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การเรียนการสอนเพื่อเสริมประสบการณ์

ชื่อโครงการ The Association between Daily PM2.5 Exposure during Forest Fire Period and Inpatient Admissions for Respiratory Diseases in Northern Thailand: A Case-crossover Analysis

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SENIOR PROJECT

Title	The Association between Daily PM2.5 Exposure during Forest Fire Period and Inpatient Admissions for Respiratory Diseases in Northern Thailand: A Case-crossover Analysis
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Faculty of Science	Department of Environmental science
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Department of Environmental Science

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ASSOCIATION BETWEEN DAILY PM2.5 EXPOSURE DURING FOREST FIRE PERIOD AND INPATIENTS ADMISSION FOR RESPIRATORY DISEASES IN NORTHERN THAILAND: A CASE-CROSSOVER ANALYSIS

ความสัมพันธ์ระหว่างการรับสัมผัส PM2.5 รายวันจากช่วงเหตุการณ์ไฟไหม้ป่าและการเข้าโรงพยาบาล
ด้วยโรคระบบทางเดินหายใจในภาคเหนือของประเทศไทย : การศึกษาแบบเคส-ครอสโอเวอร์

Mr. Chavis Ariyakhajorn

A Senior Project Submitted in Partial Fulfillment of the Requirements
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Department of Environmental Science, Faculty of Science
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หัวเรื่อง	ความสัมพันธ์ระหว่างการรับสัมผัส $PM_{2.5}$ รายวันจากช่วงเหตุการณ์ไฟไหม้ป่าและการเข้าโรงพยาบาลด้วยโรคระบบทางเดินหายใจในภาคเหนือของประเทศไทย : การศึกษาแบบเคส-ครอสโอเวอร์
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บทคัดย่อ

ในช่วง 10 ปีที่ผ่านมา ฝุ่นละอองขนาดเล็กถือเป็นหนึ่งในปัญหาทางด้านสุขภาพที่หลายประเทศให้ความสนใจ การรับ $PM_{2.5}$ จากการจราจรและอุตสาหกรรมทำให้เกิดความเสี่ยงต่อการเกิดโรคของระบบทางเดินหายใจ แต่ความรู้ทางด้านระบาดวิทยาของ ความเสี่ยงจาก $PM_{2.5}$ ในพื้นที่ที่มีการเผาไหม้ของมวลชีวภาพเป็นหลัก ยังมีการศึกษาไม่เพียงพอ การศึกษานี้วิเคราะห์ความสัมพันธ์ระยะสั้นของ $PM_{2.5}$ และ การเข้ารับการรักษาในโรงพยาบาลด้วยโรคระบบทางเดินหายใจ ในพื้นที่ไฟไหม้ป่าของภาคเหนือประเทศไทย การศึกษานี้วิเคราะห์ข้อมูลผู้ป่วยในของโรคระบบทางเดินหายใจทั้งหมด 816,139 เคสผู้ป่วยในโรคระบบทางเดินหายใจ จาก 118 โรงพยาบาลใน 9 จังหวัด ช่วงเวลาตั้งแต่ปี 2016-2020 โดยได้รับข้อมูลมาจากศูนย์เทคโนโลยีสารสนเทศและการสื่อสาร สำนักงานปลัดกระทรวงสาธารณสุข ข้อมูล $PM_{2.5}$ มลพิษตัวอื่น รวมถึงข้อมูลทางอุตุนิยมวิทยา ได้รับมาจาก 15 สถานีตรวจวัดคุณภาพอากาศ กรมควบคุมมลพิษ การรับ $PM_{2.5}$ ประเมินโดยใช้ตำแหน่งของโรงพยาบาลที่ใกล้กับสถานีวัดฝุ่นมากที่สุด ข้อมูลถูกจัดการด้วยโปรแกรม SAS® OnDemand for Academics. วิธีทางสถิติ การแบ่งช่วงของเวลาและแบบจำลองการถดถอยโลจิสติก เพื่อหาความสัมพันธ์กับความเสี่ยงต่อ 1 IQR ที่เพิ่มขึ้นของ $PM_{2.5}$ โดยรายงานเป็นค่า OR และช่วงความเชื่อมั่น วิธีการเคส-ครอสโอเวอร์ ช่วยควบคุมผลปัจจัยส่วนบุคคลและ confounders ที่ขึ้นกับเวลา โดยวิธีการจับคู่ และนำไปวิเคราะห์ด้วย แบบจำลองการถดถอยโลจิสติกแบบหลายตัวแปร เพื่อควบคุมผลของ confounders (PM_{10}, ozone, temperature, and relative humidity) โดยใช้โปรแกรม R® program ผลการศึกษาทำให้เห็นว่า $PM_{2.5}$ มีความสัมพันธ์อย่างมากกับ PM_{10} (ρ= 0.89, $p < 0.001$) สันนิษฐานได้ว่ามีแหล่งกำเนิดเดียวกันจากการจราจรและไฟไหม้ป่า Ozone ก็มีความสัมพันธ์อย่างมากกับ $PM_{2.5}$ (ρ = 0.78, $p < 0.001$) เนื่องจากว่าสารตั้งต้นเกิดมาจากการจราจร ค่า IQR ของ $PM_{2.5}$ เท่ากับ 25.87 $\mu g/m^3$ (9.63 - 35.50 $\mu g/m^3$) และมีค่าสูงสุดของค่าเฉลี่ยรายวันเท่ากับ 398.13 $\mu g/m^3$ ค่าเฉลี่ยสูงสุดรายวันของ PM_{10} เท่ากับ 438.88 $\mu g/m^3$ และ Ozone มีค่าสูงสุด 8 ชั่วโมงเท่ากับ 128.50 ppb ซึ่งทั้งหมดนี้เกินค่ามาตรฐานของมลพิษอากาศ ในช่วงไฟไหม้ป่าที่มีความอันตราย ค่า $PM_{2.5}$ PM_{10} และ Ozone พบค่าที่สูง 56.18 $\mu g/m^3$

81.73 μg/m^3 และ 62.70 ppb ตามลำดับ การเพิ่มขึ้น 1 IQR ของ $PM_{2.5}$ ถูกพบว่ามีความสัมพันธ์กับการเพิ่มขึ้นของเข้าโรงพยาบาลผู้ป่วยในโรคระบบทางเดินหายใจ ค่า OR สำหรับช่วงเวลารวม(ช่วงไฟไหม้และช่วงสถานการณ์ปกติ)ได้ค่าดังนี้ lag3 (OR = 1.002, CI: 0.994 to 1.011, $p < 1$) และ lag1 (OR = 1.013, 95% CI: 1.000 to 1.026, $p < 0.1$) สำหรับเพศหญิง ส่วนการวิเคราะห์ในเพศชาย ไม่พบความเสี่ยงที่เพิ่มขึ้น สำหรับการวิเคราะห์ช่วงไฟไหม้ได้ค่า OR สูง เมื่อเทียบกับช่วงเวลารวม โดยพบที่ lag1 (OR = 1.058, CI: 1.041 to 1.075, $p < 0.001$) และ lag2 (OR = 1.057, CI: 1.035 to 1.079, $p < 0.001$) สำหรับเพศชาย ส่วนเพศหญิงพบที่ lag1 (OR = 1.082, 95% CI: 1.055 to 1.108, $p < 0.001$) การวิเคราะห์โรคย่อย ได้ค่าดังนี้ lag3 (OR = 1.121, CI: 1.059 to 1.186, $p < 0.001$) สำหรับการติดเชื้อทางเดินหายใจส่วนบนเฉียบพลัน สำหรับไข้หวัดใหญ่และปอดบวมพบที่ lag0 (OR = 1.048, 95% CI: 1.019 to 1.078, $p < 0.01$) และการติดเชื้อทางเดินหายใจส่วนล่างเฉียบพลันที่ lag7 (OR = 1.069, CI: 1.015 to 1.127, $p < 0.05$) และโรคแบบอื่นของระบบหายใจ lag3 (OR = 1.060, CI: 1.012 to 1.111, $p < 0.05$) การวิเคราะห์แยกช่วงอายุ พบค่า OR สูงที่สุดในผู้สูงอายุ 60 ปีขึ้นไปพบที่ lag1 (OR = 1.070, 95% CI: 1.047 to 1.093, $p < 0.001$) และพบที่ lag7 (OR = 1.055, 95% CI: 1.018 to 1.093, $p < 0.01$) สำหรับเด็ก อายุ 6 ปีลงไป จากผลการศึกษาในโรคย่อยและแยกอายุ ในกลุ่มผู้สูงอายุ พบความเสี่ยงที่มีนัยสำคัญ สำหรับไข้หวัดใหญ่และปอดบวมพบที่ lag0 (OR = 1.061, CI: 1.020 to 1.103, $p < 0.01$) และพบที่ lag7 (OR = 1.129, CI: 1.013 to 1.258, $p < 0.05$) สำหรับการติดเชื้อทางเดินหายใจส่วนล่างเฉียบพลัน และพบความเสี่ยงในเด็กที่ lag3 (OR = 1.116, CI: 1.031 to 1.208, $p < 0.01$) สำหรับการติดเชื้อทางเดินหายใจส่วนบนเฉียบพลัน และ lag7 (OR = 1.059, CI: 1.004 to 1.117, $p < 0.05$) สำหรับไข้หวัดใหญ่และปอดบวม ความเสี่ยงที่มีนัยสำคัญทางสถิติ ถูกพบเฉพาะในช่วงไฟไหม้ป่า และไม่ถูกพบในช่วงเวลารวม ความเสี่ยงที่มีนัยสำคัญที่พบในช่วงไฟไหม้ป่าแบบแยกเพศ แบบแยกโรคย่อย และแบบแยกอายุ ได้ยืนยันว่า $PM_{2.5}$ ที่เพิ่มขึ้น มีบทบาทสำคัญในการเพิ่มความเสี่ยงของการเข้าโรงพยาบาลด้วยโรคระบบทางเดินหายใจในภาคเหนือของประเทศไทย ความเสี่ยงที่มีนัยสำคัญของกลุ่มย่อยแสดงให้เห็นว่าก่อนช่วงไฟไหม้ หน่วยงานของทั้งส่วนกลางและส่วนภูมิภาค ควรจะมีมาตรการในการรับมือกับ $PM_{2.5}$ จากไฟไหม้ที่ดีขึ้น มีการแจ้งเตือนล่วงหน้าอย่างมีประสิทธิภาพ ส่งเสริมให้ชุมชนป้องกันการรับ $PM_{2.5}$ เพื่อรักษาระบบทางเดินหายใจของตนเอง และโรงพยาบาลมีการเตรียมพร้อมที่ดีขึ้น การศึกษาในอนาคตสามารถปรับปรุงจากการศึกษานี้โดยเพิ่ม confounders ซึ่งส่งผลต่อทั้งการป่วยและการเพิ่มลดของ $PM_{2.5}$ รวมถึงมลพิษตัวอื่นๆ และรวมการวิเคราะห์โรคหัวใจและปอด

Title	The Association between Daily $PM_{2.5}$ Exposure during Forest Fire Period and Inpatient Admissions for Respiratory Diseases in Northern Thailand: A Case-crossover Analysis
Student name	Chavis Ariyakhajorn Student ID: 6033312023
Project Advisor	Assistant Professor Sitthichok Puangthongthub, Ph.D.
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Academic Year	2020

Abstract

For decades, $PM_{2.5}$ has been one of the most concerned public health problems in many countries. $PM_{2.5}$ exposure from traffic and industry contributes the risk of developing respiratory diseases but still lack of epidemiological knowledge in areas where biomass burning fire are dominant. This research analyzed an acute association between $PM_{2.5}$ and respiratory disease hospital admission in forest fire areas of the northern Thailand. This study covered 816,139 cases of respiratory system inpatients (codes J00-J99) from 118 hospitals in 9 provinces from 2016 to 2020. The data was obtained from the Ministry of Public Health. $PM_{2.5}$, co-pollutants and meteorological data were obtained from 15 monitoring stations provided by the Pollution Control Department. Pollutants and weather exposure were assigned to hospital locations using their nearest monitoring station, performed by SAS®. A time- stratified case-crossover approach with conditional logistic regression used to estimate the association and odd ratio and confidence interval (OR and CI) per an interquartile range (IQR) increase of $PM_{2.5}$. The case crossover design controlled personal and time-dependent confounders by matching while the multivariate regression model was fit to control other confounders (PM_{10}, ozone, temperature, and relative humidity) in R® program. Results showed $PM_{2.5}$ well correlated with PM_{10} (ρ= 0.89, $p < 0.001$) likely from same sources of traffic and forest fire and ozone also correlated with $PM_{2.5}$ ($\rho = 0.78$, $p < 0.001$) as its precursors possibly originated from traffic sources. The IQR of $PM_{2.5}$ was 25.87 µg/m^3 (9.63 - 35.50 µg/m^3) with a max of daily mean of 398.13 µg/m^3, a max of daily PM_{10} mean of 438.88 µg/m^3 and a max of 8-hour ozone of 128.50 ppb, all far exceeding their standards. During the hazard fire period (mid of Febuary to mid of May), 5-year daily means of $PM_{2.5}$, PM_{10} and ozone were observed high at 56.18 µg/m^3, 81.73 µg/m^{3}and 62.70 ppb respectively. The $PM_{2.5}$ IQR rise was found associated with the increases of the inpatient admission for respiratory diseases. In total period

(fire and non-fire), ORs were found increased but not significant at lag3 (OR = 1.002, CI: 0.994 to 1.011, $p < 1$), for female at lag1 (OR = 1.013, CI: 1.000 to 1.026, $p < 0.1$), and for male showing no increased risk. In hazard fire period, ORs were increased significantly at higher level at lag1 (OR = 1.058, CI: 1.041 to 1.075, $p < 0.001$), for male at lag2 (OR = 1.057, CI: 1.035 to 1.079, $p < 0.001$) and for female at lag1 (OR = 1.082, CI: 1.055 to 1.108, $p < 0.001$).For subgroup respiratory conditions, increased signifiant risks were observed for acute upper respiratory infections at lag3 (OR = 1.121, CI: 1.059 to 1.186, $p < 0.001$), influenza and pneumonia at lag0 (OR = 1.048, CI: 1.019 to 1.078, $p < 0.01$) and other acute lower respiratory infections at lag7 (OR = 1.069, CI: 1.015 to 1.127, $p < 0.05$) and other diseases of respiratory system at lag3 (OR = 1.060, CI: 1.012 to 1.111, $p < 0.05$). ORs for age groups were found highest in elderly ≥ 60 yr at lag1 (OR = 1.070, CI: 1.047 to 1.093, $p < 0.001$) . and in children ≤ 6 yr. at lag7 (OR = 1.055, CI: 1.018 to 1.093, $p < 0.01$). For age-sub disease risk, in eldery it was siginificantly increased in influenza and pneumonia at lag0 (OR = 1.061, CI: 1.020 to 1.103, $p < 0.01$) and in other acute lower respiratory infections at lag7 (OR = 1.129, CI: 1.013 to 1.258, $p < 0.05$) and in children in acute upper respiratory infections at lag3 (OR = 1.116, CI: 1.031 to 1.208, $p < 0.01$) in influenza and pneumonia at lag7 (OR = 1.059, CI: 1.004 to 1.117, $p < 0.05$). These reported statistically significant risks were only detected in the forest fire period and can not be noticed in total period. These significant risks during the fire period by sex, sub-disease, and age have confirmed that elevated $PM_{2.5}$ played an important role in increasing risk of hospitalization for respiratory diseases in northern Thailand. These significant group-specific risks suggested that before the hazard fire period, central and local authorities need extra specific $PM_{2.5}$ fire abatement, more efficient precaution and respiratory protection for community and greater hospital preparation. Future research could improve this analysis by controlling more inpatient confounders and more pollutants as well as combining cardiopulmonary diseases.

Keywords: Fine particulate matter, $PM_{2.5}$, Air pollution, Respiratory diseases, Inpatients admission, Risk, Exposure, Northern Thailand, Time-stratified, Case-crossover analysis, Conditional logistic regression

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Chapter 1 Introduction

1.1 Problem statement

Fine particulate matter (PM) with a median aerodynamic diameter < 2.5 µm . $PM_{2.5}$ was the fifth-ranking risk factor for mortality worldwide in 2015 (Chen et al., 2008), (Hoek et al., 2013). $PM_{2.5}$ originates from various sources, including both anthropogenic and natural sources. There has been concern whether specific sources may contribute to adverse health effects of $PM_{2.5}$. As stated by the World Health Organization (WHO) Working Group: “There is strong evidence to conclude that fine particles ($PM_{2.5}$) are more hazardous than coarse particles in terms of mortality and cardiovascular and respiratory endpoints in panel studies” (Lodgejr, 1996).

Air-pollution and weather exposure beyond region-specific thresholds have serious effects on the public health (De Sario et al., 2013),(Jerrett et al., 2009). $PM_{2.5}$ was found to be associated with respiratory tract diseases. After subdivision by age group, respiratory tract disease, and continent, $PM_{2.5}$ had strong association with respiratory diseases in children, people with cough, lower respiratory illness, and in individuals from Europe, North America, and Asia. The risk of respiratory tract diseases was greater for exposure to traffic-related than non-traffic-related air pollution (Liu et al., 2017).

Natural forest fires cause an environmental change in many aspects such as the renewal of soil, remove low-growing underbrush and clean the forest floor of debris. However, some wildfires got so large and severe which caused strong changes in the structural and functional processes of forest ecosystems and wildlife (M. Oliveira et al., 2020). Climate change occurred and caused an increase in intensity and frequency of extreme weather events (Stott, 2016). Severe forest fires cause significant ecological, economic, and social problems(Adame et al., 2018; Földi & Kuti, 2016). These studies forest fires are one of the problems that cause big and strong impacts for the environment and absolutely will affect the human health. In recent years, northern Thailand also faces the same problem from the forest fire which affect local people. As one of Thai people, I would like to see whether $PM_{2.5}$ from fire period have significant impact on the admission of respiratory diseases.

Although different results have previously been found for the association of fine particulate matter less than 2.5 μm in aerodynamic diameter ($PM_{2.5}$) and acute events of respiratory diseases. A conclusion based on epidemiological evidence can still not be made.

In addition, Thailand has few works conducted to explore the association between short-term $PM_{2.5}$ exposure and inpatient admission for respiratory diseases.

1.2 Research Objectives

1.2.1 To explore the $PM_{2.5}$ and investigate its correlation to co-pollutants and meteorological variable in Northern Thailand.

1.2.2 To explore the respiratory diseases prevalence in Northern Thailand.

1.2.3 To investigate the association between daily $PM_{2.5}$ exposure from forest fire and inpatient admission for respiratory diseases in Northern Thailand.

1.2.4 To examine the influence of $PM_{2.5}$ on inpatient admission in different 4 subgroup respiratory conditions.

1.3 Scope of the research

1.3.1 This study was a Case-crossover analysis.

1.3.2 The study population were inpatients who were admitted in 118 hospitals in 9 provinces including Chiang Mai, Lamphun, Lampang, Phrae, Nan, Phayao, Chiang Rai, Mae Hong Son and Tak.

1.3.3 The period of this study was between January 1st,2016 – December 31st, 2020

1.3.4 The study covered respiratory diseases

Chapter 2 literature review

2.1 Particulate matter with aerodynamics diameter ≤ µm.

Air pollution is a world public health problem (Li et al., 2018). Particles with an aerodynamics diameter of 10 microns or less, (≤ PM_{10}) can penetrate deep inside the lungs, the more dangerous chemical are those with an aerodynamics diameter of 2.5 microns or less, (≤ $PM_{2.5}$). $PM_{2.5}$ can penetrate the alveoli in lung and enter the circulatory system which circulate blood to every part of the body. Recent studies reported that the respiratory diseases prevalence rate was increased by 2.07%, while hospitalization rate raised by 8%, when the daily $PM_{2.5}$ increased by 10 µg/m3 (Dominici et al., 2006; Zanobetti et al., 2009). Chronic exposure to particles contributes to the risk of developing cardiovascular and respiratory diseases. Air quality measurements are typically reported in terms of daily or annual mean concentrations of PM_{10} particles per cubic meter of air volume (m^3). Routine air quality measurements typically describe such PM concentrations in terms of micrograms per cubic meter (µg/m^3). When sufficiently sensitive measurement tools are available, concentrations of fine particles ($PM_{2.5}$ or smaller), are also reported. There is an Air quality guideline values from WHO to make sure the $PM_{2.5}$ concentration is at the safe level for human. WHO Air quality guideline for $PM_{2.5}$ and PM_{10} is shown in Table 2.1.

Table 2.1 Air quality guideline for $PM_{2.5}$ and PM_{10} according to the World Health Organization.

Pollutants	Guideline values (µg/m^3)	
	Annual means	24-hour means
$PM_{2.5}$	10	25
PM_{10}	20	50

2.2 $PM_{2.5}$ and its effects to human health

Air pollution is a complicated process involving the spread of distinct pollutants throughout the atmosphere. Air pollution has been found to induce diseases in humans and disorders in other living organisms, as well as destruction of the natural environment (Brauer et al., 2012; K. H. Kim et al., 2013). $PM_{2.5}$ sources come various of activity, including road dust from traffic, dust from burning for agricultural purposes, industrial emissions, construction sites, mining operations, river beds, crustal materials, and combustion, or as secondary aerosols from distant sources (Eeftens et al., 2014; E. Kim et al., 2005; Schwarze et al., 2006). $PM_{2.5}$ also act as a carrier of other harmful substances, such as heavy metal ions (Weinmayr et al., 2010). The study (Analitis et al., 2006) showed that an increase in PM_{10} by 10 μg/m3 (lag 0 + 1) was associated with increases of 0.76% (95% confidence interval = 0.47 to 1.05%) in cardiovascular deaths and 0.58% (0.21 to 0.95%) in respiratory deaths. Furthermore, elderly, pregnant women, adolescents, infants, and other high-sensitivity populations have even stronger correlation (B. F. A. De Oliveira et al., 2012; Huynh et al., 2006; Martinelli et al., 2012). From the above-mentioned studies, more serious conditions of respiratory diseases were also associated with increased particulates matter such as raised mortality of cardiopulmonary diseases and damaged lung function.

2.3 Epidemiological study

Epidemiological study is aims to investigate the distribution and determinants of health-related event in a population and applying the results of those studies for health prevention and control. Epidemiological evidence can't be made because of the variation of time, population, space such as activities, occupation, and local weather condition. Epidemiological studies consisted of 2 types of studies: experimental and observational studies. For observational studies, were also classified into 2 studies: analytical and descriptive studies. Analytical studies comprise of cross-sectional studies, cohort studies, ecological studies, and case-control studies. And there are 3 experimental studies: field trials, clinical trials, and community trials as illustrated in Figure2.1 (Kasim, 2012).

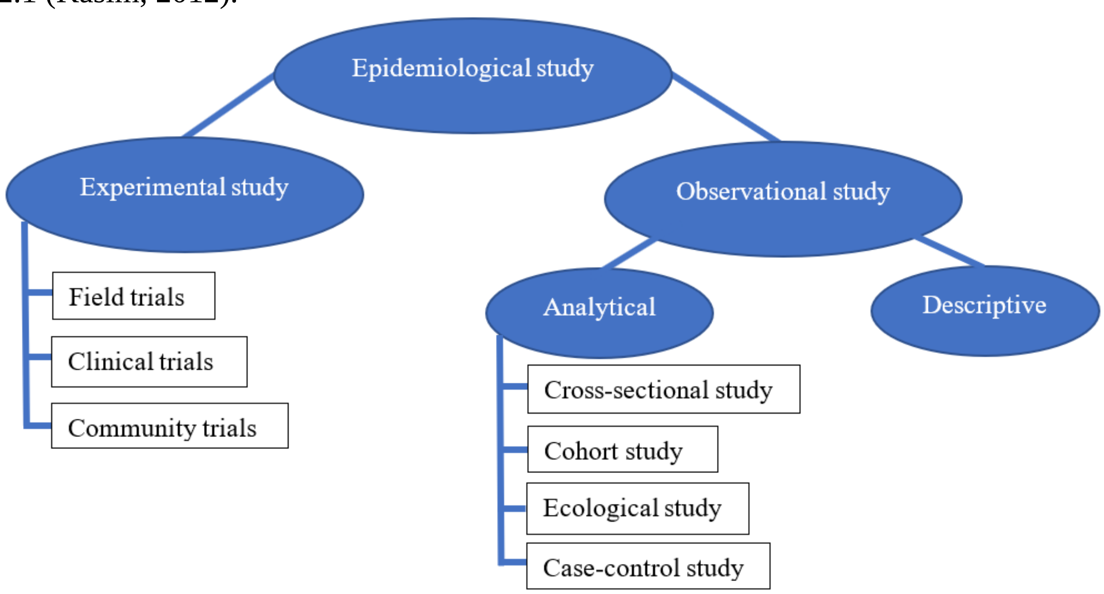


Figure2.1 Epidemiological study design

2.4 Case crossover study

The case–crossover design is widely used to analyze the association of air pollution with the hospital emergency room (ER) visits for the respiratory diseases (Ma et al., 2018). The conditional logistic regression model is commonly used to calculate the odds ratio (OR) of exposures for subject during the case time and the control time, respectively. To evaluate the effect of air pollutants, the distributed lag model was used. The hazard period was defined as the same day, previous day up to the 3rd day prior to the hospital visit. These hazard period could be change depends on researcher studies design. Mostly, the same day of last week for the hospital visit was used as control, for example, if the subject went to hospital ER on Monday, the last Monday would be used as control. Therefore, the concentrations of air pollutants in the hazard period were compared with the control period. The relevant daily data of air temperature and relative humidity were fit into the models as confounding factors (Ferreira Braga et al., 2001; Schwartz, 2005).

A time-stratified case-crossover approach with conditional logistic regression to estimate associations between air pollution and hospital admissions. This design compares each subject's exposure level preceding the case defining event day with corresponding exposure levels on control days in the same month (generally a multiple of 7 days apart). Case– crossover analysis involves binary outcome data with values 0 for control and 1 for case days.

Moreover, case– crossover analysis has several strengths: it does not require a control sample (and hence avoids bias associated with improper control selection); it makes effect modification assessment relatively simple; it controls for fixed confounders by design; and it controls for long-term time trends, seasonality, day–of–week effects and time-dependent confounders by matching. To estimate βc or regression coefficients in each of 7 different groups of cardiovascular diseases. (95% confidence interval βc, low to βc, high), when c is denoted each disease groups, by fitting a conditional logistic regression model (Equation 2.1) to all pairs of case days and matched control days (Maclure, 1991)

Equation 2.1: $P(Y_{i1}=1, Y_{i2}=0, Y_{i3}=0, Y_{i4}=0|X_{i1}, X_{i2}, X_{i3},)= \frac{\exp(\alpha_i+\beta X_{i1})}{\exp(\alpha_i+\beta^T X_{i1})+\exp(\alpha_i+\beta^T X_{i2})+\exp(\alpha_i+\beta^T X_{i3})}$

; where Yil ∈ {0,1} is the inpatient visits indicator ("1" represented as case day and "0" represented as control days) of the lth observation in the ith stratum; Xil is the predictors included $PM_{2.5}$, air temperature and humidity; β are regression coefficients; αi is stratum-specific intercepts.

Chapter 3 Methodology

3.1 Description of study area

Study location is in the Northern region of Thailand as in Figure3.1. The pink parts show study boundaries which consisted of 9 provinces located in Northern Thailand including: Chiang Mai, Lamphun, Lampang, Phrae, Nan, Phayao, Chiang Rai, Mae Hong Son and Tak. Northern Thailand is a region of green mountains, misty jungles, fertile valleys, spectacular ruins, colorful hill tribes, and temperatures that are cooler than the rest of country.

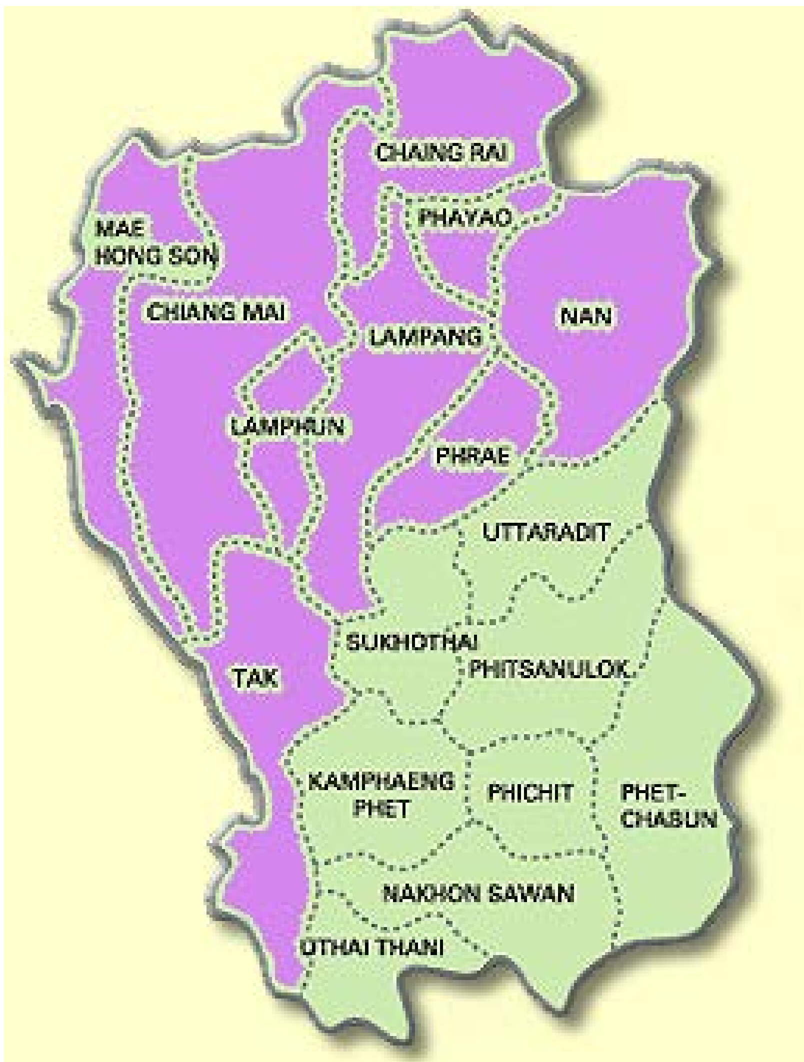


Figure3.1 Map of Northern Thailand with pink parts showing area of study

(a photo from https://www.amazing-thailand.com/north-northeast-thailand.html)

3.2 Inpatients admission data

Experimental Design and Methods Medicare data Diagnosis inpatient department records in Thailand, were acquired from January 1^{st}, 2016 – December 31^{st}, 2020. Health data was retrieved from hospital records of inpatients which obtained from the Information and Communication Technology Center, Office of the Permanent Secretary, Ministry of Public Health. This study acquired inpatient data of total 816,139 cases of respiratory system inpatients from 118 hospitals in 9 provinces, Northern Thailand. Electronic hospitalization data were used in this analysis. We focus on hospital admissions for respiratory diseases. The subgroup respiratory conditions which were identified using the International Classification of Diseases and Related Health Problems, 10th Revision, Thai Modification (ICD-10-TM). Diagnosis code in this analysis were respiratory diseases (J00-J99) which can subgroup into 10 respiratory conditions as filled in Table 3.1. The Obtained data of inpatients include the following characteristic: birthdate, sex, date of admission, hospital code, province code, and the diagnosis code.

For the effects of forest fire events which always occurs every year, inpatient cases within the forest fire period were selected to analyze the influence of forest fire on inpatient admission. The period is between February 15^{th} to May 15^{th} in every year of study period (2016-2020).

Table 3.1 Respiratory conditions classified by ICD-10-TM

Code	Respiratory conditions
J00 - J06	acute upper respiratory infection
J09 - J18	Influenza and pneumonia
J20 - J22	Other acute lower respiratory infection
J30 - J39	Other diseases of upper respiratory tract
J40 - J47	Chronic lower respiratory diseases
J60 - J70	Lung diseases due to external agents
J80 - J84	Other respiratory diseases principally affecting the interstitium
J85 - J86	Suppurative and necrotic condition of lower respiratory tract
J90 - J94	Other diseases of pleura
J95 - J99	Other diseases of respiratory system

3.3 Pollutants and meteorological variable data

Air pollution and meteorological data including $PM_{2.5}$, PM_{10}, ozone, temperature and relative humidity were obtained from 15 monitoring stations in 9 provinces provided by the Pollution Control Department. The pollutants data were acquired from January 1st, 2016 – December 31st, 2020.

Due to lacks monitoring station in the first period of study, 2016-2018, the data from 4 monitoring station were used. For 2019 and 2020, 15 monitoring station were used. The hourly data of $PM_{2.5}$, PM_{10}, ozone, temperature, relative humidity was obtained. There were possible 612,167 hours of $PM_{2.5}$ concentration during 5 years with missing of 45,553 hours which is 7.44 %. After adjusted by using neighboring stations or using measurements from prior and following days, the $PM_{2.5}$ missing values was 0.54 %. They were aggregated from hourly to daily average metric. For ozone, 8-hour maximum metric used in the analysis. The pollutants metrics were applied according to (The United States Environmental Protection Agency, 2020). The low repeated values caused by calibration of machine, or some error of machine functioning were deleted. Exposure to pollutants and meteorological data of individuals were obtained from the station with shortest distance between station and admitted hospital. Google map was used to plotting location and matching the monitoring station with the nearest hospital. Pollutant's data cleaning and managing was perform using SAS OnDemand for Academics software.

Normally, the forest fire in Northern Thailand covered around the mid of February to the mid of May. According to the announcement (Forest Fire Control Division, Natural Park, Wildlife and Plants Conservation Department, n.d.) on December 8th, 2020 from the Forest Fire Control Division, Natural Park, Wildlife and Plants Conservation Department, Thailand, they prepared to cope with forest fire in 2021. The document divided the measures into 3 parts as follow; prevention of the forest fire, Action procedures to control forest fire and Corrective action to help severe events back to normal situation. Action procedures period was from January 16th to February 15th, 2021. Corrective action period was from February 16th to May 15th, 2021 The remaining period was the prevention period. For this study, the fire period was selected February 16th to May 15th, 2021, which line up with the announcement.

3.4 Statistical analysis

A time- stratified case- crossover approach with conditional logistic regression to estimate associations between air pollution and hospital admissions. This design compares each subject's exposure level preceding the case defining event day with corresponding exposure levels on control days in the same month (generally a multiple of 7 days apart). Case– crossover analysis involves binary outcome data with values 0 for control and 1 for case days.

Moreover, case– crossover analysis has several strengths: it does not require a control sample (and hence avoids bias associated with improper control selection); it makes effect modification assessment relatively simple; it controls for fixed confounders by design; and it controls for long-term time trends, seasonality, day–of–week effects and time-dependent confounders by matching. Short-term exposure to $PM_{2.5}$ will be evaluated by exposure to daily average $PM_{2.5}$ on the same day of the hospital admission day (lag0) up to 7 days before admission (lag1, lag2, …, lag7).

The correlation analysis of $PM_{2.5}$, co-pollutants and meteorological variables were conducted with the Spearman rank-order correlation test.

To estimate odds ratio or OR (95% confidence interval lower to upper limit) of inpatient admission for respiratory diseases associated with per Interquartile range increment of $PM_{2.5}$ concentration adjusted for PM_{10}, Ozone, temperature, and relative humidity in order to exclude the effect of other co-pollutants and meteorological factors. Using conditional logistic regression model as the equation below.

$$\text{Logistic}(P) = C + \beta(PM_{2.5}) + \beta(PM_{10}) + \ldots. + \text{Strata (ID)}$$

Where P is possibility of an events which is respiratory admissions. β refers to linear regression coefficients solved from the multivariate regression model. $PM_{2.5}$, PM_{10}, ozone, temperature and relative humidity was fitted in the model. ID refers to an individual's cases.

The findings were reported in ORs with 95% confidence interval for an incidence of respiratory diseases associated with an interquartile range (IQR) increment in the daily $PM_{2.5}$ concentration. R software (version 4.0.2) was used for conditional logistic regression analysis. An interquartile range (IQR) is a value that tell how data is distributed. It is calculated by 75th percentile subtracted by 25th percentile or, the third quartile subtracted by the first quartile. If an interquartile range (IQR) is great, telling the data has wide range of distribution.

In addition to the main model using data in full total period, the partial data were fitted to test the association during only the hazard forest fire period starting from mid of February to mid of May when the $PM_{2.5}$ is expected at acute level. The ORs analysis was then further stratified by sex, sub-disease, and age groups. Due to the reason that results showed the significant risk for the 4 subgroups, that 4 out of 10 sub-respiratory conditions were reported in Chapter 4 including with acute upper respiratory infection**,** influenza and pneumonia**,** other acute lower respiratory infection and other diseases of respiratory system. For age group, a children age of 6 years and below and an elderly age of 60 and above are analyzed.

Chapter 4 Result and discussion

4.1 Data description

From the 5 years of observation, a total of 816,139 cases of respiratory system inpatients were investigated. The basic characteristics of the study population who were admit in hospitals due to the respiratory diseases in Northern Thailand, 2016-2020 is shown in Table 4.1. These 816,139 cases of respiratory system were classified into 10 respiratory conditions. Influenza and pneumonia (J09-J18) and chronic lower respiratory diseases (J40-J47) are the 2 largest proportion which accounted for (261,948 cases, 32.10%) and (240,296 cases, 29.47%) of the total, respectively. Those 2 respiratory conditions add up almost 1/3 of the total inpatient cases. Male cases (463,329 cases, 56.77%) were slightly greater than female cases (352,810 cases, 43.23%). To investigate the influence of fire events which might affect the risk of respiratory diseases admission. Forest fire period admissions were the cases admitted from February 16th to May 15th which were a part of total period cases. Forest fire period cases (187,584 cases) accounted for 22.98% of the total period cases (816,139 cases).

Table 4.1 Basic Characteristics of the Study Population, 2016 – 2020.

Characteristics	n	Percent (%)
Diseases of respiratory system	816,139	100.00
<u>Respiratory condition</u>		
J00 - J06 acute upper respiratory infection	61,848	7.58
J09 - J18 Influenza and pneumonia	261,948	32.10
J20 - J22 Other acute lower respiratory infection	73,860	9.05
J30 - J39 Other diseases of upper respiratory tract	17,705	2.17
J40 - J47 Chronic lower respiratory diseases	240,496	29.47
J60 - J70 Lung diseases due to external agents	8,707	1.07
J80 - J84 Other respiratory diseases principally affecting the interstitium	7,009	0.86
J85 - J86 Suppurative and necrotic condition of lower respiratory tract	5,074	0.62
J90 - J94 Other diseases of pleura	29,434	3.61
J95 - J99 Other diseases of respiratory system	110,058	13.49
<u>Age</u>		
6 years and less	178510	21.87
60 years and above	426812	52.30

Characteristics	n	Percent (%)
Sex		
Male	463,329	56.77
Female	352,810	43.23
Period of admission		
Forest fire	187,584	22.98
Total full period	816,139	100.00

The descriptive statistics of Air pollutants and Meteorological variables were given in Table 4.2. In the 5 years study period, for example the originally $PM_{2.5}$ given hourly measurements was missing for 7.4%, after adjusted by using neighboring stations or using measurements from prior and following days the daily average value missing was then reduced to 0.5%. The 5-year averages of daily means of $PM_{2.5}$ and PM_{10} were 27.13 µg/m^3 and 42.75 µg/m^3 respectively and an average of 8-hour maximum was used for ozone at 39.63 ppb which were all below the Thai air quality standards of 50 µg/m^3 for $PM_{2.5}$, 120 µg/m^3 for PM_{10} and 70 ppb for ozone. The 25 percentile of $PM_{2.5}$ was 9.63 and the 75 percentile was 35.50 µg/m^3, equivalent to IQR at 25.87 µg/m^3. Maximum of $PM_{2.5}$ concentration almost reached 400 µg/m^3 of which was obviously hazardous level. PM_{10} with a maximum of 438.88 µg/m^3 and ozone max of 128.50 µg/m^3 which certainly far exceeded the standard level. For Meteorological variables, they were averages of 25.89 ^oC and 73.03% for temperature and relative humidity respectively, which represented tropical wet and dry or savanna climate.

For the forest fire period which consisted of 3-month interval from February 16th to May 15th, 2016-2020. Obviously, $PM_{2.5}$, PM_{10} and ozone in forest fire period had a higher mean, median, 25th percentile and 75th percentile than the total period. $PM_{2.5}$ average of daily means in forest fire period was 56.18 µg/m^3. It was twice as high as all year period which was 27.13 µg/m^3. The twice value continued on PM_{10} and ozone with values of 81.73 µg/m^{3}and 62.70 ppb. On the other hand, the relative humidity was much lower in the fire period because the effect from the drough conditon which started from the beginning of March to in the middle of May. There was no obviously change in temperature between both periods of total and forest fire..

There was the result from the study (Nhung et al., 2020). This study aimed for risk of hospitalization for cardiovascular disease. They found that air pollutants were higher concentrations in the cold season than the warm season. This occurred with all PM including PM_{10}, $PM_{2.5}$ and PM1. In contrast, our pollutants data showed that fire season had obviously higher concentration of $PM_{2.5}$, PM_{10}, and Ozone during the forest fire season compared to the average in the total period. This could be related to an effect of high temperature in the hot season in Thailand which can light the fire up naturally in some forest areas and results in increase $PM_{2.5}$ and other air pollutants in ambient air.

Table 4.2 Descriptive statistics of Air pollutants and Meteorological variables, 2016-2020

Variable		Missing* (%)	Mean	Min	Max	P_{25}	P_{50}	P_{75}	Standard
Total Period	$PM_{2.5}$ (µg/m^3)	0.54	27.13	1.83	398.13	9.63	17.08	35.50	50
	PM_{10} (µg/m^3)	1.48	42.75	2.33	438.88	19.35	30.71	54.25	120
	Ozone (ppb)	0.65	39.63	0.63	128.50	23.75	35.50	53.50	70
	Temperature (°C)	1.01	25.89	6.89	39.76	23.96	26.01	27.84	-
	Relative humidity (%)	1.34	73.03	3.13	100.00	64.29	75.58	83.83	-
Forest Fire Period	$PM_{2.5}$ (µg/m^3)	0.00	56.18	4.00	398.13	33.54	51.54	70.79	50
	PM_{10} (µg/m^3)	0.41	81.73	8.86	438.88	52.40	76.21	100.54	120
	Ozone (ppb)	0.27	62.70	6.38	128.50	5$_{2.5}$0	64.13	73.63	70
	Temperature (°C)	0.29	27.98	15.16	38.20	25.64	27.97	30.36	-
	Relative humidity (%)	0.37	57.37	25.54	99.00	47.63	56.50	66.42	-

*After adjusted by using neighboring stations or using measurements from prior and following days

$PM_{2.5}$ and PM_{10} 24-h average concentration series plot is illustrated in Figure 4.1 and 4.2, respectively. Different metric was used for ozone which is 8-hour maximum concentration plotted in Figure 4.3 according to the Thai ambient ozone standard. For meteorological factors, temperature and relative humidity shared the same metrics with $PM_{2.5}$ and PM_{10} (24-h average concentration) shown in Figures 4.4 and 4.5. All 5 series plot shared the same period from January 1st, 2016, to December 31st, 2020. The first 3 years of study period of 2016-2019, number of monitoring stations (5 stations) were less than those (15 stations) in 2019- 2020. Different plot line colors indicate the different stations. In 2019 and 2020, $PM_{2.5}$ concentrations increased dramatically. The maximum daily $PM_{2.5}$ concentration in the period of 5 years was 400 µg/m^3 which was about 8 time greater than the Thai air quality standard for $PM_{2.5}$ which was set at 50 μg/m^3. In $PM_{2.5}$ plot, it can be seen that the maximum of the Y-axis was 300 μg/m^3 but actually the $PM_{2.5}$ peaked at 398.13 μg/m^3 as shown in Table 4.2. The values above 300 were cut out to see a better illustration of the fluctuation. Every year it showed the same fluctuating trend that $PM_{2.5}$ concentration started rising from the beginning of the year and reached the peak in March and April. These two months were the most hazard period of the forest fire season usually starting from mid of Febuary to mid of May. The rising temperatures and dropping of relative humidity shared the same timeline. For PM_{10} fluctution, it elevated and dropped corresponding to $PM_{2.5}$ behavior and PM_{10} also exceeded the standard of 120 μg/m^3 in the forest fire season which is March and April. In addition, ozone concentration level also shared the same behavior as $PM_{2.5}$ and PM_{10}.

Therefore, the forest fire season was a truly critical period in Northern Thailand which need to take action and manage to decrease the air pollutants level. As mention in the above paragraph, there was some relevance among those pollutants. When one rised, another followed the same trend or in the opposite way. In addition, the value of ambient air pollutants and meteorological variable showing harmful substances suspended in air. Not only does what matter it indicate but also the way it behaves in space and time which benefits decision making on a pollution control policy and can further reduce PM-related health effect in the future.

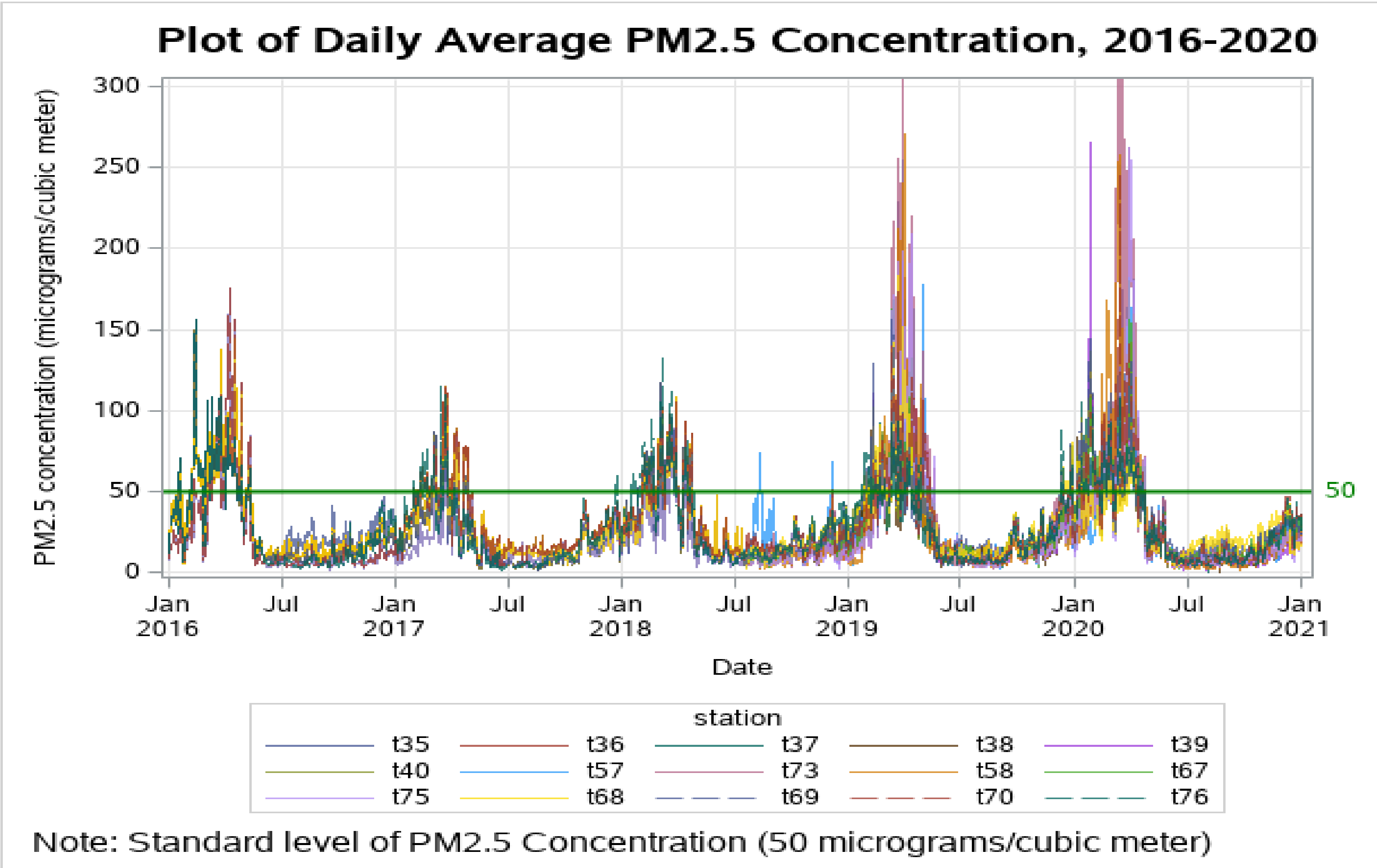


Figure 4.1 Time-series plot of daily $PM_{2.5}$ concentration during 2016 – 2020, in Northern, Thailand.

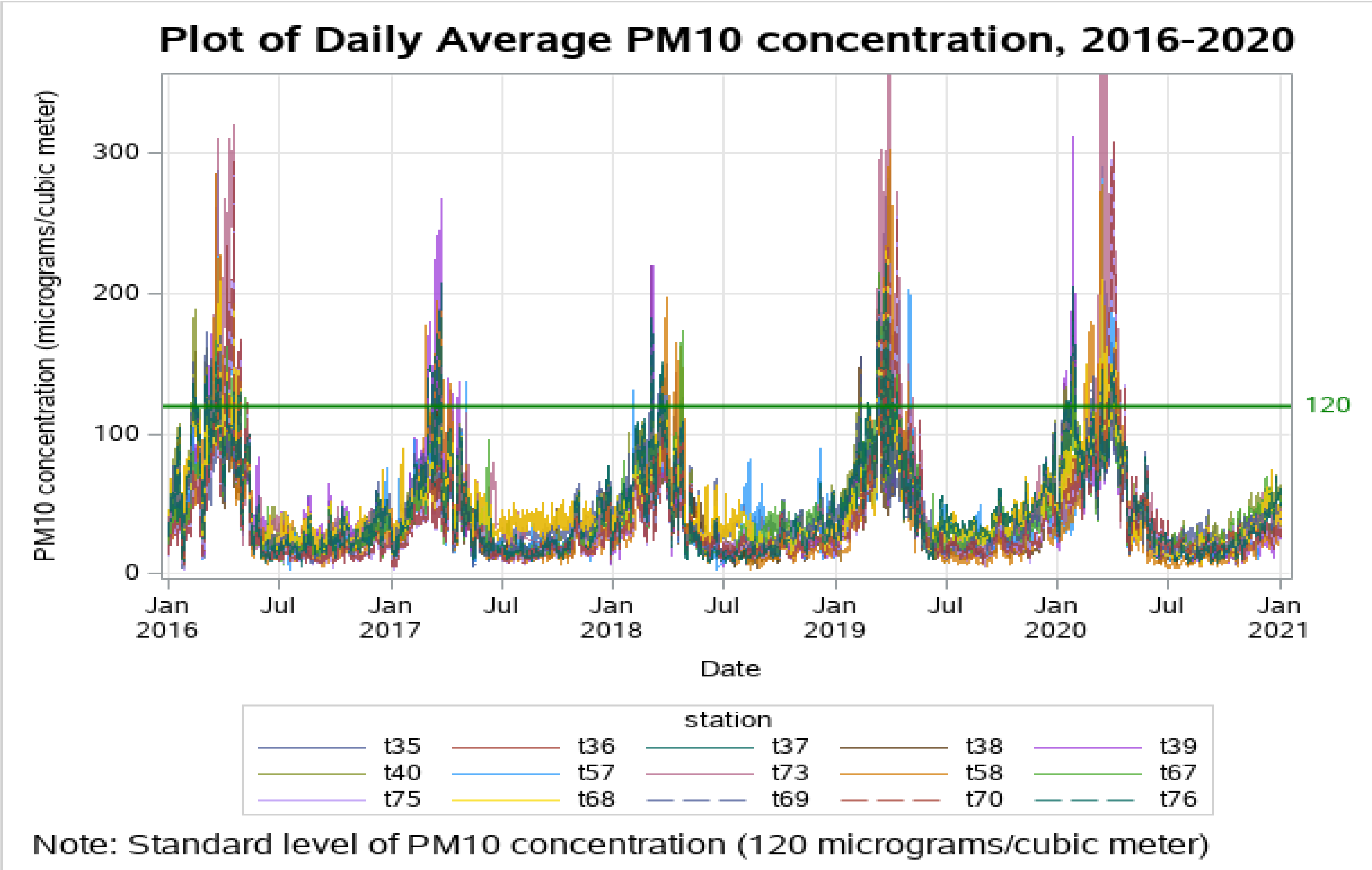


Figure 4.2 Time-series plot of daily PM_{10} concentration during 2016 – 2020, in northern, Thailand.

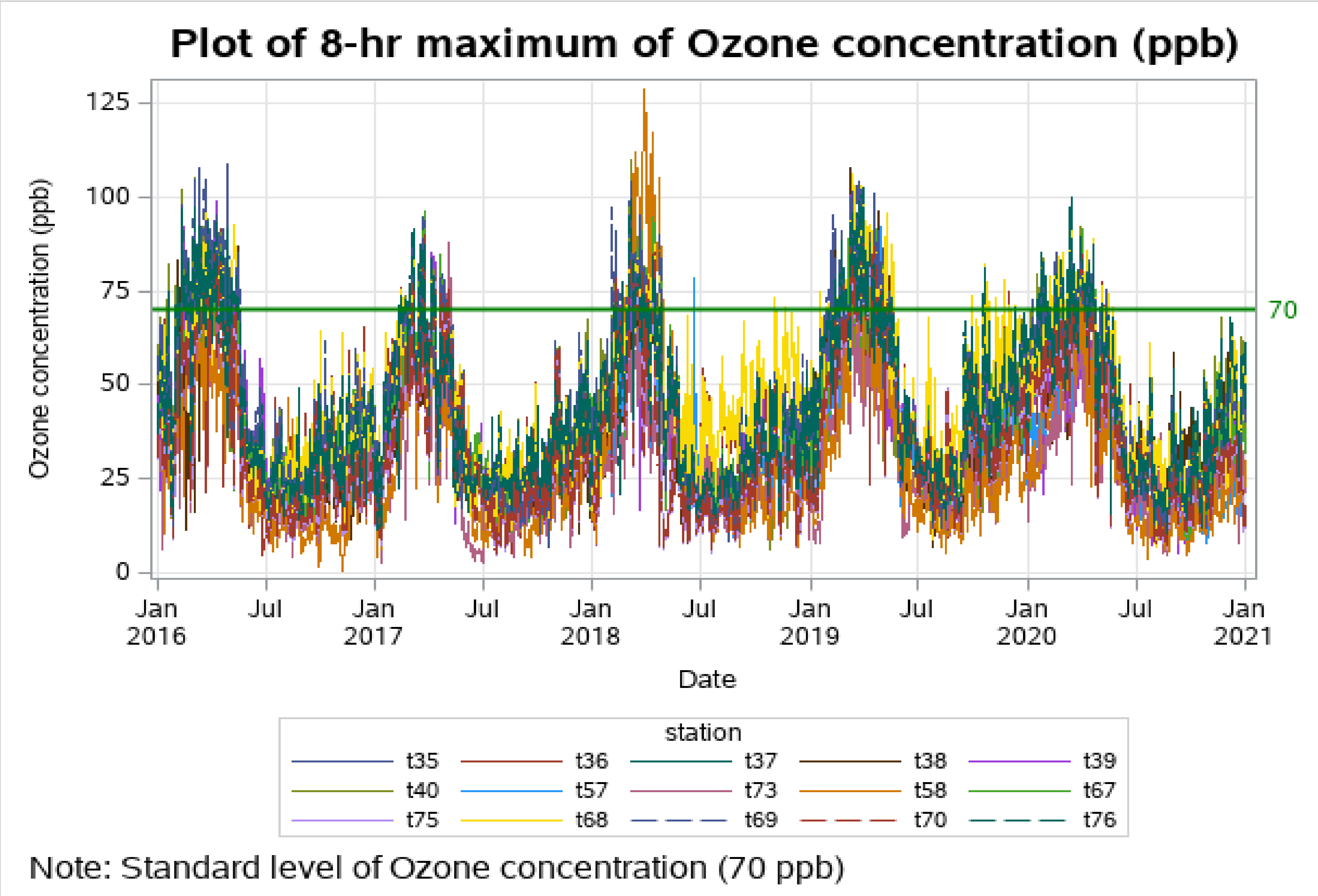


Figure 4.3 Time-series plot of 8-h maximum of O_3 concentration during 2016 – 2020, in northern, Thailand.

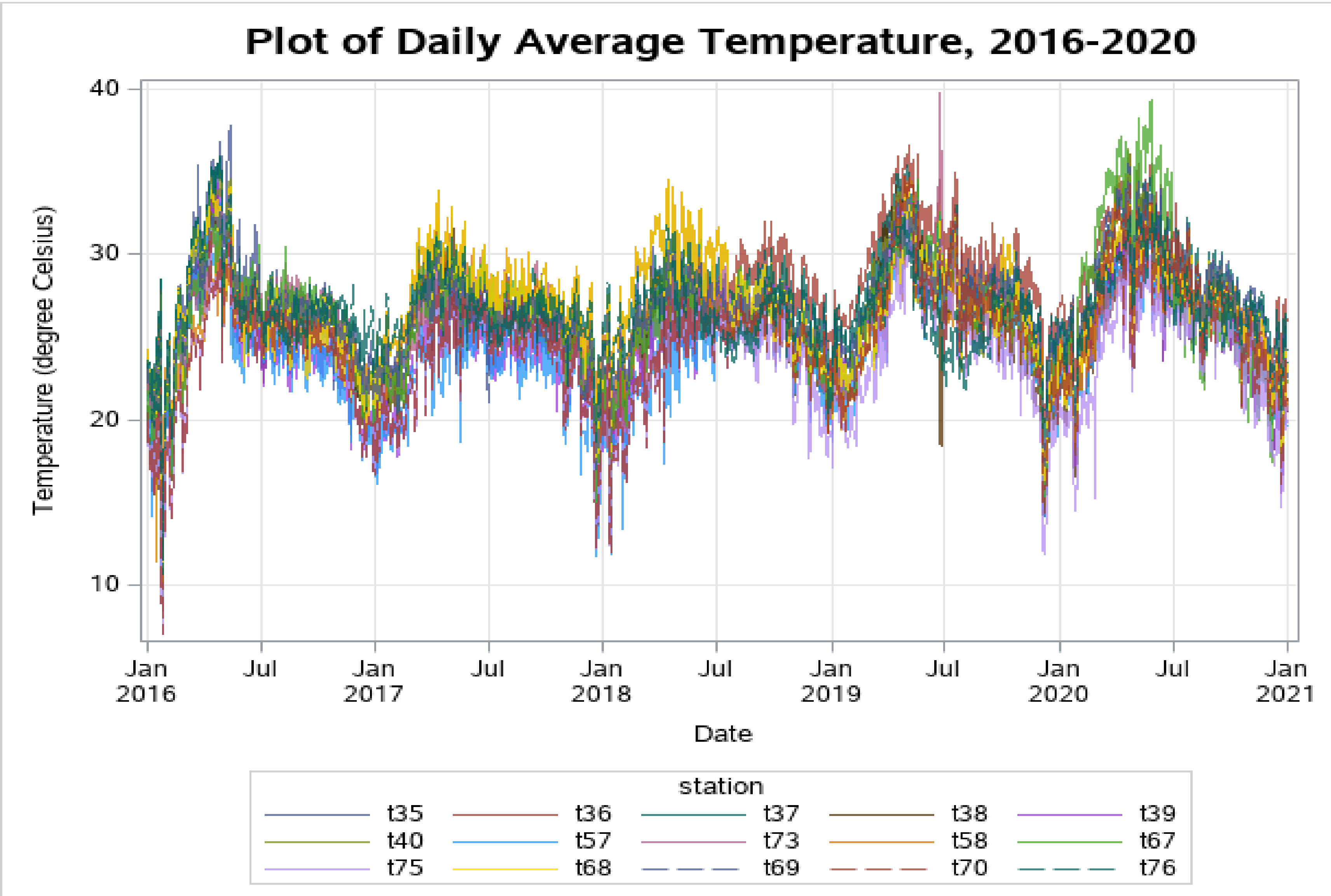


Figure 4.4 Time-series plot of daily temperature during 2016 – 2020, in northern, Thailand

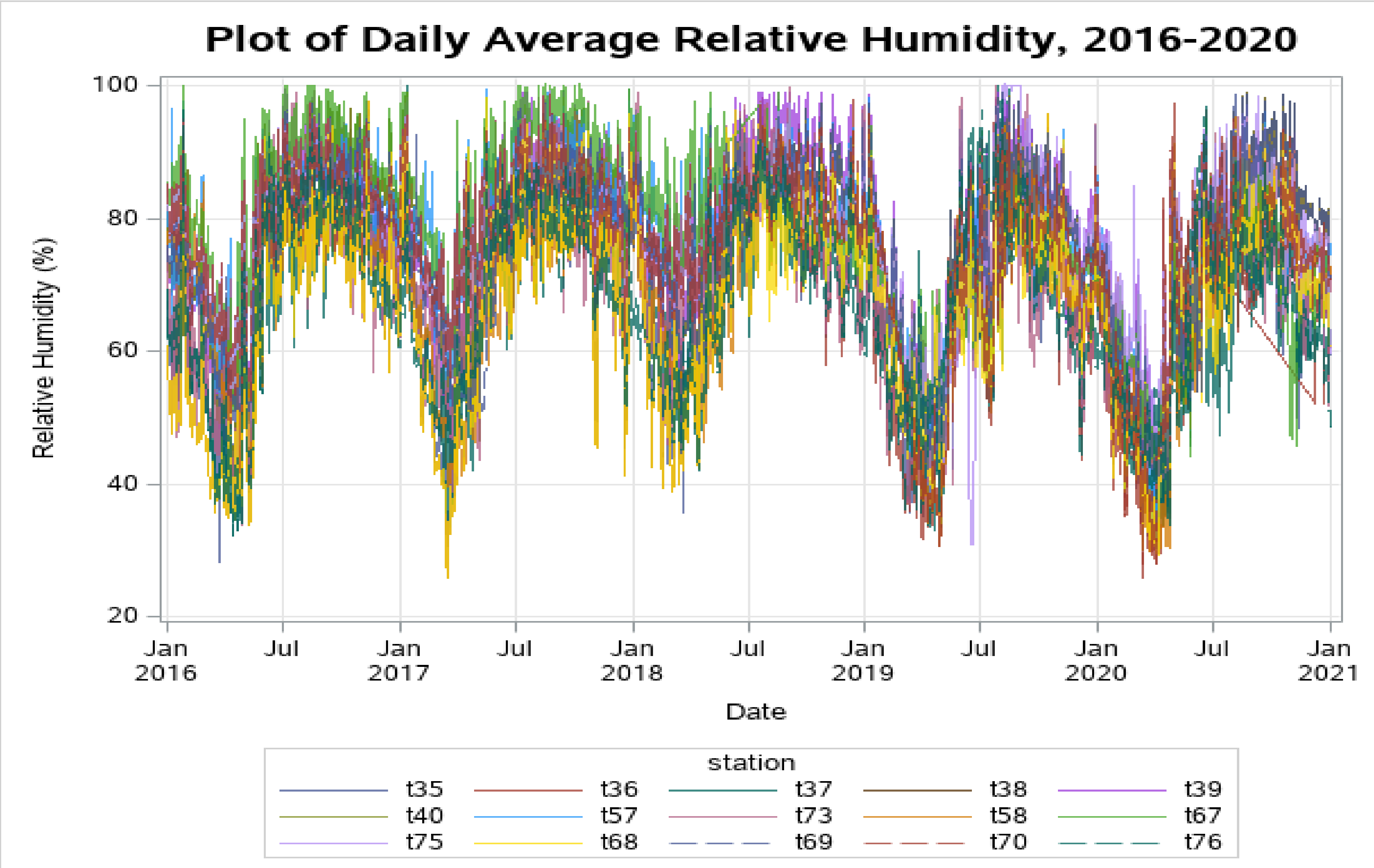


Figure 4.5 Time-series plot of relative humidity during 2016-2020, in Northern, Thailand

Correlation between the $PM_{2.5}$ concentration, other co-pollutants and meteorological variables is tested by the Spearman's rank-order test shown in Table 4.3. $PM_{2.5}$ was positively correlated with PM_{10} ($\rho = 0.89$, $p < 0.001$), supporting the thought that $PM_{2.5}$ and PM_{10} might have shared the same emission sources such as traffic yearround and biomass burning during the hazard fire period . Also ozone was strongly correlated with $PM_{2.5}$ ($\rho = 0.78$, $p < 0.001$) as its precursors nitrogen oxides and volatile organic compounds could posibly originated from traffic soures of $PM_{2.5}$. On the other hand, $PM_{2.5}$ and humidity were negative correlated ($\rho = -0.70$, $p < 0.001$) which probably caused by the rain wash which can decrease $PM_{2.5}$ concentration. Lastly, very weak correlation was found between $PM_{2.5}$ and temperature ($\rho = 0.04$, $p < 0.001$) as temperuatue was not fluctuating much regarding to high fluctuation of $PM_{2.5}$ observed.

Table 4.3 The Spearman's rank-order correlation coefficients between daily air pollutant concentrations and Meteorological variables.

Variable	$PM_{2.5}$	PM_{10}	Ozone	Temperature	Relative humidity
$PM_{2.5}$	1	0.89	0.78	0.04	-0.70
PM_{10}		1	0.80	0.11	-0.69
Ozone			1	0.20	-0.71
Temperature				1	-0.33
Relative humidity					1

4.2 $PM_{2.5}$ and Inpatient admission association

The result is divided into 2 parts. The hazard forest fire only period and the total period analyses. ORs shows the association between an interquartile range (IQR) increment of $PM_{2.5}$ concentration and the hospital admission for respiratory diseases. These ORs of $PM_{2.5}$ were adjusted for other pollutants and meteorological variables; PM_{10}, ozone, temperature, and relative humidity. Figures 4.6 indicate ORs in lag0, lag1, lag2, …, lag7. Figures 4.6 A and B illustrate the odds ratio of inpatient admission for respiratory diseases associated with an IQR increment in $PM_{2.5}$ exposure in different lags. Figures C and D male inpatient admission was filtered to show the sex influence on the ORs during the total period and during the hazard fire period respectively, similar to female inpatients as shown in Figures 4.6 E and F during total period and during hazard fire period respectively.

For the total period analysis, 793,118 cases were analyzed. The ORs for the total period (combined fire and non-fire seasons) was found at lag3 (OR = 1.002, CI: 0.994 to 1.011, $p < 1$), and lag1 (OR = 1.013, 95% CI: 1.000 to 1.026, $p < 0.1$) for female. For male, no increased risk was observed. Mostly, the OR value was less than 1 among all the lags. Some of them was above but there was no significant risk in both sex analysis. The same no-risk results also found in male and female model.

On the contrary during the hazard forest fire period, the OR values of all the lag was above 1 and its lower interval was also above 1 (Figure 4.6 B). In addition, almost all lags, the lower OR interval was above 1 except the male analysis lag 5 (Figure 4.6 D). The maximum OR was in lag1 (OR = 1.058, 95% CI: 1.041 to 1.075, $p < 0.001$) for the both-sex model (Figure 4.6 B), lag2 (OR = 1.057, 95% CI: 1.035 to 1.079, $p < 0.001$) for male model (Figure 4.6 D) and lag1 (OR = 1.082, 95% CI: 1.055 to 1.108, $p < 0.001$) for female model (Figure 4.6 F). The result indicates that for the forest fire period, $PM_{2.5}$ was an important trigger which was strongly associated with respiratory inpatient admission. Focusing on both sex model (Figure 4.6 B), at lag0 the ORs started increasing and reached the peak on lag1 then slowly dropped until lag4 and lag5 before rising up again in lag6 and lag7. This OR trend pattern could possibly be due to different sub-diseases having different risk levels at different exposure day lags. Importantly, OR lower limit at 95% confidence interval on every lag was all above the red line (value of 1) which meant an IQR increment in $PM_{2.5}$ concentration was confirmed significantly as driving up the risk for respiratory admission. To be clear, it is important to focus on the rise of $PM_{2.5}$ concentration because it potentially increases the substantial number of admissions in following days regarding related significant lags. This would benefit policies making and planning to control the $PM_{2.5}$ itself and further support management and preparation for the availability of admission rooms, work shift, relevant people such as doctors and nurse with maximized efficiency and making an advance precaution announcement to communities regarding exposure lag days for those having pre-existing respiratory conditions by local environmental authorities.

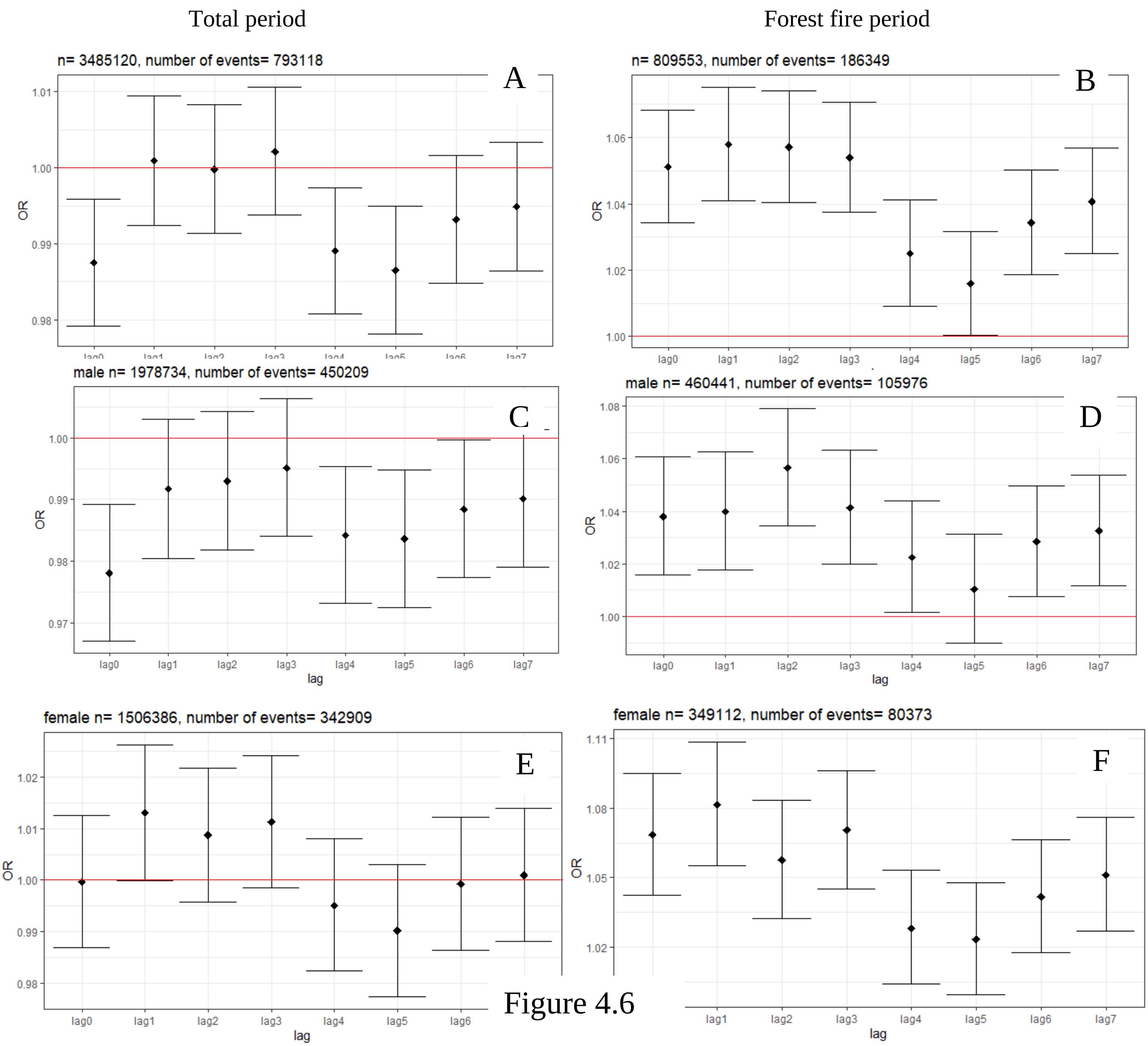


Figure 4.6 Odds ratios (with 95% CIs) of inpatient admission for total respiratory diseases associated with an IQR increase in exposure to $PM_{2.5}$

(A) Total period (C) Male (E) Female

(B) Forest fire period (D) Male (F) Female

Total period Forest fire period

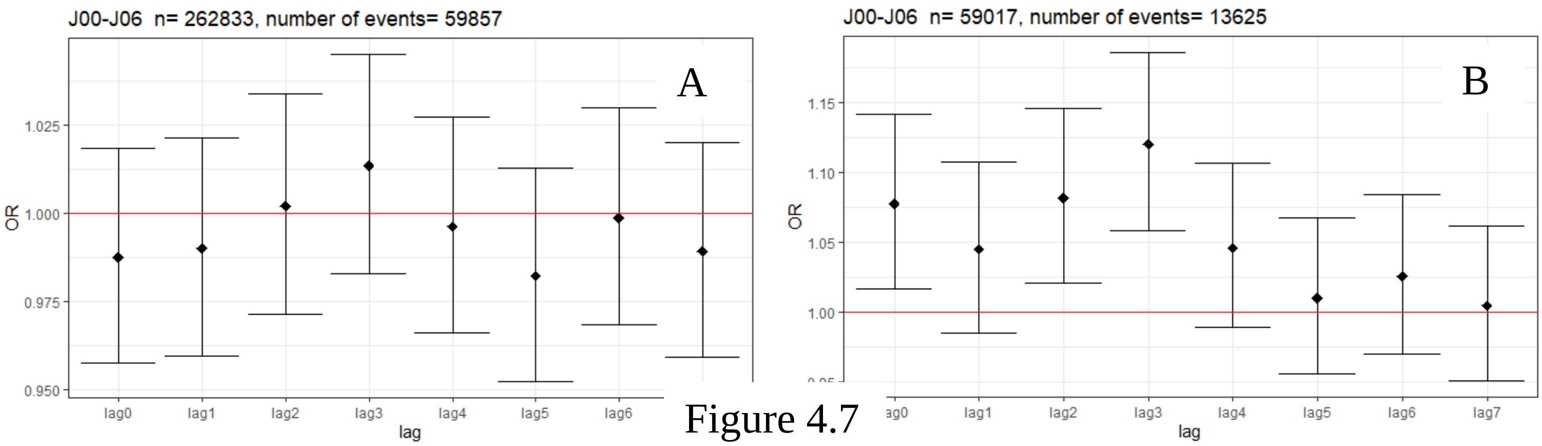


Figure 4.7

Figure 4.7 Odds ratios (with 95% CIs) of inpatient admission for acute upper respiratory infections (J00-J06) associated with an IQR increase in exposure to $PM_{2.5}$

(A) Total period (B) Forest fire period

Total period Forest fire period

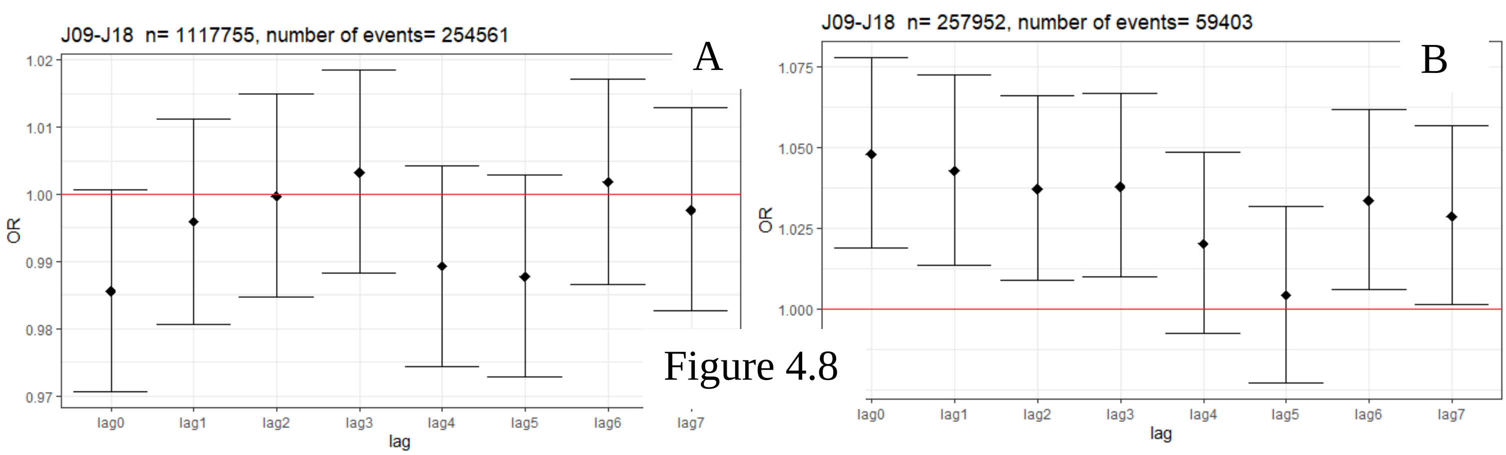


Figure 4.8

Figure 4.8 Odds ratios (with 95% CIs) of inpatient admission for influenza and pneumonia (J09-J18) associated with an IQR increase in exposure to $PM_{2.5}$

(A) Total period (B) Forest fire period

ORs of inpatient admission for acute upper respiratory infections (J00-J06) associated with an IQR increment in $PM_{2.5}$ exposure is illustrated in Figures 4.7 A and B. Figures 4.8 A and B illustrates the OR of admission for influenza and pneumonia (J09-J18) associated with an IQR increment in $PM_{2.5}$ exposure. ORs of inpatient admission for other acute lower respiratory infections (J20-J22) associated with an IQR increases $PM_{2.5}$ exposure is shown in Figure 4.9 A and B. For Figures 4.10 A and B, ORs of admission for other diseases of respiratory system (J95-J99) associated with an IQR increases $PM_{2.5}$ exposure is shown. Each of the figures shows the ORs at 8 different lags including lag0, lag1, lag2, …, lag7. The left figures are total period analysis, and the right figures are forest fire period analysis. For the all-respiratory disease analysis, ORs of forest fire model (Figure 4.6 B) were obviously higher than the total period analysis (Figure 4.6 A). The same trend occurred to the subgroup respiratory condition analysis all major 4 respiratory conditions includes acute upper respiratory infections, influenza and pneumonia, other acute lower respiratory infections, and other diseases of respiratory system. The ORs of forest fire model was considerably higher compared to the total period model in total respiratory diseases and in 4 subgroup respiratory conditions. Not mentioning about the total period analysis due to the reason that there was no statistically significant increased risk (Figure 4.6 A).

In fire period, subgroup acute upper respiratory infections (J00-J06) ORs started to rise at lag1 and were peaked at lag3 (OR = 1.121, 95% CI: 1.059 to 1.186, $p < 0.001$) in Figure 4.7 B. ORs of influenza and pneumonia (J09-J18) and other acute lower respiratory infections (J20-J22) were peaked at lag0 (OR = 1.048, 95% CI: 1.019 to 1.078, $p < 0.01$) in Figure 4.8 B and lag7 (OR = 1.069, 95% CI: 1.015 to 1.127, $p < 0.05$) in Figure 4.9 B respectively. Lastly, other diseases of respiratory system (J95-J99) ORs were peaked at lag3 (OR = 1.060, 95% CI: 1.012 to 1.111, $p < 0.05$) in Figure 4.10 B. Nearly all fire period ORs in Figures 4.7 B, 4.8 B, 4.9 B, and 4.10 B were greater than a value of 1. These confirmed increased risks were really common during hazard period of biomass burning from forest fire. Moreover, risks were found statistically increased for 3 lags in acute upper respiratory infections, 6 lags in influenza and pneumonia, 1 lag in other acute lower respiratory infections and 2 lags in other diseases of respiratory system. These findings emphasized that before the hazard fire period, central and local authorities need an extra specific $PM_{2.5}$ fire abatement, more efficient respiratory protection for community and greater hospital service preparation. Such statistically significant ORs in 4 sub-respiratory diseases were not found in total period analysis. This could possibly be due to more months having no fire event so $PM_{2.5}$ sources were more purely relevant to traffic.

Total period Forest fire period

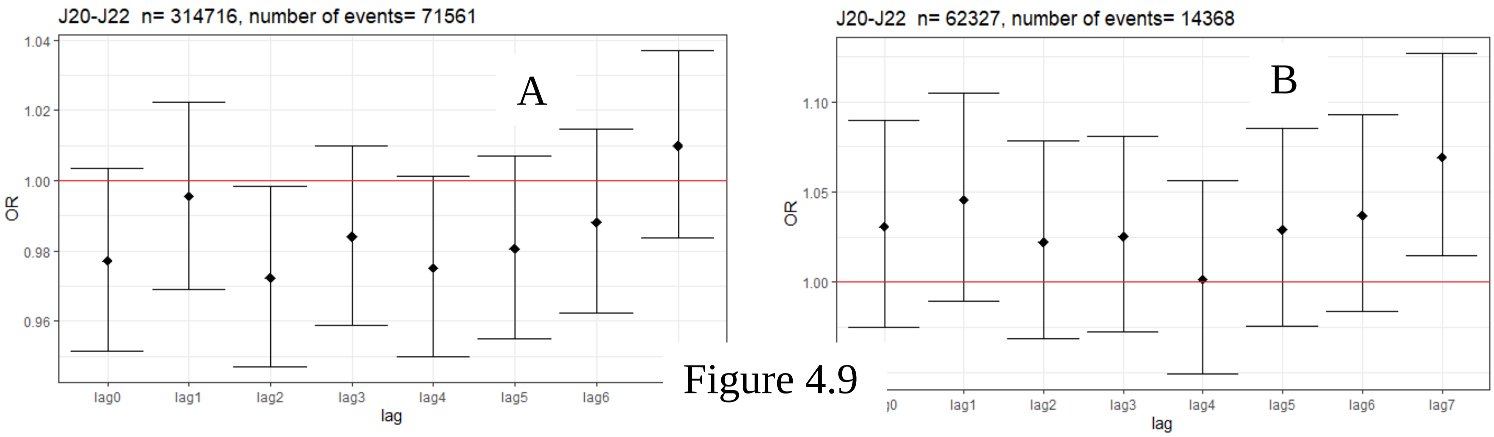


Figure 4.9

Figure 4.9 Odds ratios (with 95% CIs) of inpatient admission for other acute lower respiratory infections (J20-J22) with an IQR increase in exposure to $PM_{2.5}$

(A) Total period (B) Forest fire period

Total period Forest fire period

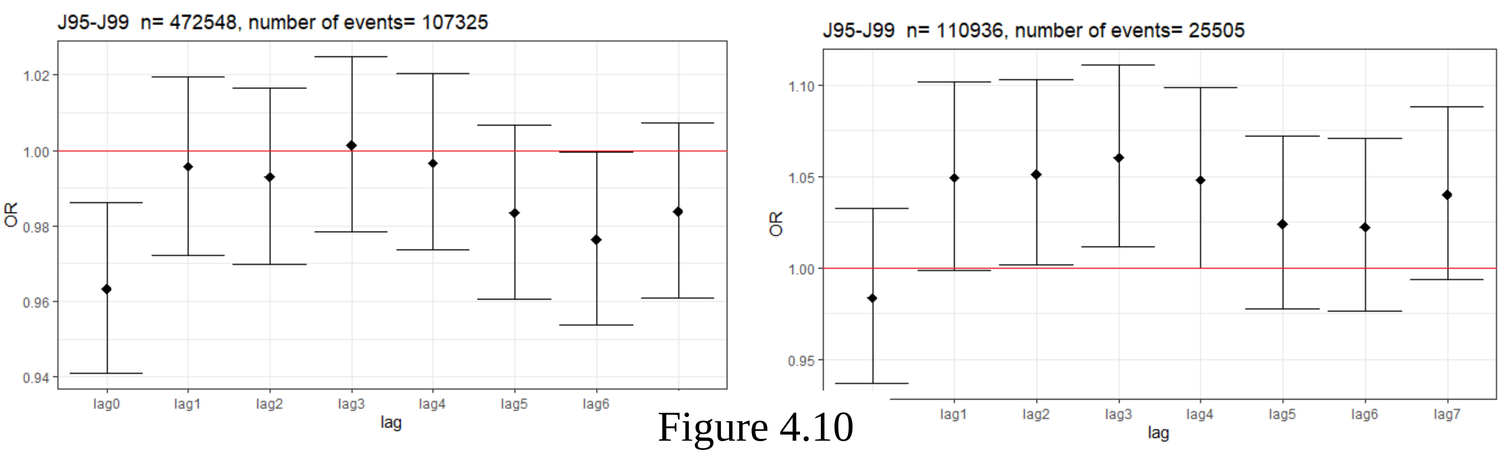


Figure 4.10

Figure 4.10 Odds ratios (with 95% CIs) of inpatient admission for other diseases of respiratory system (J95-J99) with an IQR increase in exposure to $PM_{2.5}$

(A) Total period (B) Forest fire period

Total period | Forest fire period

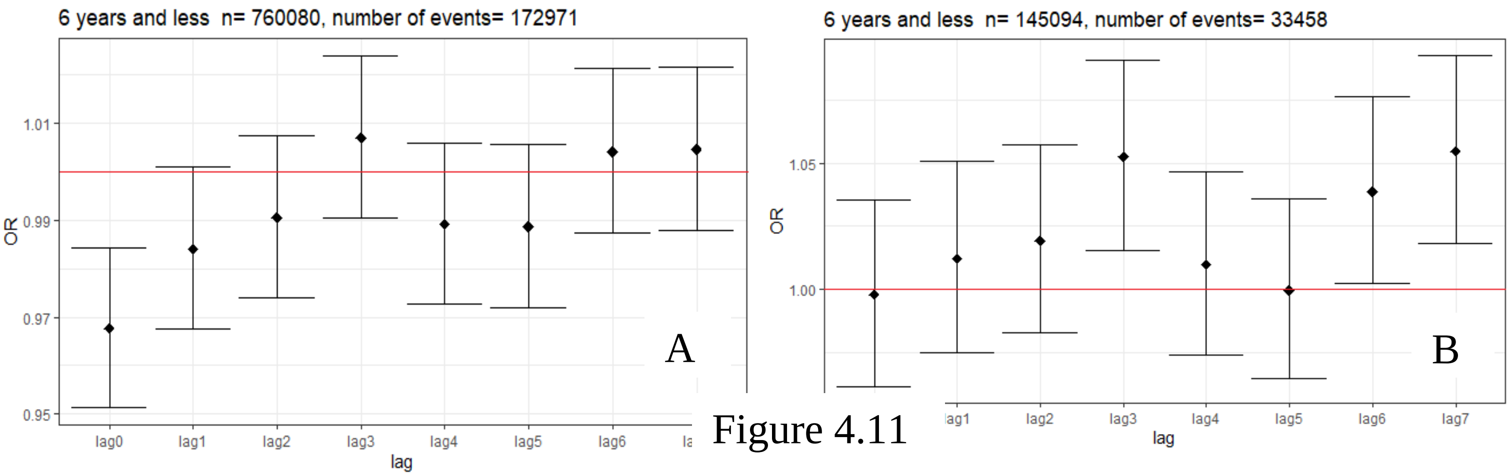
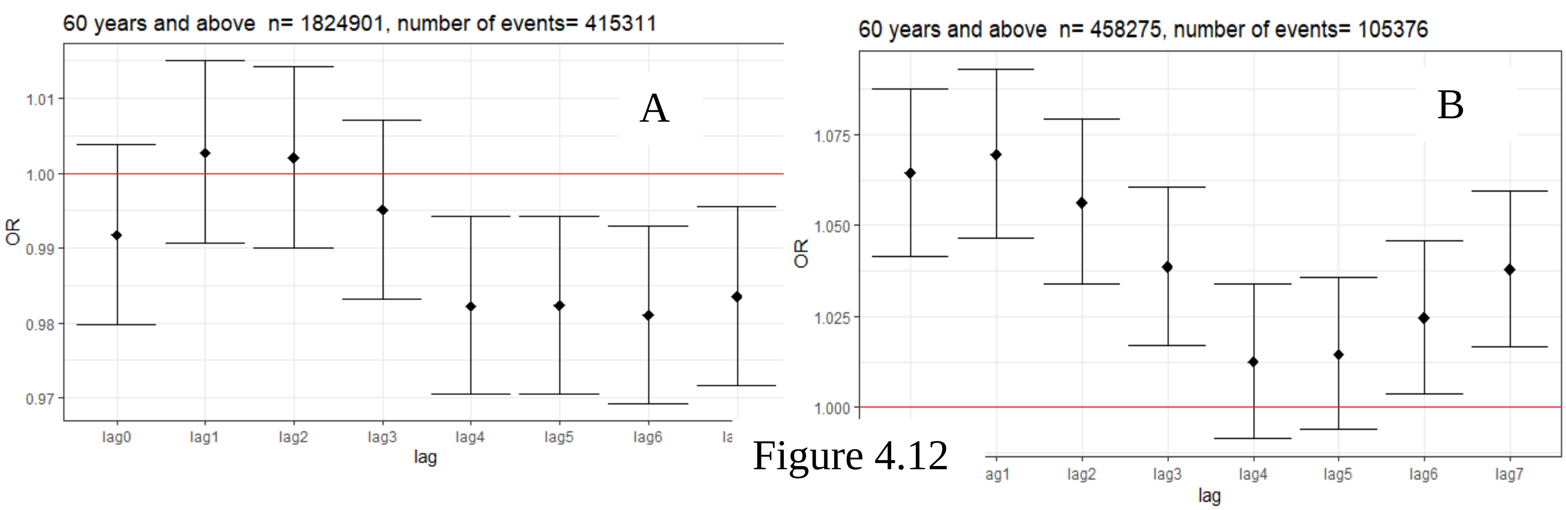


Figure 4.11 Odds ratios (with 95% CIs) of inpatient admission of children age of 6 years and below with an IQR increase in exposure to $PM_{2.5}$
(A) Total period (B) Forest fire period

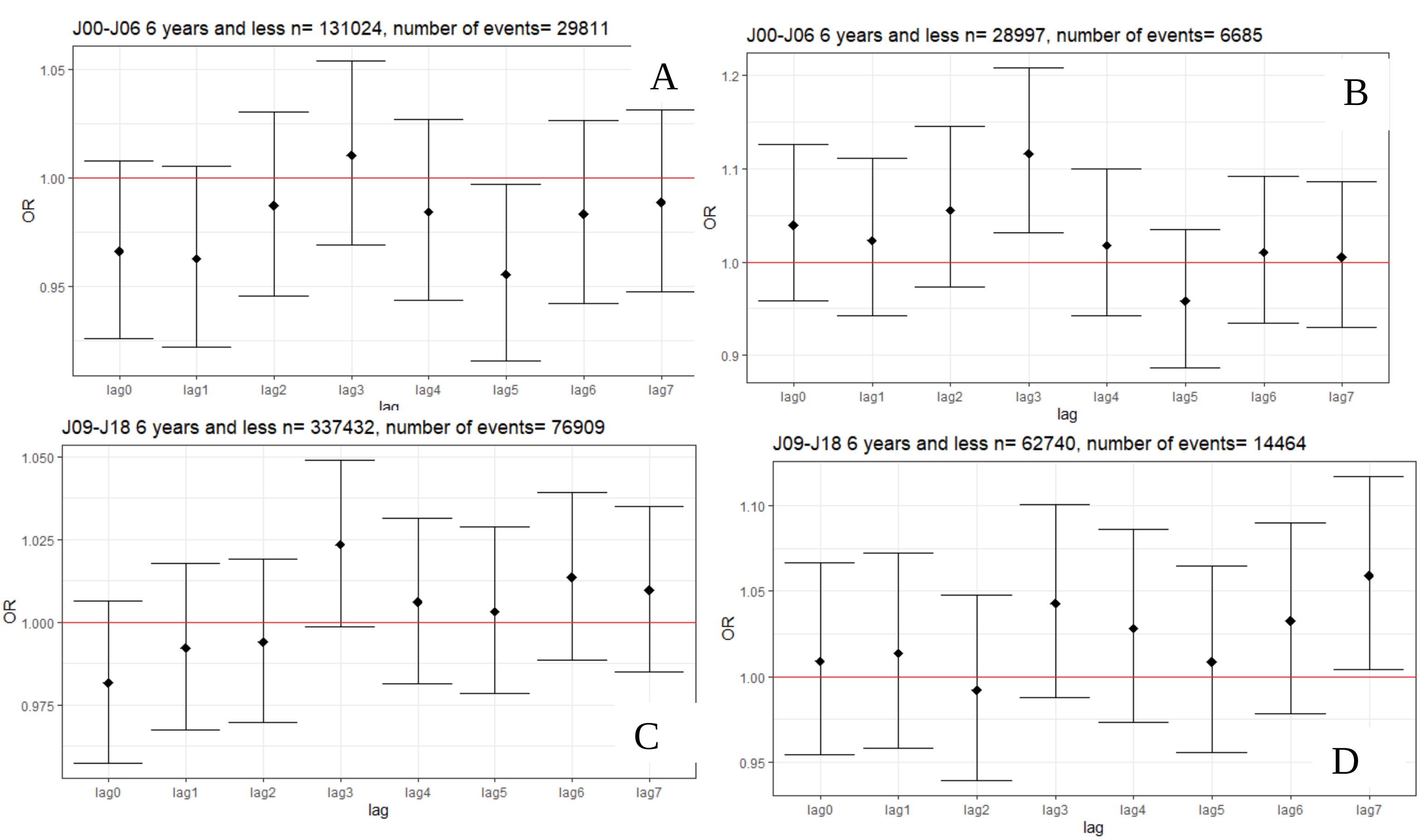


Total period | Forest fire period

Figure 4.12 Odds ratios (with 95% CIs) of inpatient admission for elderly age of 60 years and above with an IQR increase in exposure to $PM_{2.5}$
(A) Total period (B) Forest fire period

Age is another factor which can affect hospital admission for respiratory diseases. The 2 subgroups for age were analyzed including children and elderly. The age is classified according to the guideline of Ministry of Public Health, 6 years and below as children before entering primary school and 60 and above as the elderly. Odds ratios (with 95% CIs) of inpatient admission of children with per IQR increase in exposure to $PM_{2.5}$ is shown in Figures 4.11 A and B. Figures 4.12 A and B shows ORs (with 95% CIs) of inpatient admission for elderly age of 60 years and above with per IQR increase in exposure to $PM_{2.5}$. For the total period analysis on the left, both children and elderly, there were no significant risk because the ORs lower limit was not exceed 1. On the other hand, right side figures showing the fire period analysis, most ORs of all the lags were more than 1. For the children, the fire model also had higher ORs than the total period model. The ORs for Children in fire period model peaks at lag7 (OR = 1.055, 95% CI: 1.018 to 1.093, $p < 0.01$) in Figure 4.11 B. For the elderly, ORs were considerably higher than the total period analysis. OR was significantly peaked at lag1 (OR = 1.070, 95% CI: 1.047 to 1.093, $p < 0.001$) in Figure 4.12 B.

Total period | Forest fire period



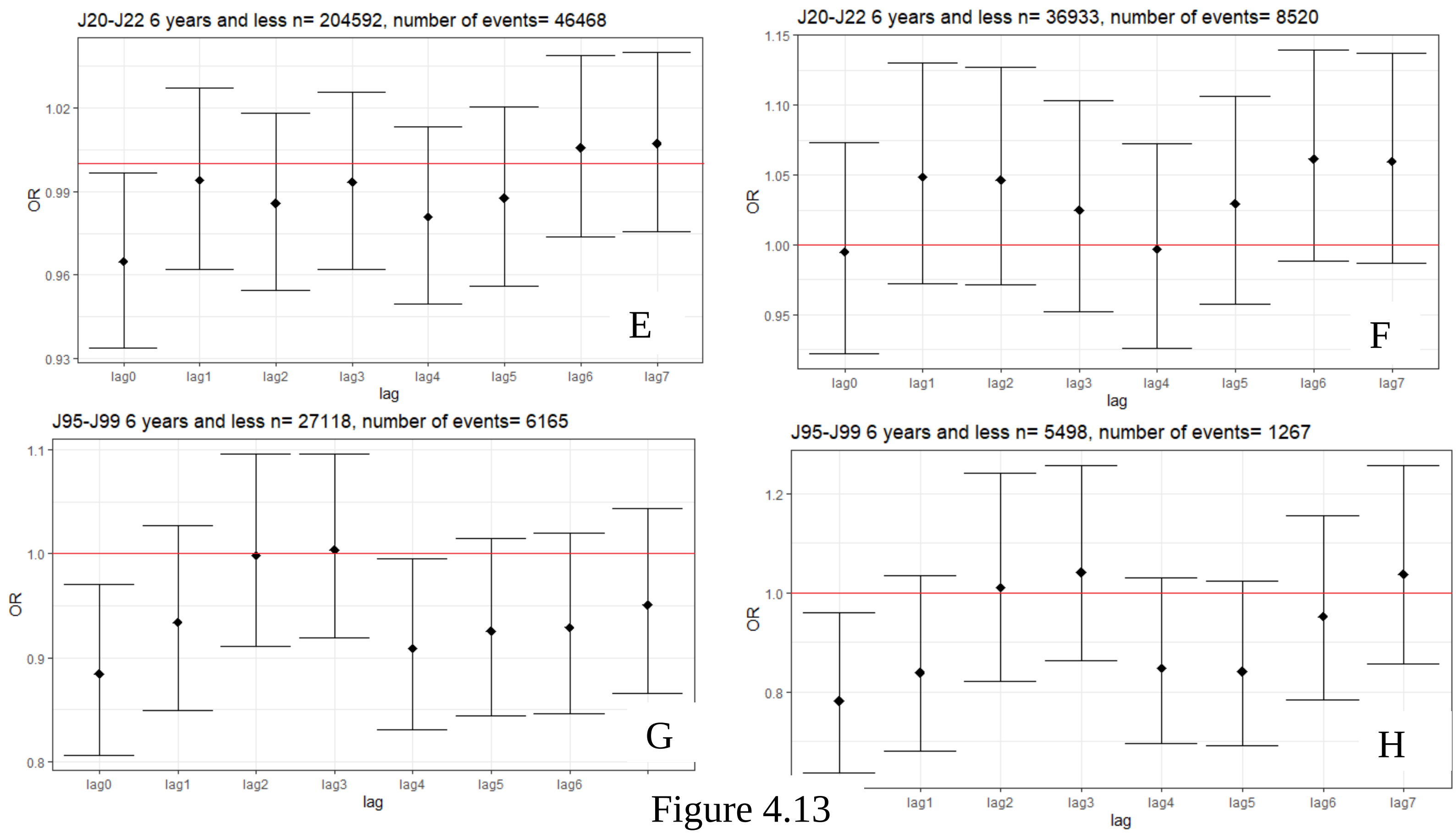


Figure 4.13

Total period Forest fire period

Figure 4.13 Odds ratios (with 95% CIs) of inpatient admission of children age of 6 years and below with an IQR increase in exposure to $PM_{2.5}$ (sub diseases-age specific)

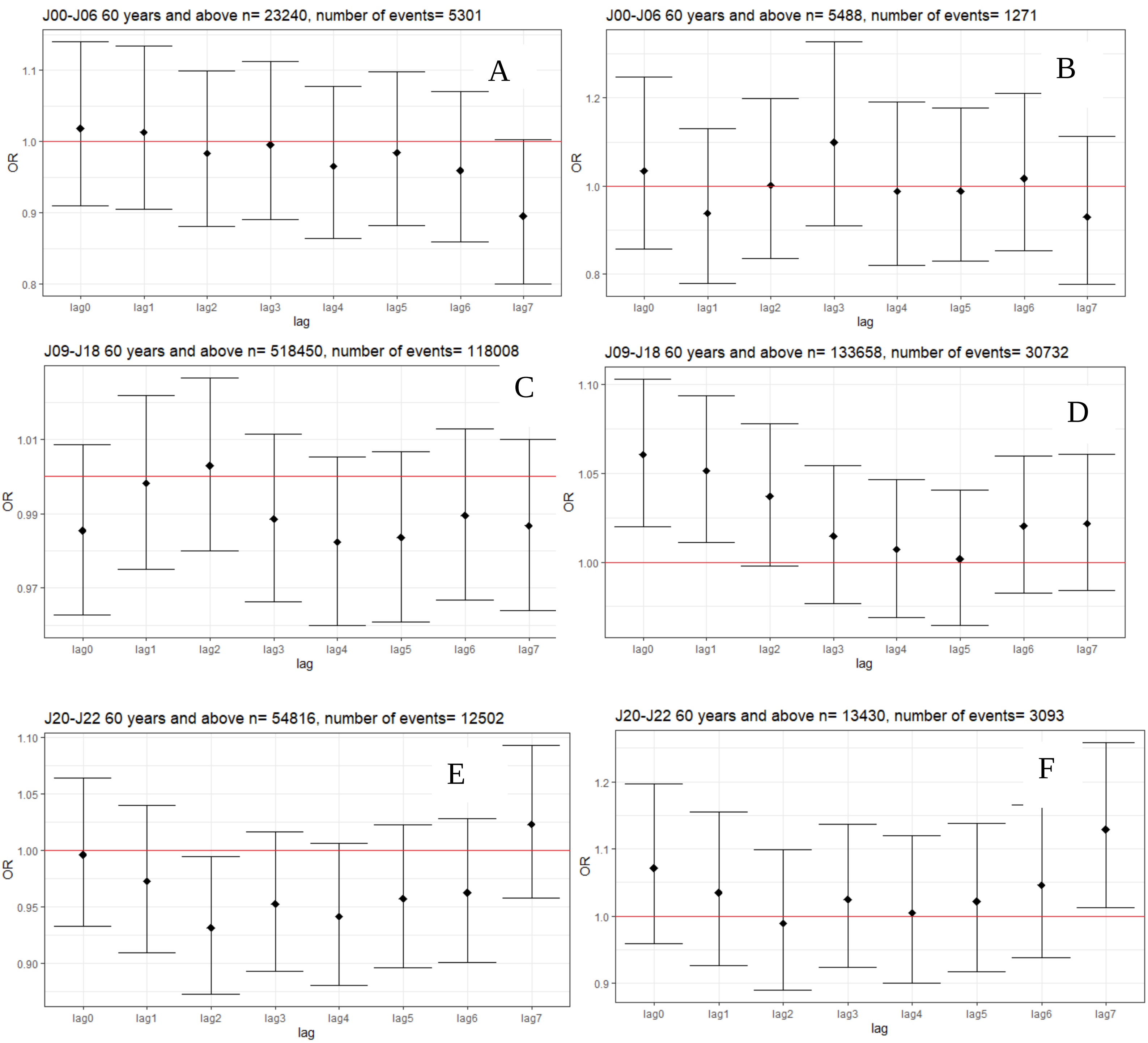
A and B =J00-J06, B and C =J09-J18, E and F =J20-22, G and H =J95-99

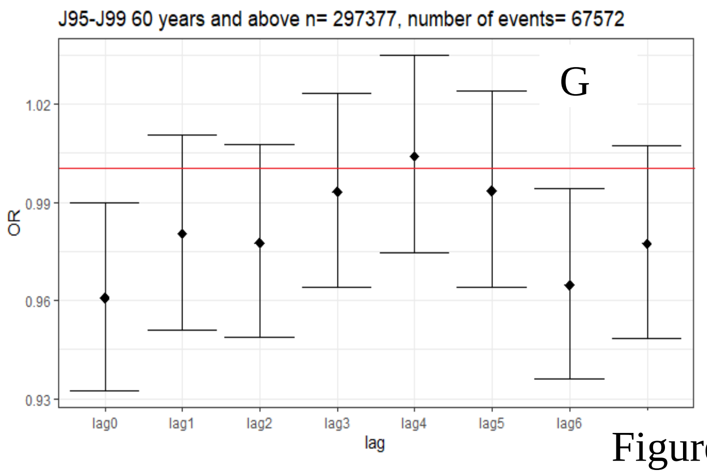
A, C, E and G =Total period B, D, F and H = Forest Fire period

For sub disease analysis in children age of 6 years and less, fire period analysis had higher ORs than total period like others previous model. There was no statistically significant risk observed in the total period in all 4 sub diseases shown in left side plots (Figures 4.13 A, C, E, and G). For fire period, ORs of acute upper respiratory infections (J00-J06) peaked at lag3 (OR = 1.116, 95% CI: 1.031 to 1.208, $p < 0.01$) in Figure 4.13 B, ORs of influenza and pneumonia (J09-J18) and other acute lower respiratory infections (J20-J22) were peaked at lag7 (OR = 1.059, 95% CI: 1.004 to 1.117, $p < 0.05$) in Figure 4.13 D and lag6 (OR = 1.061, 95% CI: 0.989 to 1.139, $p < 0.1$) but not statistically significant in Figure 4.13 F respectively. Lastly, other diseases of respiratory system (J95-J99) ORs were peaked at lag3 (OR = 1.042, 95% CI: 0.863 to 1.256, $p < 1$) in Figure 4.13 H but not statistically significant.

Total period

Forest fire period





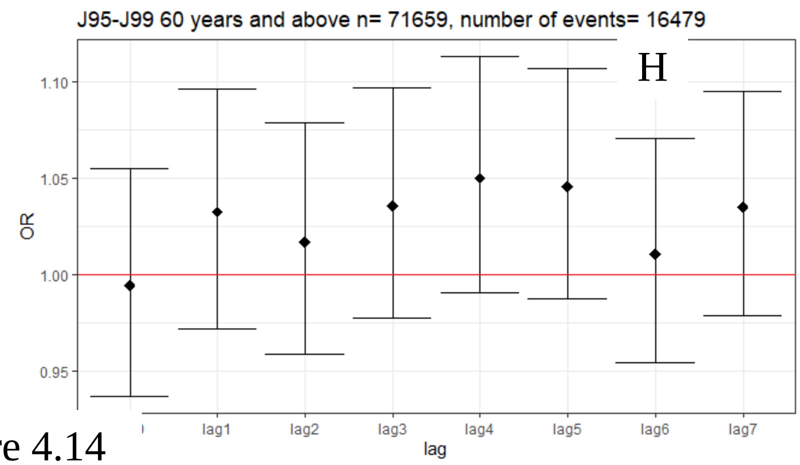


Figure 4.14

Figures 4.14 Odds ratios (with 95% CIs) of inpatient admission of elderly age of 60 years and above with an IQR increase in exposure to $PM_{2.5}$ (sub diseases-age specific)

A and B =J00-J06, B and C =J09-J18, E and F =J20-22, G and H =J95-99

A, C, E and G =Total period B, D, F and H = Forest Fire period

For sub-disease in elderly age of 60 years and above, same as the children model, there was no statistically significant risk observed in the total period in all 4 sub diseases (Figures 4.14 A, C, E, and G). For fire period, ORs of acute upper respiratory infections (J00-J06) peaked at lag3 (OR = 1.099, 95% CI: 0.910 to 1.327, $p < 1$) in Figure 4.14 B. ORs of influenza and pneumonia (J09-J18) and other acute lower respiratory infections (J20-J22) were peaked at lag0 (OR = 1.061, 95% CI: 1.020 to 1.103, $p < 0.01$) in Figure 4.14 D and lag7 (OR = 1.129, 95% CI: 1.013 to 1.258, $p < 0.05$) in Figure 4.14 F respectively. Lastly, other diseases of respiratory system (J95-J99) ORs were peaked at lag4 (OR = 1.050, 95% CI: 0.991 to 1.113, $p < 0.1$) but not statistically significant in Figure 4.14 H.

From the sub diseases-age specific analysis, it was noticed that the fire period model was still detecting many of ORs values above the redline (a value of 1) which meant that positive risks were existing but their lower limits of ORs were below 1. This is likely due to the dramatic decrease in number of inpatient case events in the 3 months of fire periods, so it made a wide confidence interval due to lacking statistical power to detect the risk. Nevertheless, regarding this lacking case events and statistical power, this work confirmed the increased risk in both groups for specific sub diseases. Some sub diseases-age specific risks were statistically significant. These findings suggest a need of specific $PM_{2.5}$ risk communication, abatement strategy, and health care service in advance regarding their significant exposure lag days for age-specific sensitive population at risk.

As previous studies have confirmed similar findings, these mentioned results showed that $PM_{2.5}$ concentration had strongly associated with respiratory disease admission. Moreover, the study (Zhang et al., 2020) analyzed short-term effects of PM1 and $PM_{2.5}$ on hospital admission for respiratory diseases in Shenzhen, China. This study had analyzed seasonal effects including cold and warm seasons. The findings showed that PM-hospitalization association was stronger in the cold season than that in the warm season for both PM1 and $PM_{2.5}$. But my study found that the ORs in the fire period were significantly higher compared to the total period. In Thailand, because of the high temperature and drought condition in hot season, the fire could be occurring naturally in some forest area which can increase fire spots resulting in more $PM_{2.5}$ emission sources. So high $PM_{2.5}$ concentrations were shown in Figure 4.1 during the hot season.

There is an epidemiological evidence of $PM_{2.5}$ causing damage on human respiratory system (Xing et al., 2016). Scientists have revealed a significant correlation between fine particle pollutants and respiratory morbidity and mortality (Brunekreef & Holgate, 2002). In European Union countries, $PM_{2.5}$ decreased the average life span by 8.6 month (Orru et al., 2011). From the study of 29 European countries, Analitis (Analitis et al., 2006) found that mortality from respiratory diseases increased by 0.58% for every 10 μg/m^3 increase of PM_{10}. Another recent studies reported that the respiratory diseases prevalence rate was increased by 2.07%, while hospitalization rate raised by 8%, when the daily $PM_{2.5}$ increased by 10 μg/m3 (Dominici et al., 2006; Zanobetti et al., 2009). Even though some previous discussed articles have reported the PM_{10}-diseases association but in fact in this work $PM_{2.5}$ was well correlated with PM_{10} as observed in the correlation test (Table4.3) proving that $PM_{2.5}$ had strong association with PM_{10} (ρ= 0.89, $p < 0.001$). The higher elevated $PM_{2.5}$, the more inpatients of respiratory tract diseases whose respiratory system was undermined in lung function. This statistically confirmed association raised morbidity of cardiopulmonary diseases. Furthermore in other works, the association was more obvious in the elderly, pregnant women, adolescents, infants, patients with a history of cardiopulmonary problems and in other susceptible populations (B. F. A. De Oliveira et al., 2012; Huynh et al., 2006; Martinelli et al., 2012). From all above-mentioned articles, they have confirmed the result in which $PM_{2.5}$ is truly harmful pollutant to human respiratory tract in the northern Thailand. Not only an increment on hospitalization, but also overall of respiratory morbidity and mortality would be increased which results in shortened life span.

As the results of the subgroup respiratory conditions were found repeated for positive association for most lags and all respiratory conditions had significant increased risk at least 1 lag.

these findings have proved that increment of $PM_{2.5}$ concentration in forest fire period played an important role in stimulating and increasing risk of hospitalization for respiratory diseases in the 9 provinces, Northern Thailand.

Chapter 5 Conclusion

To sum up, the results showed that raised level of daily $PM_{2.5}$ concentration in hazard forest fire period had significant risk for inpatient admission for respiratory diseases in 118 hospitals, 9 provinces, Northern Thailand, 2016-2020. The hospital admission for all 4 respiratory conditions were strongly associated with the rise in daily $PM_{2.5}$ concentration in the forest fire period compared to the total period model. In addition, 4 subgroups of respiratory conditions for fire period model had a considerably higher ORs compared to those for total period analysis. Even though some of the lower limit was less than 1, most ORs value was still above 1, meaning that the risk was still detected. The 4 subgroups of respiratory conditions consisted of acute upper respiratory infections, influenza and pneumonia, other acute lower respiratory infections and other diseases of respiratory system were all statistically associated with an IQR increase of $PM_{2.5}$ at least 1 lag.

I hope these findings would benefit decision making and strategic planning to handle future environmental $PM_{2.5}$ in Northern Thailand along with others region of Thailand as well. Aiming to reduce the number of inpatient visits from $PM_{2.5}$ exposure and health impacts in the area of forest fire events, knowledge and education is crucial and can benefit people preventing themselves from unnecessary polluted air exposure.

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