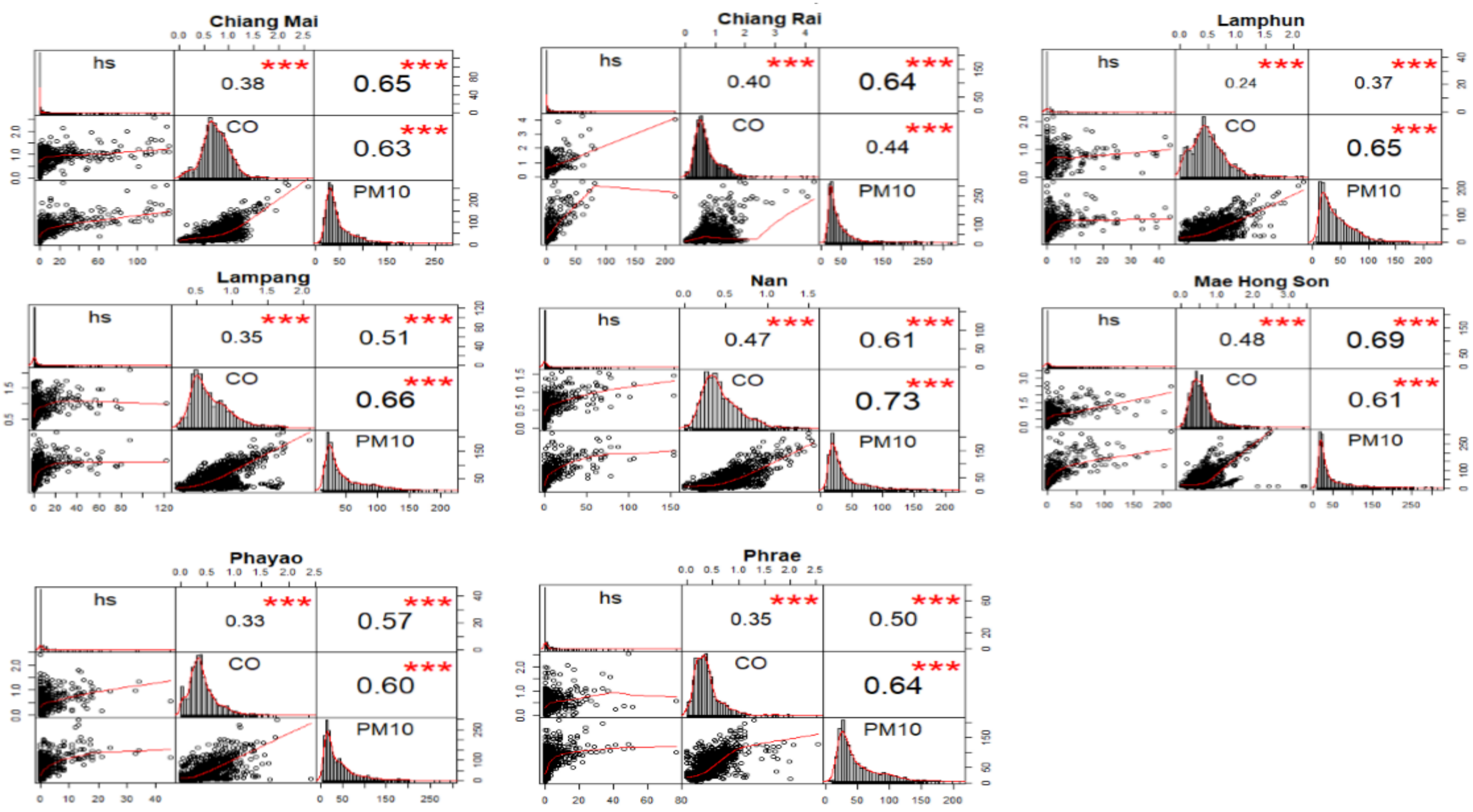

Figure A-1. Correlation of PM_{10}, Carbon monoxide, and fire hotspot of the eight provinces in UNT.

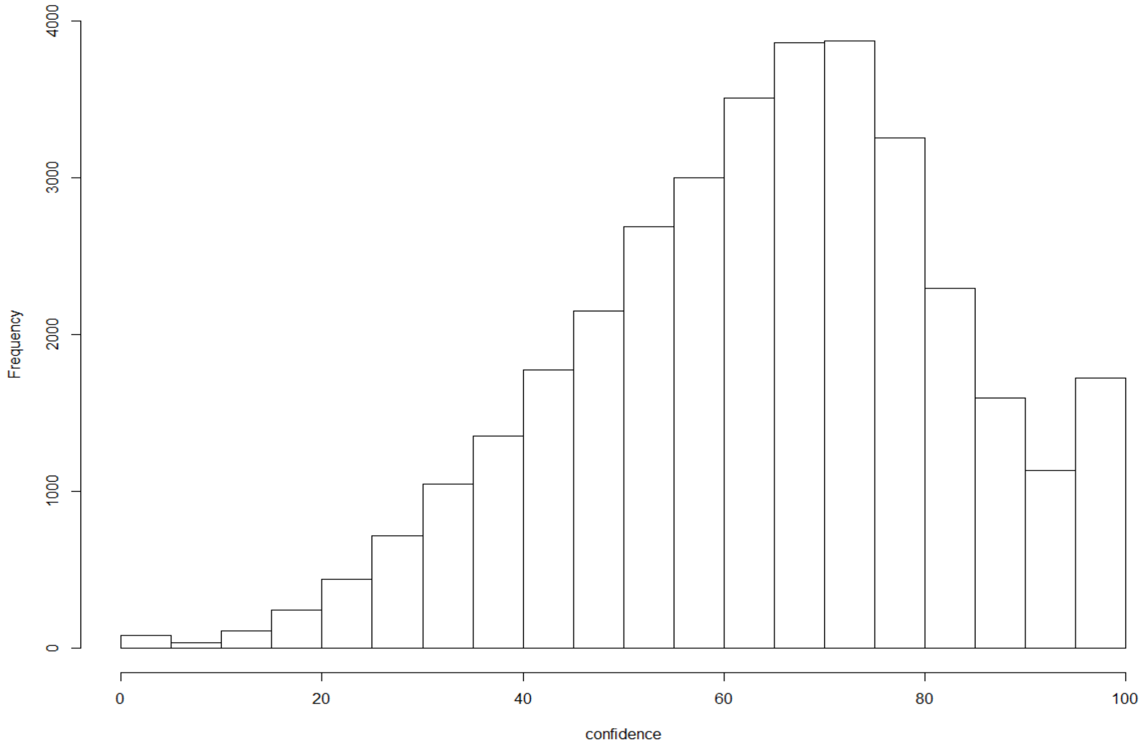

Figure A-2. Distribution of the confidence of fire hotpot.

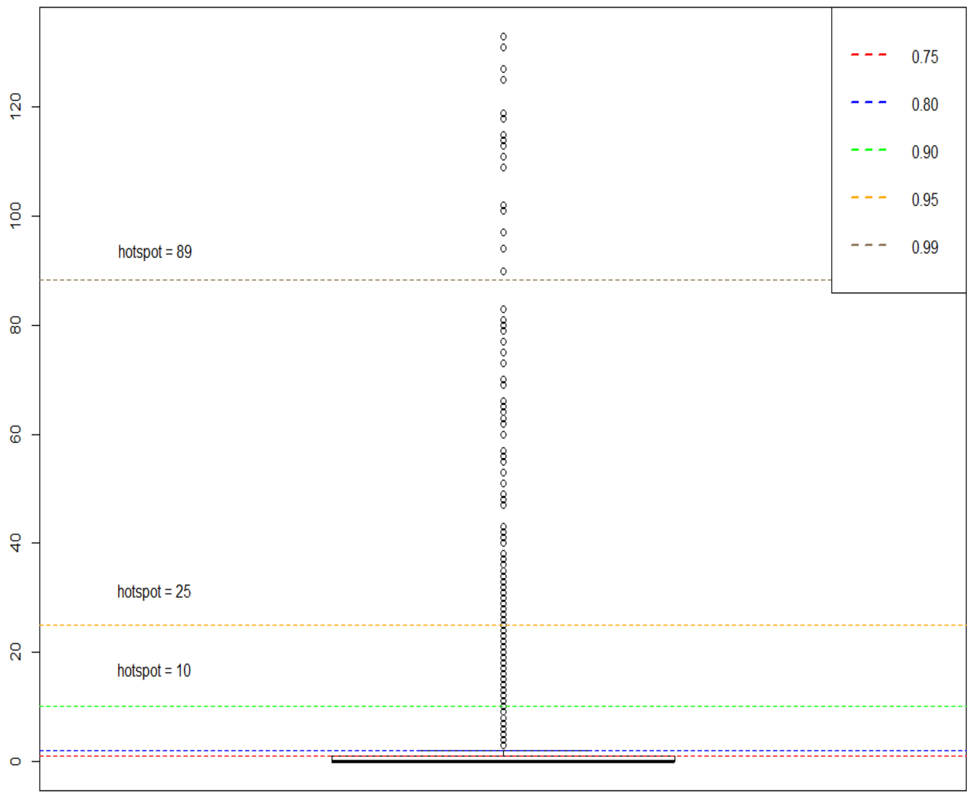

Figure A-3. Boxplot of the percentiles of fire hotspot.

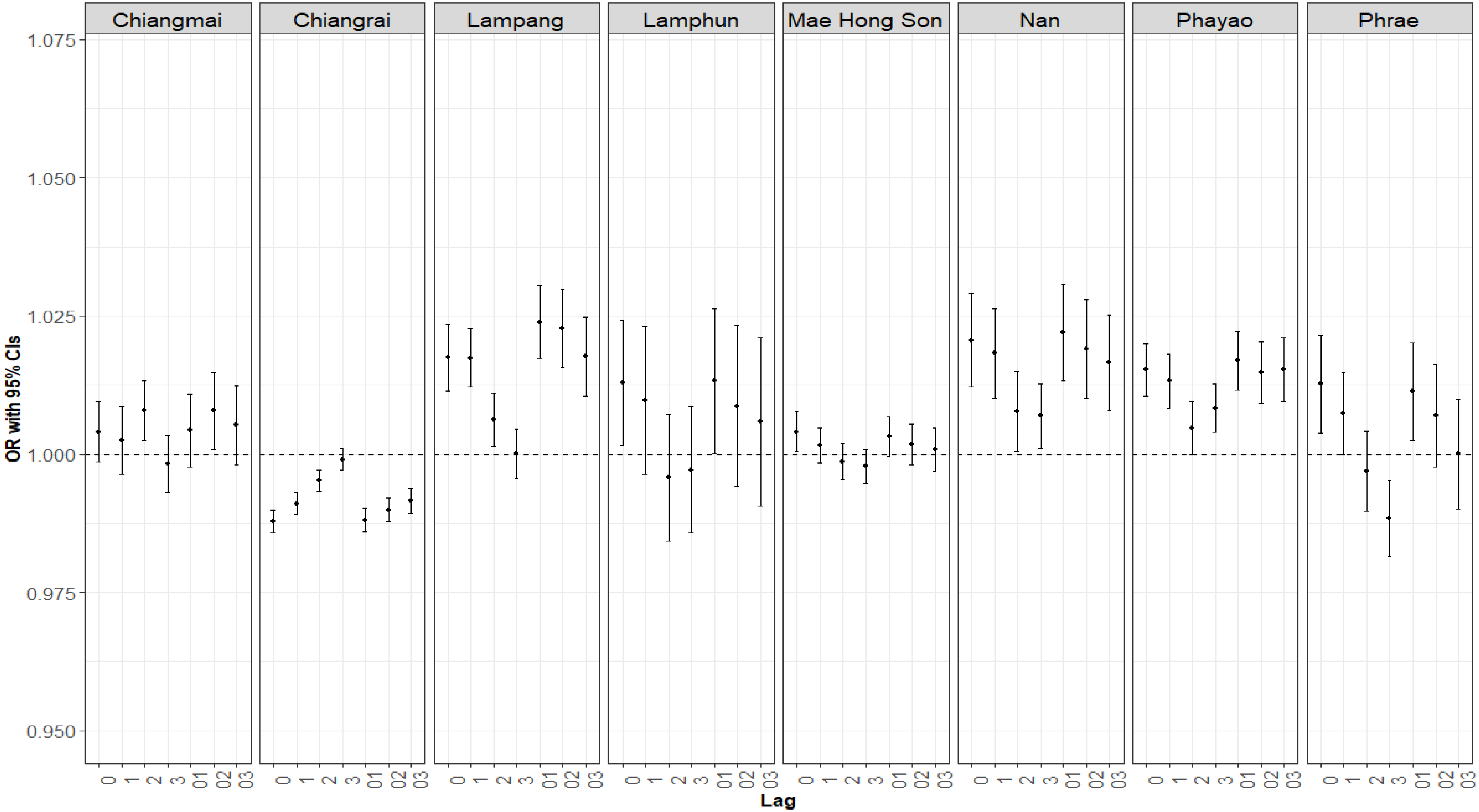

Figure A-4. Odds ratio of hospital visits for respiratory diseases as associated with a 10 μg/m^3 increase in PM_{10} concentration on burning days for single and average lag models.

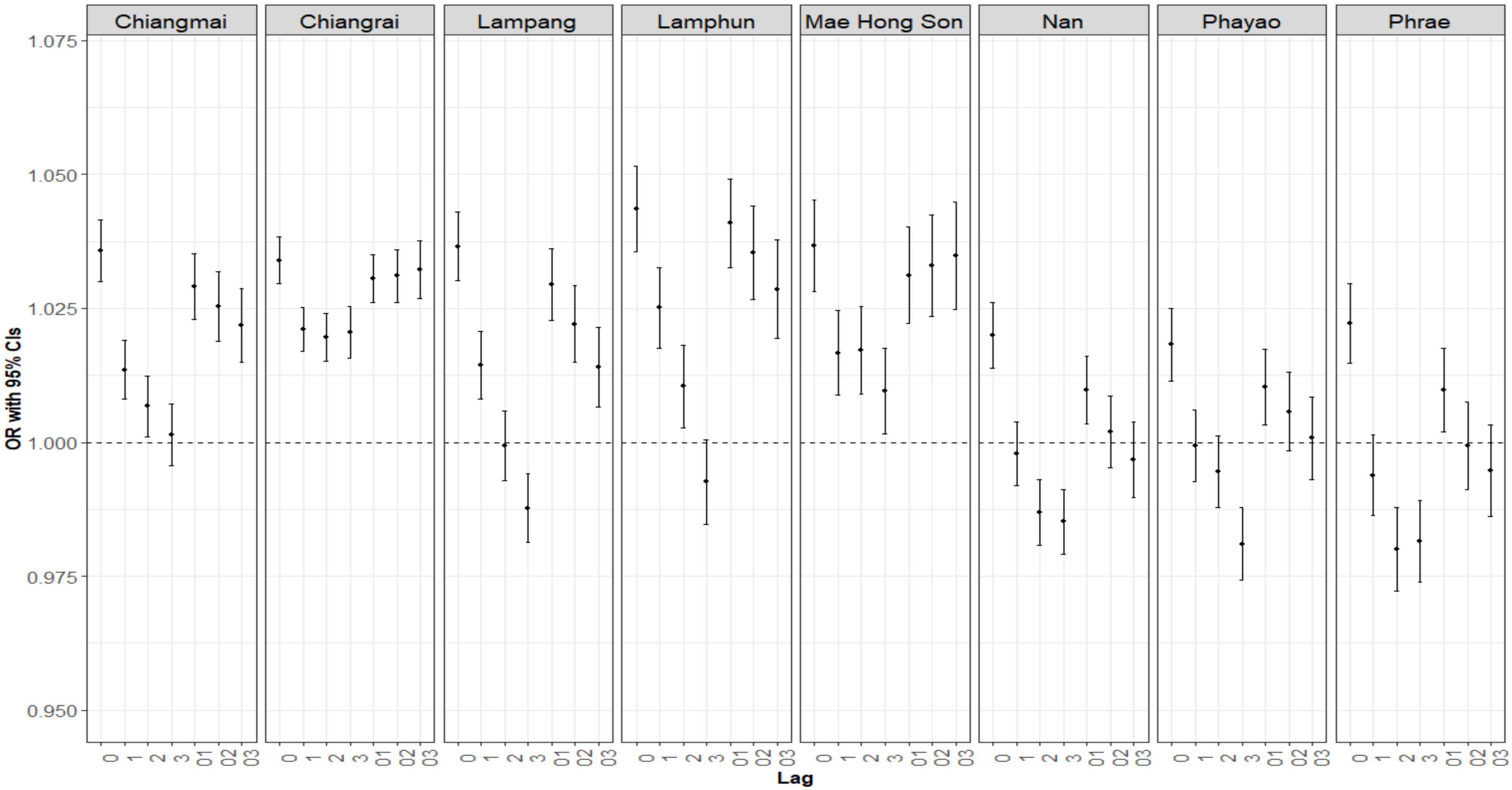

Figure A-5. Odds ratio of hospital visits for respiratory diseases as associated with a 10 μg/m^3 increase in PM_{10} concentration on non-burning days for single and average lag models.

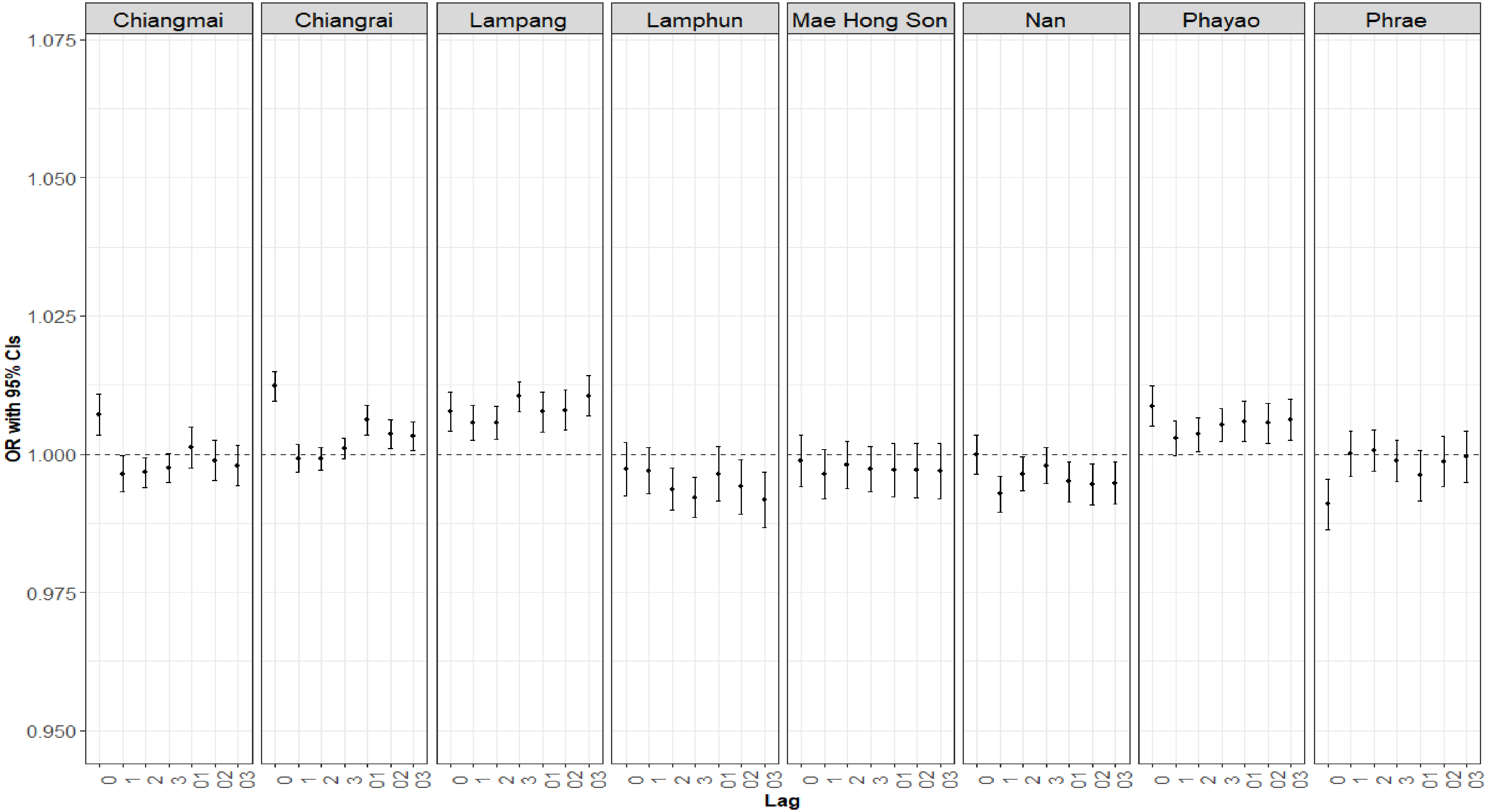

Figure A-6. Odds ratio of hospital visits for respiratory diseases as associated with a 10 μg/m^3 increase in PM_{10} concentration on mixed days for single and average lag models.

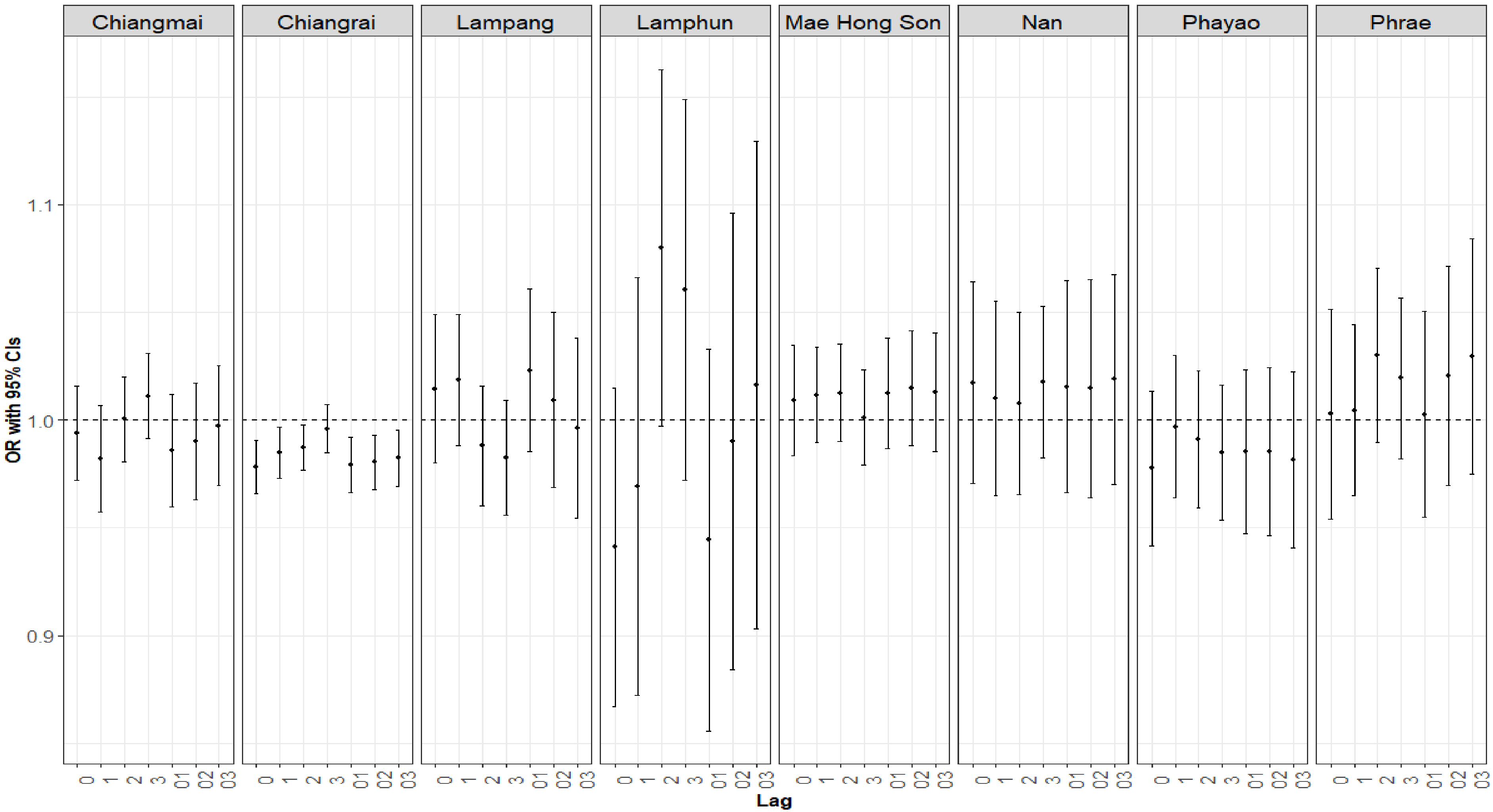

Figure A-7. Odds ratio of hospital visits for conjunctivitis as associated with a 10 μg/m^3 increase in PM_{10} concentration on burning days for single and average lag models.

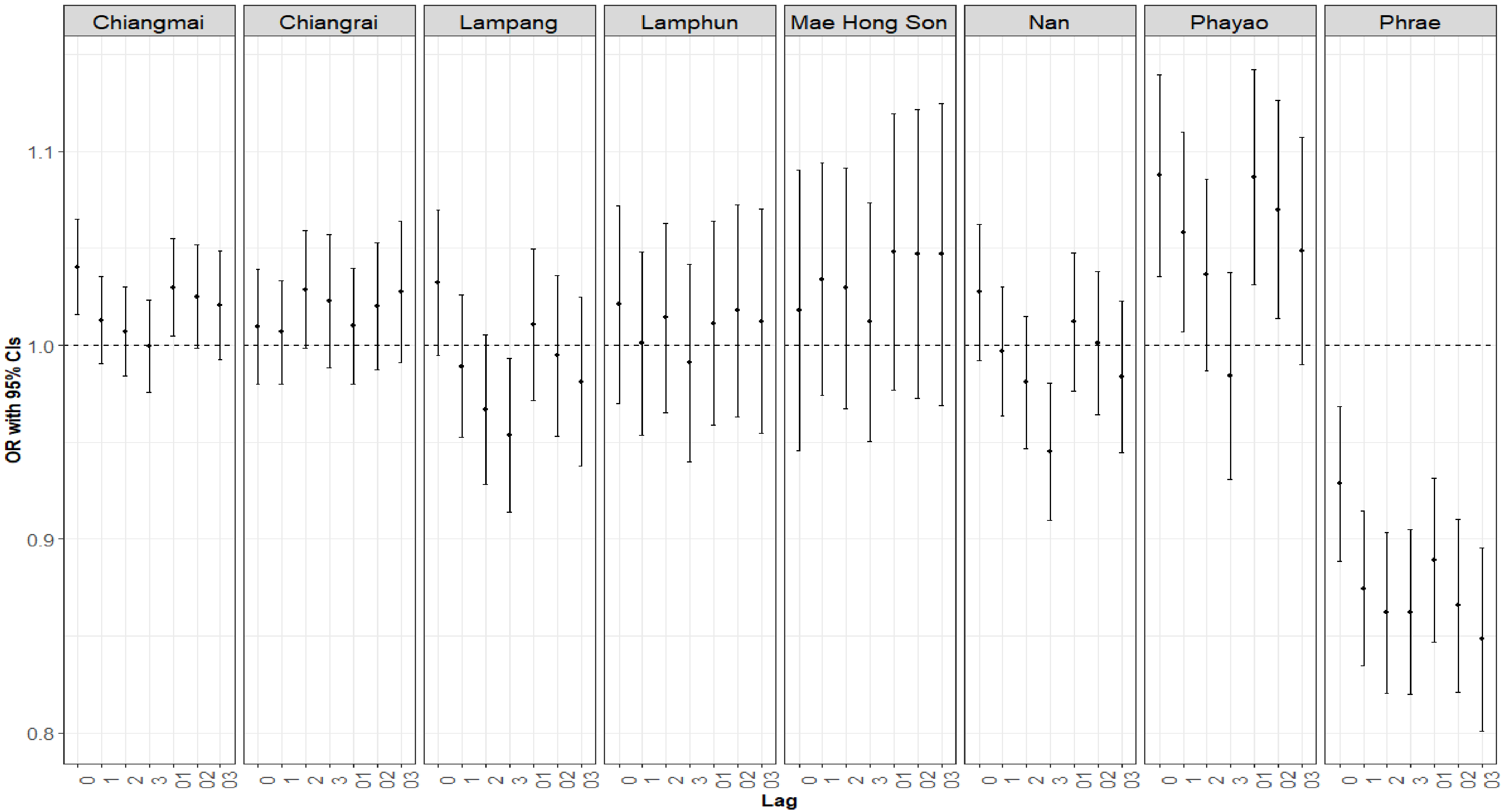

Figure A-8. Odds ratio of hospital visits for conjunctivitis as associated with a 10 μg/m^3 increase in PM_{10} concentration on non-burning days for single and average lag models.

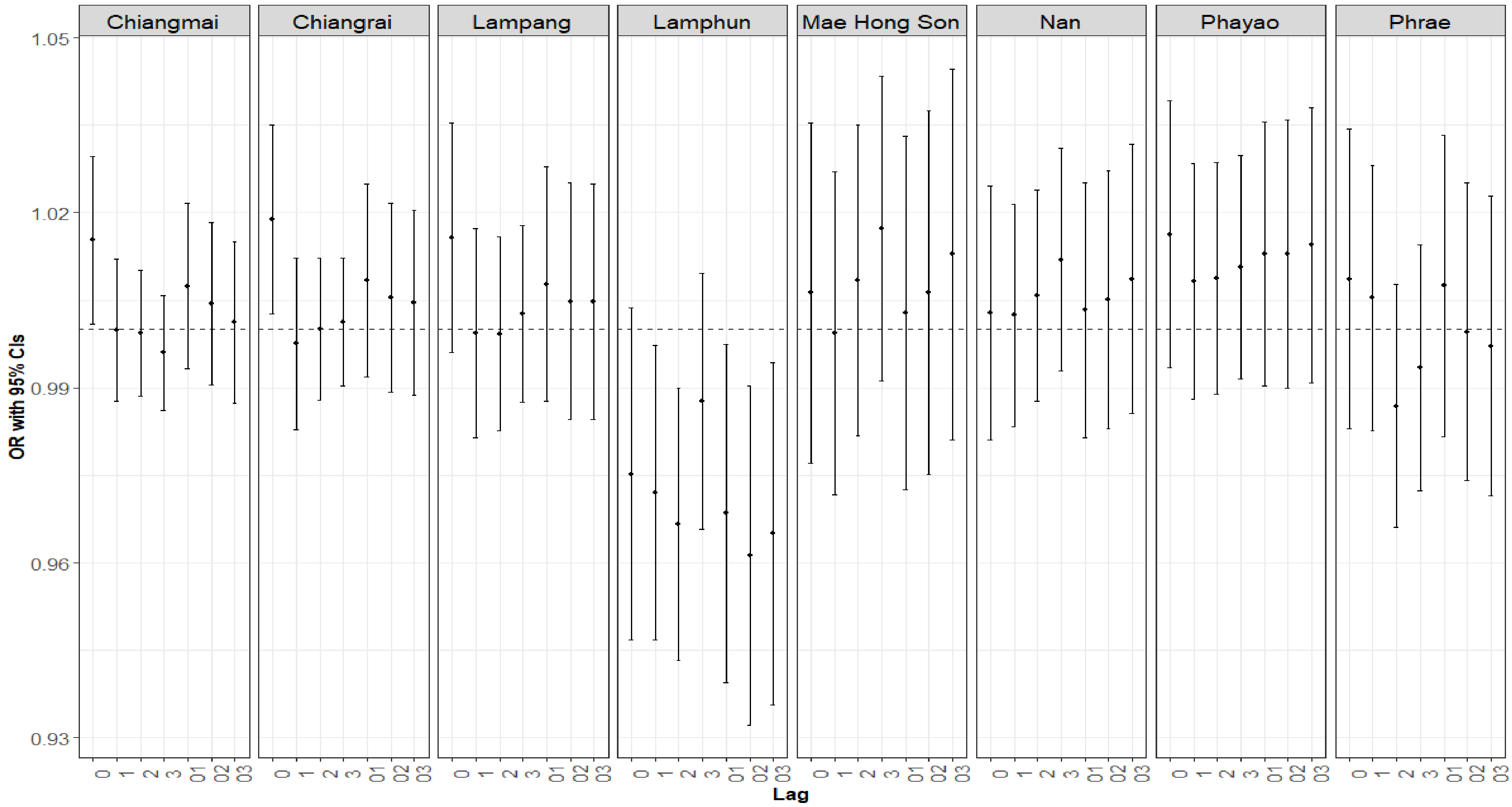

Figure A-9. Odds ratio of hospital visits for conjunctivitis as associated with a 10 µg/m^3 increase in PM_{10} concentration on mixed days for single and average lag models.

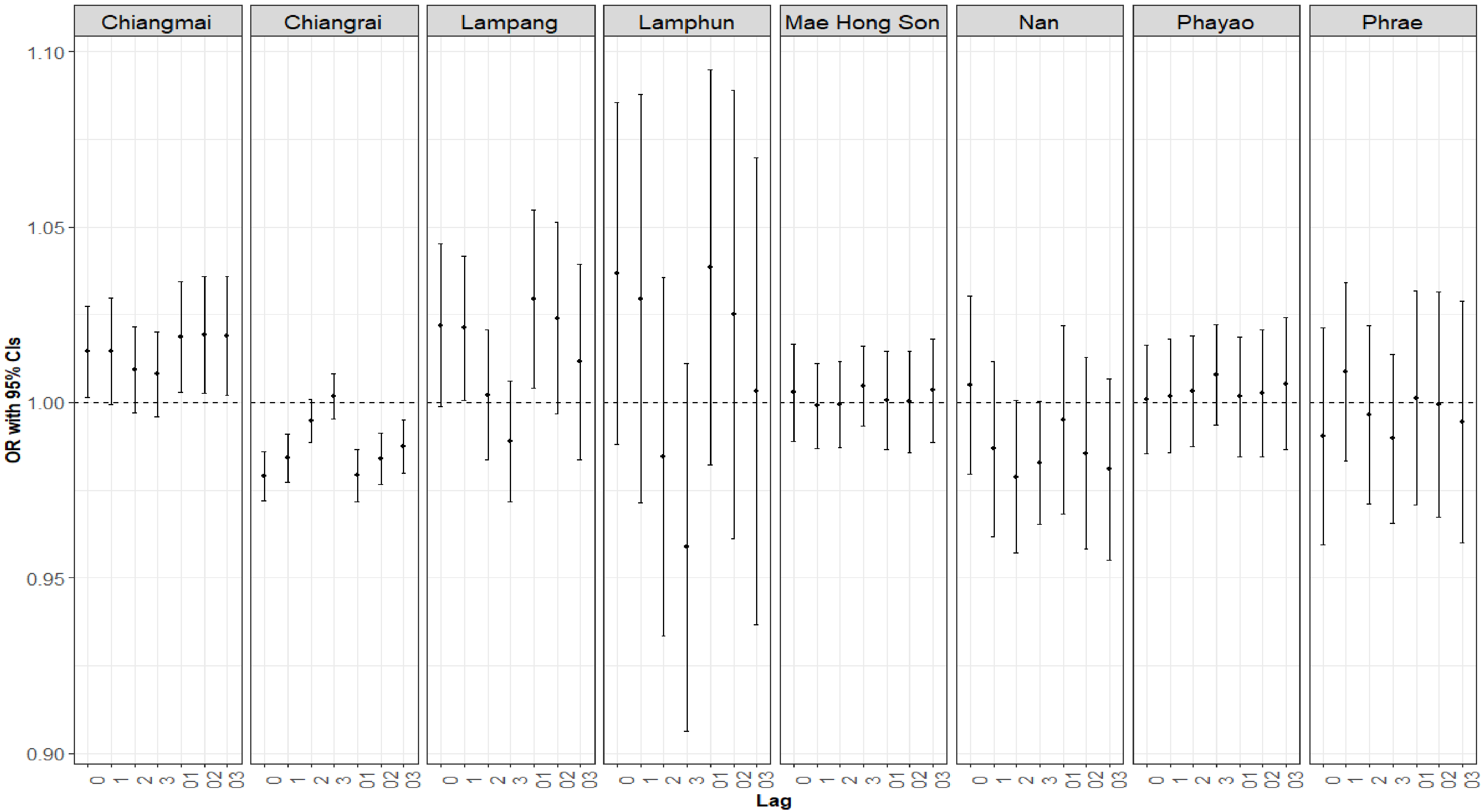

Figure A-10. Odds ratio of hospital visits for dermatitis as associated with a 10 μg/m^3 increase in PM_{10} concentration on burning days for single and average lag models.

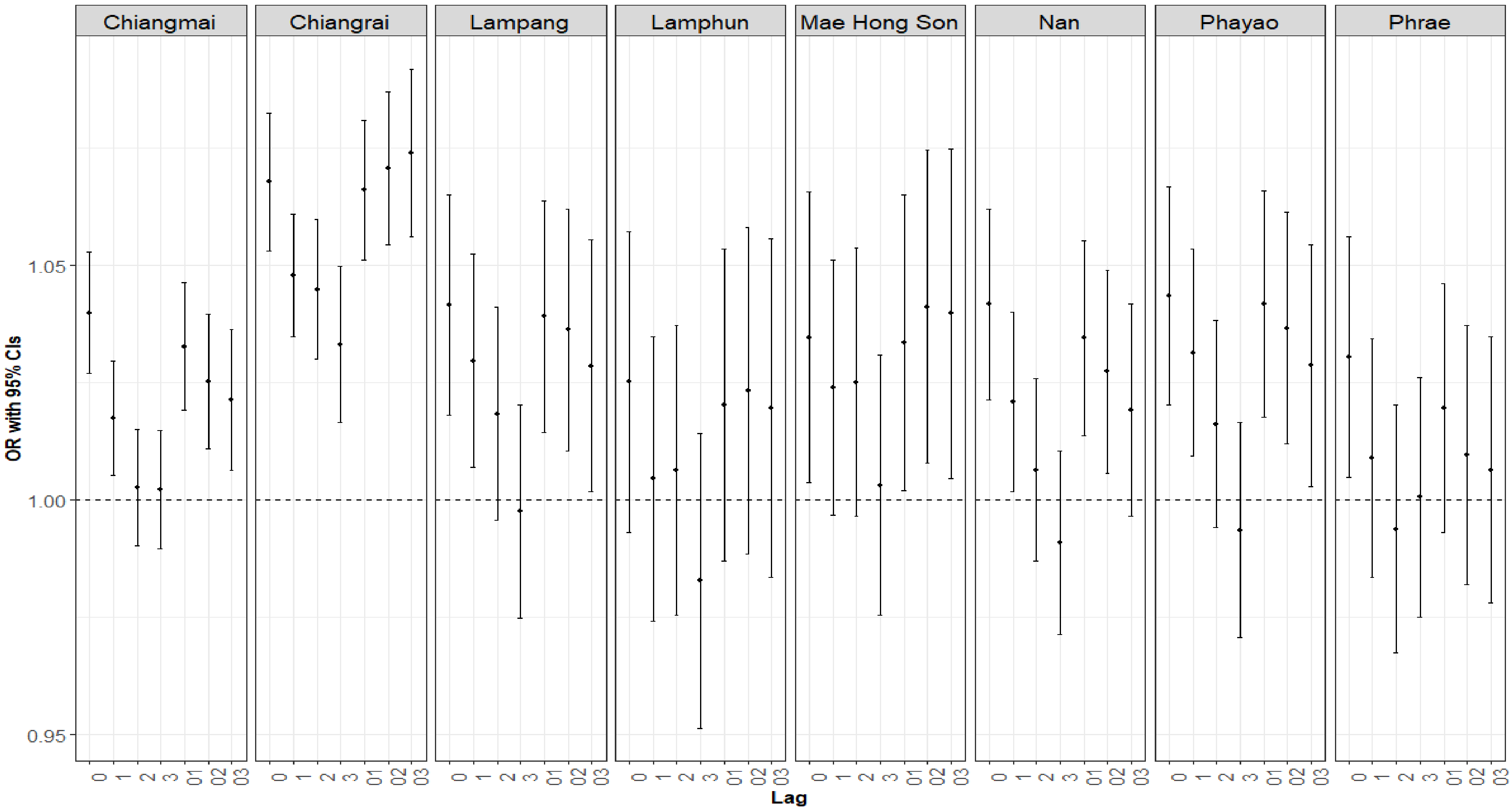

Figure A-11. Odds ratio of hospital visits for dermatitis as associated with a 10 µg/m^3 increase in PM_{10} concentration on non-burning days for single and average lag models.

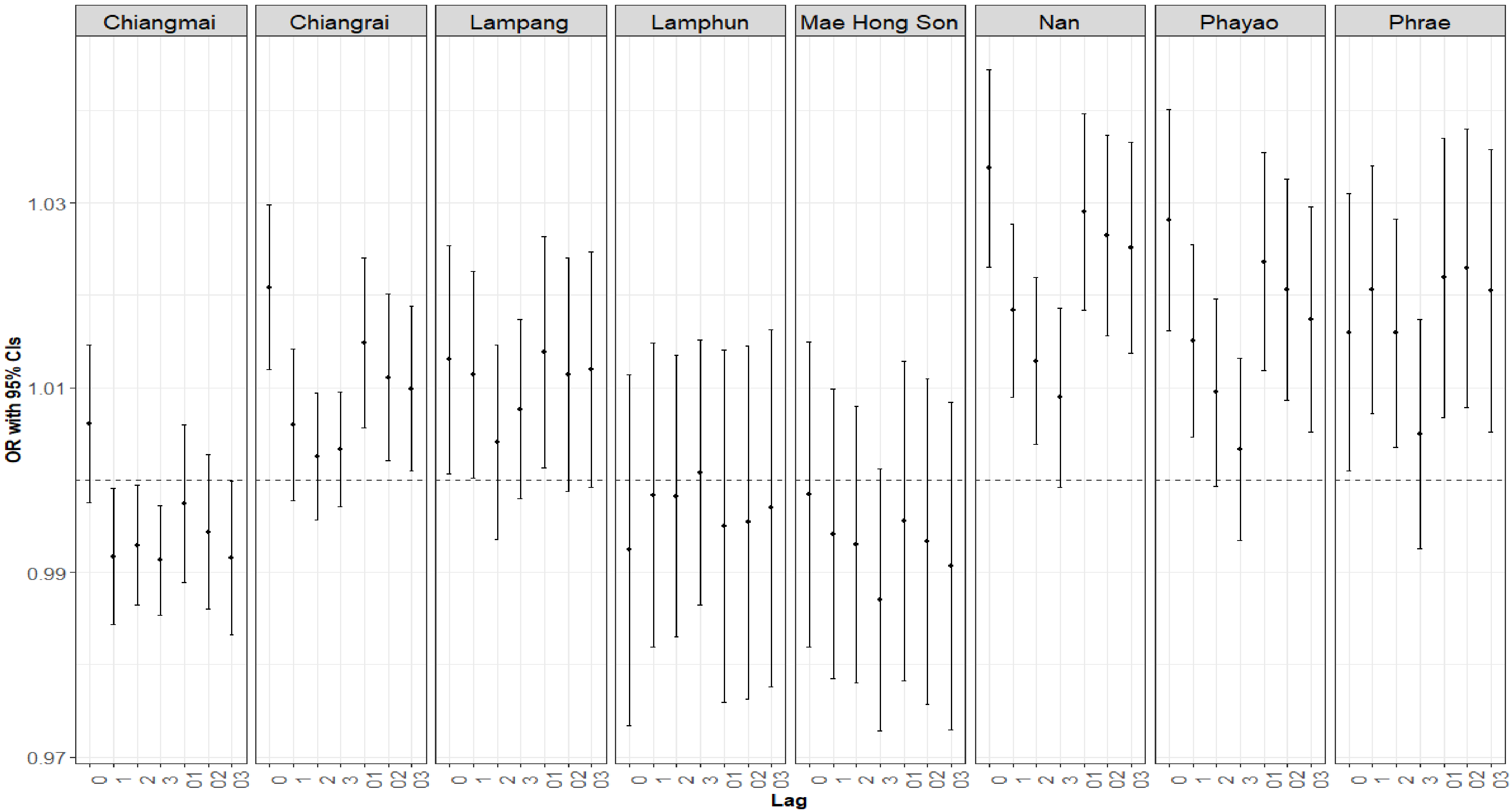

Figure A-12. Odds ratio of hospital visits for dermatitis as associated with a 10 μg/m^3 increase in PM_{10} concentration on mixed days for single and average lag models.

Appendix B

This section provides the additional information of Chapter 3 (*study II*)

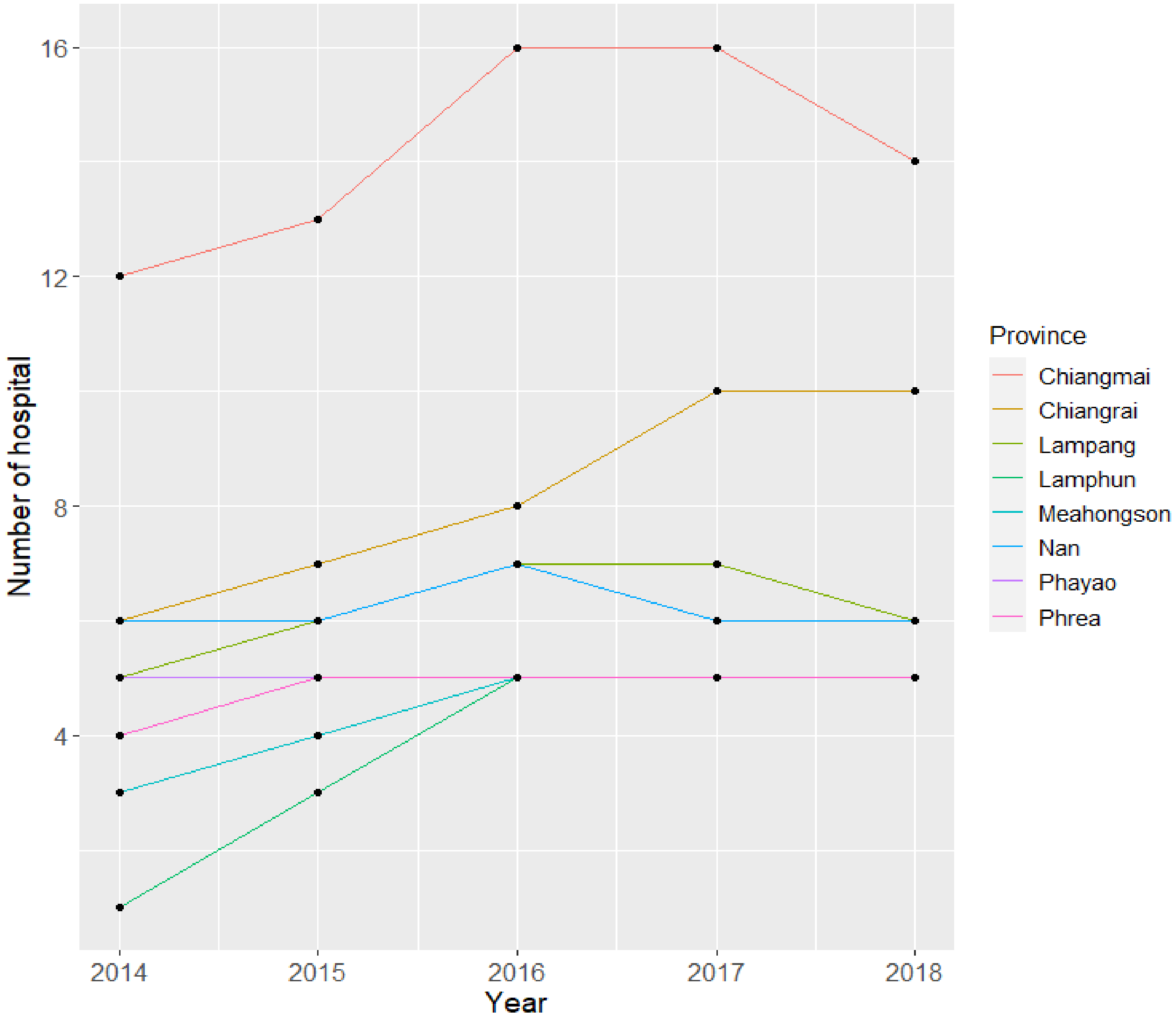

Figure B-1. Number of hospitals in each province by year.

Appendix C

This section provides the additional information of Chapter 4 (*study III*)

Table C-1. Summary of the attributable cases (total ages and children), daily average PM_{10} concentration (μg/m^3), and number of burning days by province and year.

Province	year	PM_{10} concentration	Number of burning days	Estimated of total ages			Estimated of children (below 15 years)		
				Cases	Lower limit	Upper limit	Cases	Lower limit	Upper limit
Chiangmai	2014	140.8	24	5474	802	9649	2581	378	4550
	2015	155.1	25	6332	940	11027	2896	430	5048
	2016	122.9	33	5733	834	10179	2722	396	4833
	2017	114.1	6	931	135	1659	425	62	758
	2018	111.6	15	2041	295	3642	915	132	1633
Chiangrai	2014	158.3	24	NA	NA	NA	NA	NA	NA
	2015	180.0	23	3857	578	6657	2224	333	3840
	2016	179.2	41	6219	926	10803	3663	545	6362
	2017	117.9	8	1060	154	1887	541	79	964
	2018	110.7	7	764	110	1367	373	54	667
Lampang	2014	123.1	41	4117	599	7310	1691	246	3003
	2015	133.7	26	2404	352	4247	909	133	1605
	2016	119.1	32	2839	412	5050	1098	159	1953
	2017	126.9	15	1267	185	2243	434	63	769
	2018	130.9	8	1015	148	1795	330	48	583
Lamphun	2014	125.2	19	724	105	1286	274	40	487
	2015	146.3	16	984	145	1728	387	57	679

Province	year	PM $_{10}$ concentration	Number of burning days	Estimated of total ages			Estimated of children (below 15 years)		
				Cases	Lower limit	Upper limit	Cases	Lower limit	Upper limit
	2016	127.3	17	1194	174	2117	471	69	834
	2017	111.6	3	185	27	331	62	9	111
	2018	110.8	9	497	72	887	174	25	311
Maehongson	2014	188.9	26	1243	186	2148	695	104	1200
	2015	188.8	30	2009	301	3466	1058	159	1827
	2016	151.0	34	1541	227	2708	885	130	1555
	2017	130.5	29	992	145	1757	545	80	966
	2018	139.3	20	646	95	1140	326	48	576
Nan	2014	132.2	33	2445	357	4328	1146	167	2028
	2015	131.3	19	1294	189	2288	601	88	1064
	2016	135.9	30	1771	259	3131	782	114	1382
	2018	113.2	5	221	32	393	91	13	161
Phayao	2014	146.6	33	3447	508	6045	1348	198	2366
	2015	148.3	29	2459	363	4304	891	131	1560
	2016	128.8	40	2643	385	4683	1019	149	1806
	2017	111.4	7	401	58	716	147	21	262
	2018	108.5	10	374	54	668	135	19	242
Phrae	2014	126.7	44	2316	337	4104	986	144	1747
	2015	121.6	29	1248	181	2218	485	71	863
	2016	122.9	32	1691	246	3002	742	108	1317
	2017	110.2	10	385	56	688	148	21	264
	2018	123.2	11	540	79	957	200	29	355

Noted: NA represents data not available.

Table C-2. Number of hospital visits for respiratory diseases attributable VFS-PM_{10} from sensitivity analyses.

Year	Sensitivity analyses		
	CFR		Cut-off PM_{10}
	Pothirat et al. 2016	Muller et al., 2020	50 $\mu g/m^3$
2014	87,057 (46,275 to 115,114)	41,117 (22,133 to 57,448)	31,793 (4,611 to 56,623)
2015	86,264 (47,314 to 111,368)	42,197 (23,020 to 58,256)	35,629 (5,194 to 63,173)
2016	103,862 (55,259 to 137,301)	49,107 (26,449 to 68,582)	43,432 (6,291 to 77,444)
2017	23,839 (12,376 to 32,129)	10,966 (5,846 to 15,458)	24,243 (3,467 to 43,756)
2018	27,977 (14,475 to 37,830)	12,822 (6,827 to 18,095)	24,479 (3,508 to 44,096)