THE EFFECT OF THE ENVIRONMENT FACTORS UPON AMBULANCE DESPATCHES IN LONDON AND THAILAND

By

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Supervisor's declaration

I declare that the study in this thesis was undertaken and written by Kamolrat Sangkharat. The results in chapter 4 and 5 were published in journals mentioned in chapters. Chapter 6 is in preparation for publication. All publications have Kamolrat Sangkharat as first author.

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Abstract

This thesis investigates environmental risk factors for human health. In particular, it investigates the role of extreme temperatures, air pollution and precipitation upon health. The research uses ambulance dispatch data as the indicator of health. Previous studies investigating the association between environmental factors (temperature, air pollution and rainfall) and adverse health outcomes have focused mainly on mortality and hospital admission data. Previously, relatively little research has examined the role of environmental factors upon ambulance dispatches.

This study provides three distinct ambulance dispatch studies using data from various locations. Firstly, the association between air pollution and ambulance dispatches was conducted by using a systematic review and meta-analysis using data from all global sources. Secondly, a time series analysis was applied to analyse the impact of extreme temperature (low and high) on London Ambulance Service (LAS) data. Thirdly, the Thai ambulance dispatches in the Northern and Southern provinces were used to assess the association between rainfall and road accidents. Throughout the thesis, the estimated risk is reported as relative risk (RR) with 95% confidence intervals due to exposure to environmental factors such as extreme low and high temperatures, increased level of pollutants and an increase in rainfall.

The main results reported are that, from a global systematic review, $PM_{2.5}$ and NO_2 are significantly associated with all-respiratory and asthma dispatches, respectively, for ambulance dispatch data. CO, $PM_{2.5}$ and coarse particles are significantly associated with cardiac arrest dispatch data. In London, extreme temperatures have a significant association with an increase in ambulance dispatches. For example, low temperature was significantly associated with an increase in ambulance dispatches for 999, asthma, dyspnoea, RCI and 'generally unwell' while ambulance dispatches for 999, red, COPD, chest pain and non-cardiorespiratory category

showed a significant increase for high temperatures. Moreover, in Thailand road accidents were significantly associated with rainfall.”

The results from this thesis will help public health services understand the role of the environment upon health as they can be used in environmental surveillance and early warning systems. This will help achieve an effective preparation of the emergency service under climate change. The outcomes provide new knowledge that can be used to raise awareness on how to mitigate environmental risks. This knowledge can help improve worldwide ambulance services, especially in low and middle-income countries, notably Thailand.

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List of abbreviations

AIC	Akaike Information Criterion
ALRI	Acute lower respiratory infection
AMPDS	Advanced Medical Priority Dispatch System
BADC	British Atmospheric Data Centre
BC	Black carbon
CBD	Criteria Based Dispatch
CCP	Cardiac chest pain
CI	Confidence interval
CO	Carbon monoxide
COPD	Chronic Obstructive Pulmonary Disease
Df	Degree of freedom
DLNM	Distributed Lag Non-Linear model
ER	Excess risk
ED	Ambulance dispatches
EAD	Emergency Ambulance dispatches
GAM	Generalized additive model
GHG	Greenhouse gases
GLM	Generalized linear model
HR	Hazard ratio
HRI	Heat-related illness
I^2	Heterogeneity
ICD-10	International Classification of Diseases, 10th Revision

IPCC	Intergovernmental Panel on Climate Change
LAS	London Ambulance Service
LMIC	Low and middle-income countries
Max	Maximum
MDP	Minimum dispatches percentile
Min	Minimum
MMT	Minimum Mortality Temperature
NA	No available relevant data
NHS	National Health Service
NIEM	National Institute for Emergency Medicine
NO_2	Nitrogen dioxide
NOS	Newcastle-Ottawa scale
O_3	Ozone
OHCA	Out-of-hospital cardiac arrest
OR	Odds ratio
PACF	Partial autocorrelation function
$PM_{2.5}$	Particulate matter with aerodynamic diameters less than 2.5 micrometres
PM_{10}	Particulate matter with aerodynamic diameters less than 10 micrometres
ppb	Parts per billion
ppm	Parts per million
PRISMA	The Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCI	Respiratory chest infection
RH	Relative humidity

RR	Relative risk
SD	Standard deviation
SDGs	Sustainable Development Goals
SE	Standard error
SJP	St James Park
SO_2	Sulphur dioxide
SPM	Suspended particulate matter
T_{MADT}	The Minimum Ambulance Dispatch Temperature
UFP	Ultrafine particles
UHI	Urban Heat Island
WHO	World Health Organization

CHAPTER 1 : INTRODUCTION

1.1 Background

Climate change is a global effect, which links changes in average temperature and other meteorological variables to the emissions of greenhouse gases (GHGs) since the industrial revolution. The Intergovernmental Panel on Climate Change (IPCC) predicts that by 2100 the Earth's global mean surface temperature will increase in the range of 0.3-4.8°C dependent upon the GHG emission pathway the world takes (IPCC, 2014). In addition to increasing the mean temperature, climate change will also increase the frequency of extreme temperature events.

The effects of climate change can affect human health both directly and indirectly. Climate change means that temperatures will increase, precipitation patterns will change, and sea levels will rise. There will be more heatwaves, droughts, and in general more extreme weather (Holly, 2019). The World Health Organization (WHO) states that climate change will directly affect human health by increasing the frequency and severity of exposure to extreme hot temperatures. These effects have already been observed in many countries. Vulnerable people such as elderly, children, those with pre-existing health conditions, poor and outdoor workers are more sensitive to heat effects risks compared to other groups (WHO, 2018a).

Climate change is closely linked to air pollution. In fact, many GHGs are also air pollutants that affect health, for example carbon dioxide (CO_2) and ozone (O_3). Furthermore, climate change can affect air pollution, and vice versa. For example, increases in ground-level O_3 and/or particulate matter (PM) can change atmospheric chemistry such as ozone depletion or photochemical smog. Some air pollutants are climate warming agents (for example O_3 and black carbon PM), while other PM constituents (for example sulphates) are more reflective towards sunlight leading to a global cooling effect (EPA, 2016).

The Sustainable Development Goals (SDGs) adopted by United Nations Member States in 2015 (around 170 countries) states that countries should plan to achieve the goals by 2030. The SDGs aim to end poverty and create a healthy and sustainable world. There are four goals from the 17 goals which clearly relate to air pollution, however, arguments can be made for the relevance of many of the goals to air pollution. SDG 3 indicates people should have healthy lives, for example, fresh air should be a human right. SDG 7 aims for clean and affordable energy; energy production is a leading cause of air pollution. SDG 11 relates to sustainable cities and communities with good environments. SDG 13 states to take action to reduce the climate change impact both from air pollution and temperature (United Nations, 2015).

Previous studies have examined whether there are associations between extreme temperatures, both low and high temperature, with adverse health outcomes. The results of these studies have found significant associations between temperature and various health outcomes especially cardiovascular and respiratory categories (Basu, 2009; Ebi, 2005; Elliot et al., 2016; Gasparrini, 2011; Ghirardi et al., 2015; Hajat et al., 2006; Medina-Ramón and Schwartz, 2007). Most of this previous research focused on mortality and hospital admission as the indicator of poor health. Some previous studies suggested ambulance dispatch data as an effective indicator of poor health. The benefit of ambulance dispatch data is that it provides real-time response data and can be used for spatial analyses from postcode of patients, which can be used to investigate the pattern of temperature and health outcome association (Alessandrini et al., 2011; Mahmood et al., 2017; Papadakis et al., 2018; Thornes et al., 2014; Turner et al., 2012).

Emergency medical service (ambulance) dispatches are provided for patients who have urgent life-threatening or serious health problems. Different countries use different guidelines for the diagnosis and collection of the ambulance dispatch data. For instance, there are three types of ambulance data diagnosis: 1) the data obtained from a telephone interview by ambulance operators, 2) the paramedic assessment when they reach the patient and 3) physician doctors clarify the symptom subsequent to the patient arriving at the hospitals. All ambulance services aim to ensure that patients receive the fastest response for effective pre-treatment (NHS Providers, 2019). Decreases in response times were associated with increases in survival rate (Pell et al., 2001). For instance, a reduction of response time by one minute is related to an increase of 24% (95% CI: 1.34 - 4.14%) of survival rates (O'Keeffe et al., 2011). However, it should be noted that increasing response times often has financial consequences.

Presently, few studies are investigating the impact of environmental factors such as meteorology and air pollution on ambulance dispatch data. The studies that do exist have examined the impact of temperature upon ambulance dispatches; they report exposures to low and high temperatures are related to increases in ambulance dispatches (Alessandrini et al., 2011; Kotani et al., 2018; Mahmood et al., 2017; Thornes et al., 2014). Low and/or high temperature can both be related to an increase in health risks. Most studies report that the relationship between temperature and health outcome can be described as either J-, V- or U-shaped, see Figure 1-1, corresponding with the threshold temperature which has the lowest risk (Gasparrini et al., 2015). V- or U- shaped relate to the peak of risks at low and high temperature with U-shaped curves having a region of reduced risk in the middle of increased risks at the extremes. J-shaped curves indicate only a one-directional risk at either low or high temperature as shown in Figure 1.1. Note, if the low temperature has a higher relative risk than high temperature, the reversed J- shaped (right – bottom) will be observed.

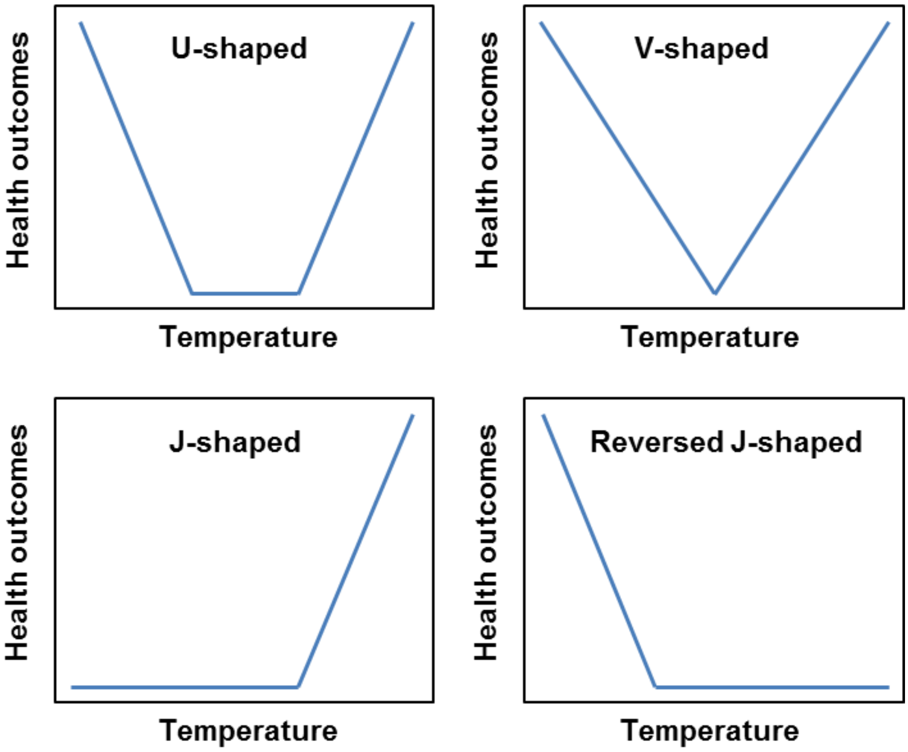

Figure 1-1 U-,V- and J- shape of the association between temperature and health outcomes

Hence, most studies hypothesize the association between temperature and health outcomes with a non-linear pattern. These results contrast to earlier findings, with many publications assuming that the association between temperature and health risks is a linear relationship (Basu and Samet, 2002). Some research does not report significant associations between temperature and specific causes (Leonardi et al., 2006).

There are other factors that can influence the association between temperature and health outcomes. The following factors can all be important in determining the effect of the environment upon the patient: demographics (age, sex, occupation, chronic disease, etc), socioeconomic (low, high incomes and educational attainment) and geographical data (urban, rural, longitude, latitude, etc.) (Basara et al., 2010; Bell et al., 2013; Berko et al., 2014; Guo et al., 2013; Stafoggia et al., 2006; Stone et al., 2010; Zeng et al., 2017; Zhang et al., 2015). Moreover, vulnerable people in developing countries need urgent support to reduce the effect of climate change (UNFCCC, 2017). Until now, most research has focused on developed countries with much fewer studies in developing countries. It can be argued, that the adaptive capacity of patients in low and middle-income countries is less than those in high-income countries. Also, it is noted, that low and middle-income countries are some of those most affected by climate change.

Recently, there has been an increase in the number of studies attempting to explain the effect of air pollutants upon ambulance dispatches. The WHO stated an increase in air pollutants are related to significant risks of premature death and diseases (WHO, 2018b). Previous studies have shown the increment of air pollutants including particulate matter with diameters less than 2.5 micrometres ($PM_{2.5}$) and 10 micrometres (PM_{10}), and other gas phase pollutants such as carbon monoxide (CO), ozone (O_3), nitrogen dioxide (NO_2) and sulphur dioxide (SO_2) have been reported to increase adverse health effects for specific outcomes. Zhao et al. (2017) performed a meta-analysis upon the association between out of hospital cardiac arrest (OHCA) and air pollutants; it included 15 studies and reported a significant association between OHCA and increments of 10 µg/m^3 of PM_{10}, $PM_{2.5}$, NO_2 and O_3. The exposure to $PM_{2.5}$ was associated with acute lower respiratory infection (ALRI) but not with PM_{10} (Mehta et al., 2013). The latest systematic review and meta-analysis from 33 studies (this work, see chapter 4) studies the association between air pollutants and ambulance dispatches.

Climate change may also changes in extreme precipitation or rainfall, which results in different areas becoming drier or wetter (Fischer et al., 2014). Previous studies have demonstrated the positive association between road accidents and rainfall (Bergel-Hayat et al., 2013; Hermans et al., 2006). However, these results differ from Yannis and Karlaftis (2010) who reported that heavy rainfall could lead to a decline in road accidents. The WHO highlights that the worldwide death from road accidents is especially high in low and middle-income countries (LMICs) and they recommend making a plan for reducing this problem by 50% in 2020 following road safety policy (WHO, 2019). The challenge now is to support road safety policies. Towards this aim, Chapter 6 in this thesis investigates the effect of meteorolgoy upon road accidents in Thailand, which is a LMIC located in South East Asia.

As detailed above, previous studies have examined the impact of temperature, air pollutants and rainfall on health impacts in many areas, but the use of ambulance dispatch data has not been fully realised or utilized. The focus of this thesis is to provide a greater examination of ambulance data and assess its applicability to understanding the role of the environment upon human health. To do this, the associations between ambulance dispatches and environmental factors need to be clarified. This thesis provides evidence to support how to consider health effects from environmental factors with three research studies:

Firstly, to examine the association between air pollutants and ambulance dispatches through use of a systematic review and meta-analysis method to report the various categories ambulance dispatch data (not only cardiovascular and respiratory categories) and several air pollutants, not solely particulate matter. The pooled estimated results reduce the variation from individual results.

Secondly, to provide the impact of extreme temperature upon ambulance dispatches using data from the London Ambulance Service (LAS). Prior to this study, little work focused on symptoms from ambulance dispatches such as respiratory, cardiovascular and non-cardiovascular categories (dizzy, vomiting and generally unwell). Time series analysis is conducted to estimate the short-term effect of air pollutants upon health. The confounding factors such as a long-term trend, seasonality, day of the week, public holidays and some meteorological were adjusted in the model. This study analysed the non-linear association (low and high) compared to the reference temperature and the delayed effect. Results can explain the pattern of association under extremely low and high temperature.

Thirdly, to investigate the association between rainfall and road accidents by using Thai ambulance dispatches from 2012 to 2018. In Thailand, ambulance dispatches for road accident are the most frequent dispatch category in every province. Previously, there have been no studies of the association between the number of ambulance dispatches for road accidents and rainfall events. The estimated risk of road accidents and the role of rainfall was examined by time-series analysis, using adjustments for a long-term trend, seasonality and meteorological variables in each province in Northern and Southern Thailand. The estimated risk was generated from the comparison between periods with no rainfall and periods with increasingly heavy rain.

1.2 Hypotheses

1.2.1 Short term exposure to air pollution has an impact on health focused on ambulance dispatches.

1.2.2 Extreme temperatures (low and high temperature) is associated with ambulance dispatches in London, UK.

1.2.3 Heavy rainfall is related to an increase the ambulance dispatches caused by road accidents

1.3 Aims and objectives

1.3.1 Overarching Aim

To examine the impact of different environmental factors upon ambulance dispatches in various locations worldwide.

1.3.2 Specific objectives

- To investigate the association between air pollutants and ambulance dispatches worldwide.
- To identify the effect of extreme temperatures (low and high temperature) on ambulance dispatches in London, UK.
- To assess how the impact of rainfall (low to heavy rainfall) on ambulance dispatches caused by road accidents in the Northern and Southern regions of Thailand.

1.4 Significance of work

This study provides evidence on the association between the environmental effects and health outcomes measured from ambulance dispatches from emergency medical services. Understanding the effect of air pollutants, temperature and changes in rainfall is beneficial and will improve the effectiveness of ambulance services during extreme changes in the environment such as warming temperature and increased air pollution levels. Public health policymakers should consider the impact of the environment because climate change problems will almost certainly increase the frequency of extreme temperature events. A surveillance system and early warning systems need to be set up in developing countries to prevent a vulnerable group like the elderly and children. Implementation of these recommendations should result in a reduction in health cost and an increase in survival rates.

The ambulance service in Thailand is young with an effective service only started in 2012. Moreover, increased its service by 32.8% every year in the years 2012-2018. The National Institute for Emergency Medicine (NIEM), which is responsible for ambulance dispatch in Thailand, currently does not consider environmental variables when preparing its seasonal service and equipment needs. The findings from this thesis will contribute to more effective planning for the Thai ambulance dispatches and public health sectors. It will also raise awareness and knowledge about how to prepare under climate change effects especially for vulnerable groups.

1.5 Thesis outline

This thesis consists of seven chapters using a publication format of three manuscripts (two published, one in preparation):

Chapter 1 explains the background, aims and objectives and the significance of this study.

Chapter 2 is a literature review of the environmental impacts, such as temperature, air pollutants and rainfall, upon ambulance dispatches. Previous studies are summarized to highlight the knowledge gap that the work in this thesis will fill. Furthermore, this chapter provides an explanation of the methods used to investigate the effect of environmental factors on health.

Chapter 3 provides the generalized methodology. It describes the study population, the rationale of studies, data collection and data analysis for each study.

Chapter 4 and chapter 5 are manuscripts in journal format. Chapter 4 uses a systematic review and meta-analysis to examine the association between air pollutants and ambulance dispatches from worldwide publications. This work was published with the full reference:

Sangkharat, K., Fisher, P., Thomas, G.N., Thornes, J. and Pope, F.D., 2019. The impact of air pollutants on ambulance dispatches: A systematic review and meta-analysis of acute effects. Environmental Pollution.

Chapter 5 investigates the temperature effect on ambulance dispatches in London, UK. The threshold temperature of each dispatch was reported and the estimated risk due to exposure to low and high temperature was analysed. The effect and consequences of lags between the date of the extreme temperature events and the ambulance dispatches are investigated. This work was published with the full reference:

Sangkharat, K., Mahmood, M.A., Thornes, J.E., Fisher, P.A. and Pope, F.D., 2020. Impact of extreme temperatures on ambulance dispatches in London, UK. Environmental Research, p.109100.

Chapter 6 demonstrates the effect of rainfall levels, from low to heavy volumes, upon road accidents in the Northern and Southern groupings of Thai provinces. In total, analyses on 23 provinces were conducted. This chapter is currently being prepared for publication.

Chapter 7 summarises the thesis with a general discussion. The conclusions from each of the research chapters are summarised. The strengths, limitations and implications of the studies are highlighted. Finally, future directions of study that are likely to be profitable with respect to preserving human health are discussed.

1.6 References

Alessandrini, E., Zauli Sajani, S., Scotto, F., Miglio, R., Marchesi, S., Lauriola, P., 2011. Emergency ambulance dispatches and apparent temperature: A time series analysis in Emilia-Romagna, Italy. Environ. Res. 111, 1192–1200. https://doi.org/10.1016/j.envres.2011.07.005

Basara, J.B., Basara, H.G., Illston, B.G., Crawford, K.C., 2010. The Impact of the Urban Heat Island during an Intense Heat Wave in Oklahoma City. Adv. Meteorol. 2010, 1–10. https://doi.org/10.1155/2010/230365

Basu, R., 2009. Environmental Health High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008. https://doi.org/10.1186/1476-069X-8-40

Basu, R., Samet, J.M., 2002. Relation between elevated ambient temperature and mortality: a review of the epidemiologic evidence. Epidemiol. Rev. 24, 190–202. https://doi.org/10.1093/epirev/mxf007

Bell, M.L., Zanobetti, A., Dominici, F., 2013. Evidence on vulnerability and susceptibility to health risks associated with short-term exposure to particulate matter: a systematic review and meta-analysis. Am. J. Epidemiol. https://doi.org/10.1093/aje/kwt090

Bergel-Hayat, R., Debbarh, M., Antoniou, C., Yannis, G., 2013. Explaining the road accident risk: Weather effects. Accid. Anal. Prev. https://doi.org/10.1016/j.aap.2013.03.006

Berko, J., Ingram, D.D., Saha, S., Parker, J.D., 2014. Deaths attributed to heat, cold, and other weather events in the United States, 2006–2010. Natl. Health Stat. Report. 2014, 1–15.

Ebi, K.L., 2005. Improving public health responses to extreme weather events, Extreme Weather Events and Public Health Responses. https://doi.org/10.1007/3-540-28862-7_5

Elliot, A.J., Smith, S., Dobney, A., Thornes, J., Smith, G.E., Vardoulakis, S., 2016. Monitoring the effect of air pollution episodes on health care consultations and ambulance call-outs in England during March/April 2014: A retrospective observational analysis. Environ. Pollut. 214, 903–911. https://doi.org/10.1016/j.envpol.2016.04.026

EPA, 2016. Air Quality and Climate Change Research [WWW Document]. URL https://www.epa.gov/air-research/air-quality-and-climate-change-research (accessed 1.9.20).

Fischer, E.M., Sedláček, J., Hawkins, E., Knutti, R., 2014. Models agree on forced response pattern of precipitation and temperature extremes. Geophys. Res. Lett. 41, 8554–8562. https://doi.org/10.1002/2014GL062018

Gasparrini, A., 2011. Distributed Lag Linear and Non-Linear Models in R: The Package dlnm. J. Stat. Softw. 43, 1–20. https://doi.org/http://dx.doi.org/10.18637/jss.v043.i08

Gasparrini, A., Guo, Y., Hashizume, M., Kinney, P.L., Petkova, E.P., Lavigne, E., 2015. Temporal Variation in Heat – Mortality Associations : A Multicountry Study. Environ. Health Perspect. 1200, 1200–1207.

Ghirardi, L., Bisoffi, G., Mirandola, R., Ricci, G., Baccini, M., 2015. The impact of heat on an emergency department in Italy: Attributable visits among children, adults, and the elderly during the warm season. PLoS One 10. https://doi.org/10.1371/journal.pone.0141054

Guo, Y., Li, S., Tian, Z., Pan, X., Zhang, J., Williams, G., 2013. The burden of air pollution on years of life lost in Beijing, China, 2004-08: Retrospective regression analysis of daily deaths. BMJ 347. https://doi.org/10.1136/bmj.f7139

Hajat, S., Armstrong, B., Baccini, M., Biggeri, A., Bisanti, L., Russo, A., Paldy, A., Menne, B., Kosatsky, T., 2006. Impact of high temperatures on mortality: is there an added heat wave effect? Epidemiology 17, 632–638.

Hermans, E., Wets, G., Van Den Bossche, F., 2006. Hermans, Wets and Van den Bossche Frequency and Severity of Belgian Road Traffic Accidents Studied by State Space Methods.

Holly, S., 2019. Effects | Facts – Climate Change: Vital Signs of the Planet [WWW Document]. Nasa. URL https://climate.nasa.gov/effects/ (accessed 12.13.19).

IPCC, 2014. Climate Change 2014 Synthesis Report Summary for Policymakers, IPCC 5th Assessment Report.

Kotani, K., Ueda, K., Seposo, X., Yasukochi, S., Matsumoto, H., Ono, M., Honda, A., Takano, H., 2018. Effects of high ambient temperature on ambulance dispatches in different age groups in Fukuoka, Japan. Glob. Health Action 11, 1437882. https://doi.org/10.1080/16549716.2018.1437882

Leonardi, G.S., Hajat, S., Kovats, R.S., Smith, G.E., Cooper, D., Gerard, E., 2006. Syndromic surveillance use to detect the early effects of heat-waves: an analysis of NHS direct data in England. Sozial-und Präventivmedizin 51, 194–201.

Mahmood, M.A., Thornes, J.E., Pope, F.D., Fisher, P.A., Vardoulakis, S., 2017. Impact of Air Temperature on London Ambulance Call-Out Incidents and Response Times. Climate 5, 61.

Medina-Ramón, M., Schwartz, J., 2007. Temperature, temperature extremes, and mortality: A study of acclimatisation and effect modification in 50 US cities. Occup. Environ. Med. 64, 827–833. https://doi.org/10.1136/oem.2007.033175

Mehta, S., Shin, H., Burnett, R., North, T., Cohen, A.J., 2013. Ambient particulate air pollution and acute lower respiratory infections: a systematic review and implications for estimating the global burden of disease. Air Qual. Atmos. Heal. 6, 69–83. https://doi.org/10.1007/s11869-011-0146-3

NHSProviders, 2019. the Ambulance Service [WWW Document]. Underst. NEW Stand. https://doi.org/10.1016/S0140-6736(64)91714-3

O'Keeffe, C., Nicholl, J., Turner, J., Goodacre, S., 2011. Role of ambulance response times in the survival of patients with out-of-hospital cardiac arrest. Emerg. Med. J. 28, 703–706.

Papadakis, G., Chalabi, Z., Thornes, J.E., 2018. Ambulance Service Resource Planning for Extreme Temperatures: Analysis of Ambulance 999 Calls during Episodes of Extreme

Temperature in London, UK. Atmosphere (Basel). 9, 182. https://doi.org/10.3390/atmos9050182

Pell, J.P., Sirel, J.M., Marsden, A.K., Ford, I., Cobbe, S.M., 2001. Effect of reducing ambulance response times on deaths from out of hospital cardiac arrest: cohort study. Bmj 322, 1385–1388.

Stafoggia, M., Forastiere, F., Agostini, D., Biggeri, A., Bisanti, L., Cadum, E., Caranci, N., De'Donato, F., De Lisio, S., De Maria, M., Michelozzi, P., Miglio, R., Pandolfi, P., Picciotto, S., Rognoni, M., Russo, A., Scarnato, C., Perucci, C.A., 2006. Vulnerability to heat-related mortality: A multicity, population-based, case-crossover analysis. Epidemiology 17, 315–323. https://doi.org/10.1097/01.ede.0000208477.36665.34

Stone, B., Hess, J.J., Frumkin, H., 2010. Urban form and extreme heat events: Are sprawling cities more vulnerable to climate change than compact cities? Environ. Health Perspect. 118, 1425–1428. https://doi.org/10.1289/ehp.0901879

Thornes, J.E., Fisher, P.A., Rayment-Bishop, T., Smith, C., 2014. Ambulance call-outs and response times in Birmingham and the impact of extreme weather and climate change. Emerg. Med. J. 31, 220–228. https://doi.org/10.1136/emermed-2012-201817

Turner, L.R., Barnett, A.G., Connell, D., Tonga, S., 2012. Review Article: Ambient Temperature and Cardiorespiratory Morbidity: A Systematic. Source Epidemiol. 23, 594–606. https://doi.org/10.1097/EDE.0b013e3182572795

UNFCCC, 2017. Developing Countries Need Urgent Support to Adapt to Climate Change | UNFCCC [WWW Document]. 2017. URL https://unfccc.int/index.php/news/developing-countries-need-urgent-support-to-adapt-to-climate-change (accessed 1.3.20).

United Nations, 2015. Sustainable Development Goals [WWW Document]. URL https://sustainabledevelopment.un.org/?menu=1300 (accessed 1.10.20).

WHO, 2018a. Information and public health advice: heat and health [WWW Document]. World Health Organisation. URL https://www.who.int/globalchange/publications/heat-and-health/en/ (accessed 12.16.19).

WHO, 2018b. Ambient (outdoor) air quality and health [WWW Document]. World Health Organisation. URL http://www.who.int/en/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health (accessed 5.11.18).

WHO, 2019. Global status report on road safety 2018. World Health Organisation.Yannis, G., Karlaftis, M.G., 2010. Weather Effects on Daily Traffic Accidents and Fatalities: A Time Series Count Data Approach, Transportation Research Board 89th Annual Meeting.

Zeng, Q., Ni, Y., Jiang, G., Li, G., Pan, X., 2017. The short term burden of ambient particulate matters on non-accidental mortality and years of life lost: A ten-year multi-district study in Tianjin, China. Environ. Pollut. 220, 713–719. https://doi.org/10.1016/j.envpol.2016.10.036

Zhang, Y., Wang, S.G., Ma, Y.X., Shang, K.Z., Cheng, Y.F., Li, X., Ning, G.C., Zhao, W.J., Li, N.R., 2015. Association between ambient air pollution and hospital emergency admissions for respiratory and cardiovascular diseases in Beijing: A time series study. Biomed. Environ. Sci. 28, 352–363. https://doi.org/10.3967/bes2015.049

Zhao, R., Chen, S., Wang, W., Huang, J., Wang, K., Liu, L., Wei, S., 2017. The impact of short-term exposure to air pollutants on the onset of out-of-hospital cardiac arrest: A systematic review and meta-analysis. Int. J. Cardiol. 226, 110–117. https://doi.org/10.1016/j.ijcard.2016.10.053

CHAPTER 2 : THE EFFECTS OF ENVIRONMENTAL FACTORS UPON AMBULANCE DESPATCHES

2.1 Climate change

Climate change refers to the long term change in average temperature and other meteorological parameters because of largely anthropogenic (human) activities since the industrial revolution. Climate change is a global phenomenon with specific effects in different locations (Met Office, 2019). The global average temperature anomaly has risen significantly from 1850 to today (see Figure 2-1).

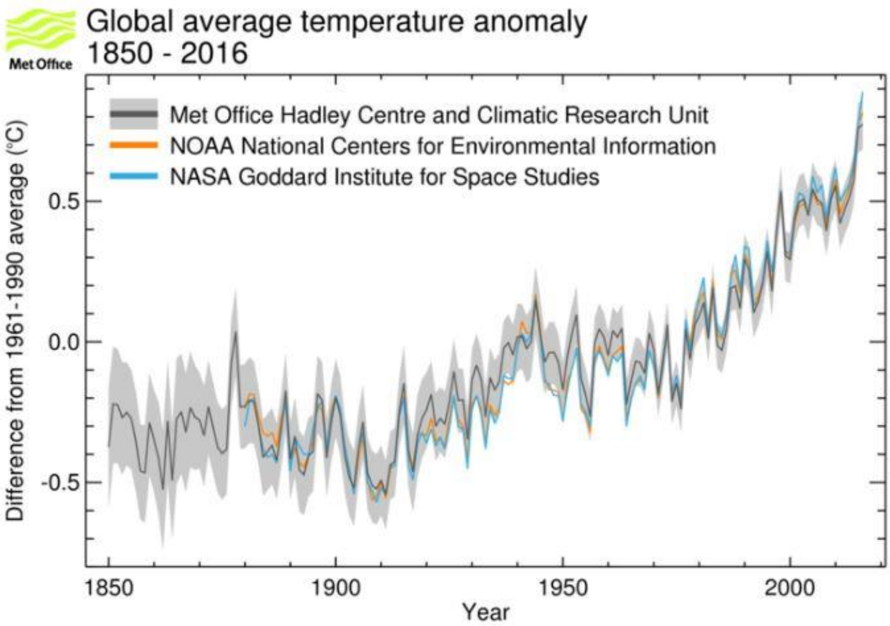

Figure 2-1 Global temperature anomaly change from 1850 to 2016, compared to the 1961-1990 average temperature. (Met Office, 2019)

The greenhouse effect is the phenomenon of additional heat captured by the Earth's atmosphere due to the build-up of greenhouse gases (GHG) such as carbon dioxide (CO_2), methane (CH_4), ozone (O_3), fluorinated gases and nitrous oxide. The additional heat captured in the atmosphere leads to greater heat at ground level. An increase in GHG leads to changes in the chemical composition in the atmosphere. Some types of particulate matter (PM), such as black carbon and O_3, are climate warming agents, while others reflect sunlight, leading to net cooling effects (EPA, 2016a; NASA, 2018). The WHO has suggested that public health sectors use public health guidelines to prevent the impact and also decrease the level of GHGs. (WHO, 2018a). The UN's Intergovernmental Panel on Climate Change (IPCC) has predicted global temperature will increase by 0.3-4.8°C in the by 2100, dependent on the emissions pathway society chooses to take (IPCC, 2014).

2.2 International governance on climate change

Many reports from international organizations evidence the problems associated with rising global temperatures.

- The IPCC: In October 2018, the IPCC Fifth Assessment Report noted that human activities are the main cause of climate change. The temperature has increased by 0.85°C between 1880 and 2012. The IPPC also noted that limiting global warming to a rise of 1.5°C will cause climate change to have a significantly lower impact than a rise of 2°C. Hence, it is recommended that carbon dioxide emissions should be reduced by 45% from 2010 to 2030 (Pachauri et al., 2014; United States Environmental Protection Agency, 2014).
- The Kyoto Protocol: This is a commitment for other countries to reduce the emissions of greenhouse gases, especially carbon dioxide, which started from 1995. At present, 192 countries are signatories (UNFCCC, 2008).
- The Paris Agreement: The main stated objective of this intergovernmental agreement is that countries should undertake action to limit rises in global mean temperature to below 2°C. As of April 22^{nd}, 175 countries were co-signatories to this agreement (United Nations, 2018). In 2019, the UN Climate Action Summit invited the leaders from many countries to present action to mitigate climate change. The leaders of 70 countries have committed to zero net emissions of GHG by 2050.

- Other international summits: Many summits have been held to encourage climate change action. For example, the Madrid Climate Change Conference – COP 25, the Youth Climate Summit and the Climate Action Summit (UN, 2019).

2.3 The association between climate change and health outcomes

The WHO notes that climate change can affect human health. The prediction for deaths caused by climate change is expected to reach 250,000 deaths per year between 2030 and 2050 (WHO, 2018a). The relationship between climate change and health outcomes have been well detailed.

2.3.1 Extreme weather and health impacts

2.3.1.1 Extreme high temperature or heatwaves

Warming temperatures are the cause of extreme temperatures, or heatwaves, a prolonged period of hot weather in a specific area. In the UK, a heatwave is defined as at least three consecutive days where daily maximum temperatures meet or exceed a heatwave temperature threshold 25°C for most of the UK and slightly higher for central and southeast England. (The Met Office, 2019). However, other countries define it as when the temperature is above the maximum temperature for more than five consecutive days (Garssen et al., 2005). The number of people worldwide who were exposed to heatwave conditions was 125 million between 2000 and 2016. Moreover, a particularly extreme example occurred in the Russian Federation in 2010, where 56,000 people died over 44 days of a heatwave. (WHO, 2018b). Many previous studies have reported associations between high temperatures and health outcomes (Basu, 2009; Gasparrini et al., 2011; Ghirardi et al., 2015; Knowlton et al., 2009; Le et al., 2014; Schinasi and Hamra, 2017).

Normally, the internal temperature of the human body is 37°C with a typical variation of approximately one degree. When the body's temperature warms up more than 1°C, the body's metabolic processes increase and pump more blood to the skin, resulting in a reduction in body heat by sweating as the evaporation of sweat from the skin leads to a cooling effect. Rapid sweating occurs under low relative humidity and high wind speeds. In a heatwave scenario, the body cannot balance the temperature, and the gain in heat is higher than the heat loss (CCOHS, 2014), which can result in heat exhaustion, heatstroke, and dehydration (Poumadère et al., 2005) or chronic conditions such as, for example, cardiovascular, respiratory, cerebrovascular and diabetes-related conditions (WHO, 2018b).

Extreme high temperatures can cause an increase in ozone concentration, which can lead to mortality and morbidity. Using heating or cooling facilities in the home or workplace can emit other pollutants such as particulate matter, which cause additional harm to humans.

2.3.1.2 Extreme low or cold waves

Exposure to low temperatures also has an impact on human health. A cold wave in this study means a temperature at the 1^{st} – 3^{rd} of the temperature distribution for at least 24 hours (Carmona et al., 2016). Heart problems and hypothermia conditions are common when the body gets cold. In the UK, 130,000 elderly people died from exposure to low temperature between 2004 and 2008 (WHO, 2016). Furthermore, exposure to extreme low temperatures can narrow the blood vessels, thereby reducing the blood flow which is required to keep warmth in the body. This can lead to high blood pressure and an increased heart rate (CCOHS, 2019). Previous research has reported a significant association between cold temperatures and health outcomes. Cardiac symptoms can be increased due to low temperatures because veins and arteries become narrower, resulting in a higher workload for cardiovascular functions, leading to hypothermia

(Seltenrich, 2015). Exposure to low temperatures can also exacerbate existing conditions, for example cardiovascular and respiratory diseases. Moreover, other symptoms are associated with exposure to cold temperatures such as colds, asthma, a sore throat, painful joints, flu, and heart attacks (NHS, 2017).

2.3.1.3 Extreme precipitation/rainfall

Some regions have seen increases in rainfall because warming temperatures generate more water vapour, leading to precipitation. In contrast, some areas have found a decrease in rainfall and lengthy periods of drought. For example, there was flooding and hurricane Harley in Houston, the U.S., in August 2017, which has not expected to happen. The effect of heavy precipitation can affect ecosystems because pollutants can wash into water sources such as streams or lakes, resulting in low quality of water (C2ES, 2014).

2.3.2 Temperature and health impacts responses

Normally, the association between temperature and health outcomes (mortality or morbidity) is observed with a V-, U- or J-shape (Gasparrini et al., 2015b; Williams et al., 2012). The U- or V-pattern mean there is a positive association between the estimated risk of health outcomes at both low and high temperatures. The J-shape refers to when health outcomes decrease when temperature increases or vice versa for a reversed J-shape. The pattern of temperature and health outcome associations can be different across cities (Iñiguez et al., 2010). The estimated risk at low temperatures is a curve of temperature at the left side of the lowest risk or called the threshold temperature (Chen et al., 2018). Conversely, the risk at high temperatures is on the right side of the threshold temperature.

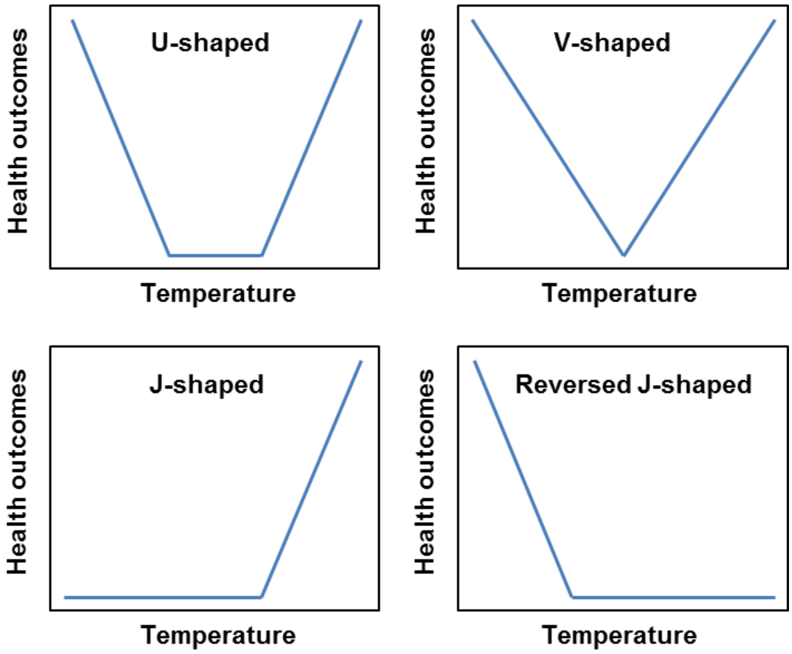

Figure 2-2 U-,V- and J-shape of the association between temperature and health outcomes

If studies hypothesise that the association between temperature and health outcomes have a non-linear pattern, the threshold temperature needs to be identified. There are two ways to ascertain the threshold temperature. First, investigation the threshold temperature from exposure-response curve and the threshold temperature is a temperature which has the lowest risk, or the Minimum Mortality Temperature (MMT) (Gasparrini et al., 2015b; Williams et al., 2012). Second, the percentile of the temperature at the median distribution is identified for the reference temperature (Chen et al., 2018). In contrast, some studies hypothesise that the association between temperature and health outcomes is linear, so the threshold temperature does not need to be tested because the estimated risk is reached when the temperature increases by 1°C (X.-J. Zhang et al., 2015). The low and high temperature effects could be different in each study. Low temperature effects can define at the 1st, 5th or 10th percentile of the temperature distribution while the high effect is identified at the 99th, 95th and 90th percentile of the temperature distribution.

2.3.3 The relationship between hazard, exposure and vulnerability

The severity of extreme or non-extreme weather and climate change is related with the level of exposure and vulnerability of each phenomenon. A climate event can be defined as natural condition such as wildfire, heatwaves and heavy rain or human activities e.g. emission from factories or transportations. Vulnerability refers to the factor leading to different susceptibilities to the effect of risk such as temporal, geographic, economic, demographic, social, health status and environmental factors. Level of exposures are different depending on individuals and hazard zones. It is important to understand the relationships between the key determinants of disaster risks because these can help the design of risk management and implementation for adaption under climate events.

The possible example of climate change scenario for low frequency but high impact such as flooding, disaster and landslide which can lead to huge losses. However, less extreme events with lower intensity lead to concern about the exposure to environment for vulnerable groups who have inadequate protection. Hence, effectiveness of risk managements and risk adaption from disasters depend on the decision making, this can be more be successful if the policy maker takes the dynamics of exposure and vulnerability factor into consideration as shown in Figure 2-3. (Cardona et al., 2012)

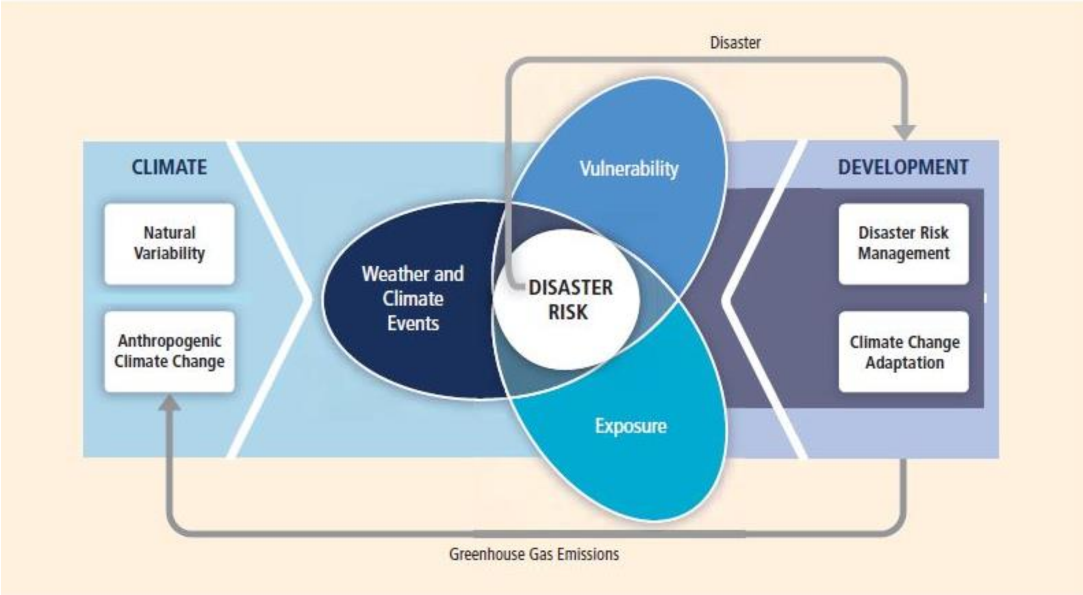

Figure 2-3 The key concept of sustainable development for disaster risk management and climate change adaption (Field et al., 2012)

2.3.4 Environmental factors and health impacts

In the atmosphere, GHGs trap the heat from sun radiation that is reflected back by earth surface, leading to an increase in mean surface temperature. Previous studies have noted that warming temperatures can increase risks in heat-related categories such as, for example, heat stroke, heat exhaustion, heat cramps and heat rashes (Gu et al., 2016). Moreover, increased temperatures are related to symptoms such as headache, dizziness, fainting and exhaustion (Pantavou et al., 2016). The increase in temperature causes an increase in water vapour (natural greenhouse gases), which probably results in high moisture in the atmosphere, leading to difficulty to sweat due to excessive evaporation in the air while low evaporation in the air leads to enhanced sweating, causing dehydration. Furthermore, the effects of rising temperatures are linked which the high rate of evaporation, which causes more precipitation, increasing flooding in some areas which causes an increase in waterborne diseases, asthma and respiratory problems such as coughing and wheezing. However, less precipitation or droughts are a possible cause of wildfires and dust storms, which are related to an increase in particulate matter (CDC, 2019).

2.3.4.1 Air pollution

Exposure to hazard from air pollution could lead to impact on health. Many previous studies have reported both short-term and long-term exposure low air quality could be linked with impacts on respiratory and cardiovascular systems. (WHO, 2018c)

Carbon dioxide (CO_2) is one of the GHGs released by natural processes such as the respiratory system of organisms, volcano eruptions and decomposition processes. Some CO_2 is produced by human activities, including burning of forests and use of fossil fuels. Since the industrial revolution, the CO_2 concentration has increased significantly, by around 0.17% per year (Haigh, 2017). Exposure to CO_2 is related to headaches, difficulty breathing, tiredness, a higher heart rate and a rise in blood pressure (DHS, 2019).

Ground-level Ozone (O_3) is another greenhouse gas. Ozone in the Troposphere is harmful ozone from chemical reactions in the sunlight by nitrogen oxide and volatile organic compounds (VOCs) from transportation. Ground-level ozone can trap the heat in atmosphere and an increased ozone level. An increase in ozone is related to rise in respiratory risks, lung damage (long- term) and asthma (US EPA, 2020). On the contrary, ozone in the Stratosphere is a positive because it absorbs the ultraviolet radiation from the sun. Ground ozone levels can lead to receiving more UV-a and UV-b radiation, resulting in skin and eye problems (NASA, 2015).

Particulate matter (PM) is air pollution in solid and liquid particles which come from combustion processes, industrial processes, forest fires and dust storms. PM may have a net warming (e.g. black carbon) or cooling (e.g. sulphate) effect on the Earth's climate, depending on the component of PM (EPA, 2016b). Human activities and natural processes can increase the level of PM. The adverse effects attributed to PM are related mainly to respiratory functions and cardiovascular diseases. The different sizes of particulate matter can have different health impacts. For example, fine particular matter with a diameter less than 2.5 micrometres ($PM_{2.5}$) can penetrate the lungs and bloodstream while big particles are related to irritation of the eyes, nose and throat (US EPA, 2019)

2.3.4.2 Water Pollution

It is important to avoid contamination of both surface and ground water sources because infection agents or chemicals can lead to get water- borne diseases such as Typhoid, Cholera, Paratyphoid Fever, Dysentery, Jaundice, Amoebiasis and Malaria. Sources of water pollution are related to discharge of low water quality, agricultural run-off, urbanization and acid rain. The impact of drinking untreated water can be linked with stomach ache and death from water-borne diseases especially in children (Mckeown and Bugyi., 2016; Haseena et al., 2017).

2.3.4.3 Toxic substance and Hazardous Wastes

There is potential hazard to the environment which can lead to contamination of soil, water and air which has an adverse effect on health outcomes. Poor management is related to causes of contaminated water. Previous studies mentioned exposure to hazardous wastes have less relationships with cancers, leukaemia and bladder lung (Fazzo et al., 2017)

2.3.4.4 Polluted food

Food pollution is food which is contaminated with biological or toxic hazards. Climate change is associated with contaminate of unsafe foods resulting in increased malnutrition and 1 in 10 world wide population have been affected on food safety and nutrition(WHO, 2019) . There is a problem of food contamination in the U.S. with more than 70 million cases and 5000 deaths each year. There are many potential causes of food pollution including the growing of food with polluted water and air, using pesticides, eating water animals from polluted water and concentration of pollutants in food chains (Environmental Pollution Centers, 2017)" Moreover, results were reported a higher number of contamination of pathogens on produce and seafood when getting hotter compared to other seasons (Gooch et al., 2002). Hence, public health should prepare plans for managing the risk from food safety (WHO, 2019).

2.3.5 Health inequalities

The association between temperature and health can be affected by a number of personal factors such as gender and age, individual behaviour, geographic location, and economic status (US EPA, 2014). Vulnerable groups are children, the elderly, pregnant women, outdoor workers and the homeless, all of whom should take extra care to prevent exposure to heat because extreme temperatures are likely to have a disproportionate impact on them. Moreover, some publications have reported that urban populations will suffer more from extreme heat than rural areas (United States Environmental Protection Agency, 2014). The UN has predicted that the number of elderly people will increase by 21.1% by 2050, so the negative health effects of exposure to high temperatures will increase significantly because elderly people are more vulnerable to such extremes (Schneider and Breitner, 2016).

2.3.5.1 Age

A number of publications have reported that older people, particularly those aged over 65, and children are at greater risk of cardiovascular and respiratory diseases. For example, the risk from exposure to $PM_{2.5}$ was associated with more/higher rates of out-of-hospital cardiac arrest among the elderly (aged >65) than for other groups (Ensor et al., 2013; Guo et al., 2013). The association of PM_{10} with daily deaths is greater among the elderly than the young (Bell et al., 2013; Guo et al., 2013; He et al., 2016; Zeng et al., 2017). In contrast, however, Schwartz (2004) and Zhang et al. (2015) reported no association between exposure to suspended particulate matter and emergency ambulance dispatches (EAD) for acute illnesses caused by age. Lenine (2016) noted that, every year, around 543,000 global of children under the age of five die from air pollution. Kovats et al. (2004) reported a significant increase in both respiratory and renal diseases in children under five years of age and only the risk of respiratory category is linked with the elderly (+75 years).

In one study, for cold effects and health outcomes, people aged 45-64 years of age showed a higher risk (excess risk which is the risk difference between exposed and unexposed groups (ER = 2.04%) than a younger group aged below 45 (ER = 1.73%) while the hot effects were vice versa (Zhang et al., 2014). During heatwaves, a greater effect was found in the age group over 65 years old for diabetes and respiratory symptoms, with relative risk (RR), RR = 1.04 (95%CI: 1.02-1.06) and RR = 1.04 (95%CI: 1.02-1.06). The youngest group (below four years of age) also showed an positive association between heat and morbidity (Knowlton et al., 2009; Kovats et al., 2004). Previous studies have noted that elderly groups are more sensitive to hot temperatures (Kovats et al., 2004; Stafoggia et al., 2006) while younger groups respond significantly to both hot and cold temperatures (Baccini et al., 2008; Schwartz, 2005). This can be explained in terms of the reduction of thermoregulatory capacity of older people to changing internal temperature, resulting in decreasing sweating due to increases in the body temperature threshold (Foster et al., 1976). In addition, the lungs and alveoli of children continue to grow until adulthood, so children's bodies cannot defend themselves as easily against infection compared to adults (World Health Organization, 2005).

2.3.5.2 Gender

Previous studies have reported that gender can be linked with different health risks and outcomes. A meta-analysis conducted by Bell et al. (2013) reported that 22 studies found women have a higher risk of exposure to PM and mortality than men, but it was not significant. Females are also more sensitive to exposure to ozone, PM_{10}, SO_2 and NO_2 than males (Kan et al., 2008). In addition, elderly women have higher exposure to the relationship between strokes and PM_{10} (Hong et al., 2002). On the contrary, African American men were at more risk of Out of Hospital Cardiac Arrest (OHCA) than African American women (Ensor et al., 2013), the reason being that men are more engaged in outside activities than women, resulting in greater exposure to air pollutants (Galizia and Kinney, 1999). However, this finding is contrary to Cakmak et al. (2006), who did not find an association between cardiac hospitalization due to air pollution levels, and Zhang et al. (2015), who did not find a relationship between suspended particulate matter (SPM) and EAD of acute illness due to gender. The previous results did not find a significant association between temperature and ambulance dispatches as a result of gender (Ye et al., 2012; Zhang et al., 2014). In summary, future studies need to investigate the association between gender and health outcomes.

2.3.5.3 Pre-existing medical conditions

Studies have identified an association between pre-existing medical conditions and adverse health outcomes. D'Amato et al. (2018) demonstrated that when the temperature declines by around 2-5°C, it leads to increasing risk of severe exacerbation of chronic obstructive pulmonary disease (COPD) and asthma. This result is consistent with Schwartz (2005), who claimed that people with COPD and exacerbated respiratory infections can suffer from cold weather. They also reported the increased risk of diabetes on hot days compared with people who have not had a medical condition. Studies have also reported that cold effects lead to increased coronary and cerebral thrombosis due to rising red blood cell counts, platelet and blood viscosity. Hence, most people who have COPD are at risk of complications from cardiovascular diseases. In addition, cold weather can cause an increase in bronchial inflammation (D'Amato et al., 2018).

People who have diabetes are more at risk from extreme hot temperatures than people who do not have a medical condition, but this is not the case for cold temperatures (Schwartz, 2005). This difference can be explained by the impaired autonomic control and endothelial function of diabetics.

Kovats et al. (2004) showed that admissions for acute renal failure are associated with heat effects and they are greater in people who have a medical condition from diabetes and cardiovascular disease. A study by Stafoggia et al. (2006) reported that people who have pre-existing medical conditions were at a higher risk of mortality than the non-hospitalised when exposure to high temperatures.

2.3.5.4 Race

Racial differences are associated with inequalities in term of diverse health outcomes such as diabetes and cardiovascular diseases (Knowlton et al., 2009). A study in California covering 1999-2003 reported that the black racial/ethnic group (different cultural groups) is at more risk (4.9%, 95%CI: 2.0-7.9%) than whites and Hispanics in terms of the association between non-accidental mortality and average daily temperature (Basu and Ostro, 2008). Similarly, results from Berko et al. (2014) reported that non-Hispanic black persons were associated with increased-mortality compared with other races. O'Neill et al. (2005) studied the association between air conditioning in households among white/other and black with heat-related mortality, finding that white/other households have double the rate of domestic air conditioning than black households. In the meta-analysis, results from four cities reported that blacks (9.0%. 95%CI: 5.3-12.8%) had an estimated risk higher than Whites (3.7%. 95%CI 1.9-5.4%) in the association between increasing temperatures and mortality (O'Neill et al., 2005). However, the meta-analysis conducted by Bell et al. (2013) did not report an association between race and mortality from exposure to PM.

2.3.5.5 Occupation

The worker can be affected by climate change impacts such as physical exposure to extreme temperature leading to heat stress because working in hot temperatures and high humidity can increase the sweating functions of body trying to keep to an internal temperature range around 37 °C (Hanna et al., 2011; Vander et al., 2001). Previous studies reported that workers who have outside activities (farm workers, athletes training and soldiers) have a higher risk of heat related illnesses (Harduar Morano et al., 2015; Shendell et al., 2010). Exposure to heat was related to loss of work at least one day and 36 deaths between in 2011 and 2013

(Bureau of Labour Statistics, 2015). Moreover, indoor workers (factory and office workers also can get an impact of heat-related illness from factory machinery (Poupart et al., 2014; Xiang et al., 2015). An increment of one degree was related to a 12.7% increase of heat illness claims and during heatwaves had a higher risk 4-7 times than non-heatwave periods (Xiang et al., 2015)"

2.3.5.6 Socio-economic factors

Socio-economic indicators can also have an impact on health outcomes. This could be in the form of family income, education levels/attainment, and other social factors. A number of previous studies have confirmed that those with a low educational attainment are at enhanced risk of exposure to air pollution than those with a high educational attainment (Bell et al., 2013; Kan et al., 2008), while income and education level factors did not find the relationship between air pollution and cardiac arrest (Cakmak et al., 2006).

In one study, an association between mortality and temperature found a higher rate of mortality in low-income countries (Berko et al., 2014; Stafoggia et al., 2006). This may be linked to an insufficient amount of facilities such as air conditioning and heating (Berko et al., 2014; O'Neill et al., 2005a), and overall odds ratios (OR) increase in people living in houses with no air conditioning (OR = 1.61, 95%CI: 1.41-1.84) (Stafoggia et al., 2006). Homeless persons are at greater risk from declining temperatures because they do not sufficient clothing (CDC, 2006; Ulrich and Rathlev, 2004).

2.3.5.7 Geographical factors

Many previous studies have revealed that geographical variables could affect the association between environmental factors and health outcomes. Urban areas show a higher risk of heat-related mortality and exposure than rural areas (Basara et al., 2010; Berko et al., 2014; Stone et al., 2010). The characteristic of urban heat islands (UHI) can be related to the temperature in the city due to less vegetation, resulting in less reflected heat. In cities, the buildings absorb the radiation and trap the heat, and decreasing evaporation and turbulent heat transport compound the situation (Oke, 1982). In addition, different geographical areas could be related to heat-related deaths. For example, the Northeast and West of the U.S. have fewer floods and storms compared to the South, resulting in fewer death in the former than in the latter from such weather events (Berko et al., 2014; Brooke Anderson and Bell, 2011). Ban et al. (2017) reported that the RR for the association between heat effects and mortality was higher in middle latitudes than higher or lower latitudes. Ban et al's results were contrary with previous studies, which had found exposure to high temperatures was accompanied by an increase in mortality risks for cold regions. Ban et al's finding are similar to those of Guo et al. (2014), who noted that the threshold temperature in warmer areas is higher than other areas, so people can adapt to extreme heat more easily than people in middle latitudes. In addition, the frequency of extreme heat was lower in colder areas (Chen et al., 2011).

2.4 Previous publications

To summarise the example of publication that investigating the relationship between exposure to extreme temperature and adverse health. The inclusion criteria are:

1) The health outcomes reported from ambulance dispatch data.

2) The study reported in risk ratios (e.g. relative risk (RR), odds ratios (OR), percent of excess risk (ER) and hazard ratio (HR).

The exclusion criteria is a study conduct data from mortality and hospital data.

Many countries have been investigated the association between cold and hot effect.

Table 2-1 Summary of studies the association between extreme temperature and ambulance dispatches

Author	Location	Population	Study period	Method	Health outcomes	Threshold temperature	Main outcomes	Lagged days	Adjustment factors
(Alessandrini et al., 2011)	Emilia–Romagn, Italy	Aged ≥ 35	2002-2006	GAM	Non-traumatic diseases Cardiovascular, Respiratory	25 °C	ER for non-traumatic diseases: 1.45% (95%CI: 0.95-1.95%) and 2.74% (1.34-4.14%) and for respiratory when ranged temperature between 25 and 30 °C per 1 °C increase in temperature	15 days	Seasonality, long-term trend, holidays, weekends, air pollution
(Bassil et al., 2011)	Utah, USA	All population	2005	GAM	Ambulance dispatches, Heat-related illness (HRI)	NA	RR for HRI: 29% ($p<0.0001$) per 1 °C increase in temperature	1 day	Seasonality, long-term trend, relative humidity, holidays, weekends
(Chen et al., 2015)	Guangdong, China	All population	2012	One-way ANOVA	Trauma	No	A positive correlation with maximum temperature ($R^2 = 0.103$, $p<0.05$)	No	No
(Cheng et al., 2016)	Huainan, China	All population	2011-2013	GLM	Ambulance dispatches	NA	RR for ambulance dispatches: 2 % (95 % CI 1–3 %) per 1 °C increase in temperature	7 days	Seasonality, long-term trend, relative humidity, holidays, weekends
(Kotani et al., 2018)	Fukuoka, Japan	All population	2005 - 2012	GLM	Acute illnesses	23.5 °C	RR for acute illnesses: 1.08 (95% CI: 1.05-1.12) and 1.12 (95% CI: 1.08-1.16) at the 85th and 95th	7 days	Seasonality, long-term trend, relative humidity,

Author	Location	Population	Study period	Method	Health outcomes	Threshold temperature	Main outcomes	Lagged days	Adjustment factors
							percentile of temperature respectively per 1 °C increase in temperature		holidays, weekends, $PM_{2.5}$
(Leonardi et al., 2006)	England	All population	2001-2004	GLM	Symptomatic calls: vomiting, fever, difficulty breathing, heat-stroke	NA	ER for fever : 2.5% (95% CI: 1.8-3.3%) for aged 0-4 years and 0.5% (95%CI: 0.2-0.8) for aged +65 years per 1 °C increase in temperature	NA	Seasonality, long-term trend, relative humidity, holidays, weekends, $PM_{2.5}$, O_3
(Mahmood et al., 2017)	London, UK	All population	2003-2015	Descriptive Statistics	Dyspnoea, pain (chest), generally unwell, alcohol related, dizzyness, respiratory chest infection, vomiting	Temperature < 2°C and > 20 °C	An increase in ambulance dispatches when temperature below 2 °C and upper 20 °C	No	Seasonality, long-term trend
(Papadakis et al., 2018)	London, UK	All population	2000-2014	NESM	Ambulance dispatches	NA	There are increases of ambulance dispatches during extreme temperatures (cold wave and heatwave)	No	NA
(Thornes et al., 2014)	Birmingham, UK	All population	2007-2011	Descriptive Statistics	Chest pain, Unconscious/fainting, Breathing problems	NA	There are increases of ambulance dispatches during extreme temperatures. A decline in temperature of 1 °C was related to a reduction of 1.3% in work performance	No	No

Author	Location	Population	Study period	Method	Health outcomes	Threshold temperature	Main outcomes	Lagged days	Adjustment factors
(Zhan et al., 2018)	Shenzhen, China	All population	2010-2016	GLM	Ambulance dispatches	19.5 °C	RR for ambulance dispatches : 1.25 (95%CI: 1.16-1.35) and 1.21 (95%CI: 1.16-1.26) at the 5th and the 95th of temperature distribution respectively per 1 °C increase in temperature	28 days	Seasonality, long-term trend, relative humidity, holidays, weekends

Abbreviations:

NA: No available relevant data; 95% CI, 95% of confidence intervals; GAM, generalized additive models; GLM, generalized linear model; NESM, nonextensive statistical mechanics; $PM_{2.5}$, particulate matter with aerodynamic diameters less than 2.5 micrometres; O_3, Ozone; RR, relative risk

2.5 The association between air pollutants and health outcomes

Air pollution is a significant risk factor for various specific adverse health effects. Previous research has reported that exposure to ambient pollution is related to increases in adverse health indicators. The study from The Global Burden of Diseases, Injuries and Risk Factors 2015 (GBD 2015) in 195 countries from 1990 to 2015 reported the estimated risk of exposure to $PM_{2.5}$ and ozone. Global $PM_{2.5}$ increased by 11.2% especially in the last six years of the study (2010-2015). Long-term exposure to ambient $PM_{2.5}$ was responsible for 4.2 million deaths in 2016, while ozone caused extra 250,000 deaths. In particular, household emissions generated from the burning of solid fuels is a principal cause of mortality especially in low-income and middle-income countries (Cohen et al., 2017). There were 4.2 million global premature deaths due to exposure to ambient air pollution, especially particulate matter, including cardiovascular and respiratory diseases (EEA, 2016). Public Health England (PHE) indicated that deaths caused by coronary heart disease, stroke, asthma and respiratory diseases from exposure to air pollution numbered around 28,000 and 36,000 per year (PHE, 2019). There are many pollutants that affect health outcomes: particulate matter (PM), ozone (O_3), carbon monoxide (CO), nitrogen dioxide (NO_2) and sulphur dioxide (SO_2). The health effects from exposure to air pollution are described as follows:

2.5.1 Particulate matter (PM)

PM is a mixture of solid particles and liquid droplets in air which regulatory regimes either monitor as PM_{10}, $PM_{2.5}$, both, or coarse fraction (PM_{10} – $PM_{2.5}$). PM_{10} and $PM_{2.5}$ is particulate matter with aerodynamic diameters less than 10 and 2.5 micrometres respectively. Previous studies reported a significant association between particulate matter, both PM_{10} and

$PM_{2.5}$, on health outcomes especially cardiovascular function (Guaita et al., 2011; Peng et al., 2008). Particle size and source are linked with the health problems (Kim et al., 2015). The PM could be from natural sources such as sea salt, bushfires and volcanoes or anthropogenic activities such as power plants, industrial flues and vehicle exhausts. The impact of PM_{10} is mostly related to respiratory organs from nasal passages to lungs by excessive penetrability. However, particle less than 5 micrometre particles are linked with impacts on bronchioles and alveoli as shown in Figure 2-4.

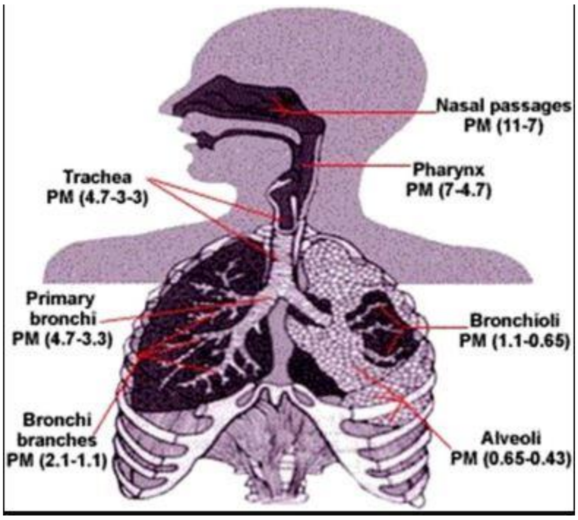

Figure 2-4 The size of particulate matter and targeted organs (Löndahl et al., 2006)

2.5.2 Ozone (O_3)

O_3 is formed indirectly from the interaction with nitrogen oxides (NOx) (comprised primarily of nitrogen dioxide (NO_2) and nitric oxide (NO), volatile organic compounds (VOC) and sunlight. Normally, the effect of ozone is measured as daily maximum 8- hour average of concentration. The effect of exposure to high ozone can obstruct lung function and lead to inflammation in the lungs. Moreover, the adverse outcomes are linked to respiratory symptoms e.g. wheezing, coughing and chest tightness (EPA, 2015). Previous studies have reported that ozone is linked with exacerbation of asthma attacks and COPD (EPA, 2017). Numerous studies have reported the association between ozone and health effects (Dennekamp et al., 2010; Pradeau et al., 2015; Rosenthal et al., 2013; Silverman et al., 2010).

2.5.3 Carbon monoxide (CO)

CO is mainly formed in many activities especially from home, typically during incomplete combustion, for example burning from appliances such as clothes dryers, heaters, boilers and cooking (gas and wood burning) (Minnesota Department of Health, 2016). Moreover, CO can be emitted from road vehicles and smoking.

2.5.4 Nitrogen dioxide (NO_2)

NO_2 is formed from oxides of nitrogen or nitrogen oxides (NO_x) but NO_2 is the most prevalent of the nitrogen oxides (US EPA, 2016). Most NO_2 comes from public transportation, power generation from fossils fuels, and other combustion processes from industries (APIS, 2016). Previous studies reported a significant association between NO_2 and health effects such as respiratory symptoms, asthma and cancer (WHO, 2017).

2.5.5 Sulphur dioxide (SO_2)

SO_2 is a gas that can cause acid rain by a chemical reaction such as H_2SO_4 and H_2SO_3 in raindrop. The emission of SO_2 comes about 99% from vehicle emission and combustion processes. The emission of SO_2 in the UK have significantly declined since the 1990s and have remained stable since 2009. The main reason is the decline using the coal and fuel oil in all industries. When people inhale SO_2 it can lead to immediate irritation, coughing, wheezing and shortness of breath (Department of the Environment and Energy, 2005).

2.6 Analytical methods

To test for associations between health effects and environmental factors, there are a wide array of statistical approaches available. In this section, the approaches deployed in this thesis are described. Health outcomes can be split into two broad categories: acute and chronic. Acute effect is a result of short-term exposure while chronic effect is a result of a long-term exposure or cumulative effect. Environment-health associations can be both acute and chronic. The outcome response can be mortality or morbidities. Datasets of health outcomes are available in databases with either binary or continuous patterns. There are four main groups of study designs for measuring environment-health associations: time series, case-crossover, panel and cohort studies (Dominici et al., 2007; Souza Tadano et al., 2012). When investigating environment-health associations it is important to control for confounding factors such as a long-term trends, seasonality, and day of the week effects.

2.6.1 Time series

2.6.1.1 Time series introduction

Time series approaches are widely used to understand the association between mortality and environment factors such as extreme temperatures or environmental pollutants. These models can provide estimated risk factors when patients are exposed to certain environmental conditions, for example extreme temperatures (Bhaskaran et al., 2013; Gasparrini and Armstrong, 2010). In times series approaches, the dependent variable is typically daily hospital admission or mortality data, which is compared with the independent environmental variables, such as temperature. Typically, successful use of time series approaches requires daily datasets of duration greater than two years (Roger and Francesca, 2008). Sometimes, time series approaches are based on weekly, monthly and yearly aggregated data. Personal factors such as age, gender and socio-economic status are not considered in the model because they do not change on a daily basis (Bhaskaran et al., 2013). In time series models, confounding factors need to be adjusted for factors such as long-term trends, seasonality, air pollutants, meteorological variables and influenza, to remove the autocorrelation between variables. Without adjusting for confounders, the model will lead to misinterpretation of results (Bhaskaran et al., 2013). Often, the associations between temperature (and other independent variables) and health have a lagged effect, i.e. the effect of the environmental factors takes time to manifest itself in the patient, with the result of delayed effects.

The statistical approach used for regression in this thesis was either the generalised additive time series model (GAM) or the generalised linear time series model (GLM). GAM and GLM are advanced regression techniques which are designed for ecological studies (a study in each level of the association between health outcomes and exposure). GLM is used to investigate the link between response variables and the combinations of explanatory variables (the variable parameters which may or may not be related to response variables (health outcomes). The GLM is an extension of linear modelling by allowing a dependent variable to be non-normal distribution, either a binomial, Poisson or gamma distribution (Guisan et al., 2002). The type of data, such as count data or binary data, is specific for the GLM.

Parametric spline is used for explanatory variables by using different functions. A natural cubic spline is performed by fitting a polynomial model with degrees. For example, GLM uses natural cubic splines as a smooth function to avoid excessive flexibility with varying degrees of freedom. By contrast, a non-parametric smoother is lowess smoothers (S-plus package) in the R programme this is used as a smooth function in GAM (He et al., 2006; Roger and Francesca, 2008).

Both the GLM and GAM model can measure both the linearity and non-linearity of the association between related factors and health outcomes (X.-J. Zhang et al., 2015). However, previous research has noted that the results from the GLM are superior to those of the GAM (He et al., 2006) because the latter has a problem with underestimation of the standard error due to the multicollinearity of independent variables, known as concurvity (Figueiras et al., 2005; He et al., 2006). Other studies have shown that the results were similar (Czado et al., 2009). Changing the study design or controlling the effect of long-term trends and seasonal trends can circumvent the concurvity problem in the GAM (Figueiras et al., 2005).

2.6.1.2 Time series model:

The generalised linear time series model (GLM) for investigating whether the association between health outcome and exposure to environmental factors. The health risks can be linked with calendar time, temperature variables and air pollutant variables so in model we can add time-varying potential confounder, weather variable and covariates as equation (1)

$$\Upsilon_t \sim \text{Poisson } (\mu_t)$$

$$\log \mu_t \; = \; \alpha + \; \beta x_t \; + \; \eta' z_t + \int (t; \lambda) + \; \varepsilon_t \qquad (1)$$

Where Υ_t is a health outcome on day t. When health outcomes are count data type, a Poisson regression in GLM is applied. The outcome of Υ_t changes to Poisson with a mean μ_t. x_t term representing the exposure (temperature or pollutants). β is the coefficient of risk of exposure x_t , z is the vector of covariates added for adjusting the confounder, such as day of the week or holidays. A smooth function of time is shown as $\int (t; \lambda)$, and the degree of freedom depends on the scale of the lambda (λ). For example, a bigger lambda is related to less smooth or rougher (Roger and Francesca, 2008). ε is an error of model.

Relative risk (RR) is used to estimate the risk result for the association between exposure to environmental factors and health outcomes by using the estimated regression coefficient from the fitted regression line (Souza Tadano et al., 2012). The coefficient of regression is a sloping regression line at the level of x. RR is described by as equations (2) and (3). Baxter et al. (1995) noted that "the ratio in (2) shows the ratio of expected number of end point at level x of independent variable to the expected number of end points if the independent variable were 0." For the Poisson regression, the RR can be calculated according to the following equation (3):

$$RR\ (x) = \frac{E(y/x)}{E(y/x=0)} \tag{2}$$

$$RR\ (x) = e^{\beta x} \tag{3}$$

2.6.1.3 Overdispersion:

Time series allows for overdispersion and residual autocorrelation. In a case where the dependent variable has variance larger than the mean, over-dispersion is observed. Overdispersion can be removed by adding a smooth function of time (Roger and Francesca, 2008). To deal with the over-dispersion problem, the quasi-Poisson or negative binomial are applied to obtain reliable results (Dormann, 2016).

2.6.1.4 Degree of freedom (df):

In the time series analysis, a natural spline function (ns) is used for the GLM. The degree of freedom (df) is linked with the smoothness of the independent variables. In the model, the df needs to be specified. If we choose 1, the generated curve is a linear fit. In contrast, a higher df leads to more bends (knots). If we choose the optimal degree of freedom, which has the smallest error and bias, the model is able to predict the association between the impact of the environment on adverse health impacts. Previous studies allow for the sensitivity of different ranges of df to be examined, in turn allowing us to determine the extent to which the regression coefficient has changed (Roger and Francesca, 2008). To verify the correct model setup, it is recommended that a model with the lowest Akaike Information Criterion (AIC) be selected.

2.6.1.5 Akaike Information Criterion (AIC)

AIC is a technique to estimate the likelihood of a selected model to identify the best number of df. A good model will generate the lowest AIC. Another way to decide the number of df is the partial autocorrelation function (PACF). The PACF gives the correlation of residual after adding the lag effect into the model due to avoidance of the autocorrelation from earlier lags (Follow, 2019).

2.6.1.6 Delayed effects

Most previous studies have recommended studying the association between the delayed effects, or lagged days, which show the relationship between the exposing pollutant from previous days and the health impacts today (Tadano et al., 2012). A single day lag shows the association between increases in pollutants and health outcomes on a specific day. For example, an effect on lag 1 means a certain level of pollutant on day 0 (current day) is related to a certain number of health outcomes on day 1 (the following day). A distributed lag model (DLM) is used to check a single lag, as in:

$$\log \mu_t \;=\; \alpha + \sum_{l=0}^{K} \beta_l \, x_{t-l} \;+\; \text{other factors}_t \quad (4)$$

The DLM result will give an estimation of pollutant coefficient of each lag until the maximum at K days. μ_t is a Poisson distribution of health outcomes, K is the range of lags. α is an intercept of the model. β is log-relative risk for x_{t-l} when day = t and lag l .The delay effect between temperature and health impacts is observed from 0 to 28 days while there are only seven days for exposure to pollutants (Bhaskaran et al., 2013; Gasparrini et al., 2015a).

The cumulative effect over multiple days can be generated from the sum of coefficients from the distributed lag model (Roger and Francesca, 2008).

2.6.1.7 Distributed Lag Non-Linear Model (DLNM)

The DLNM package in the R software was proposed by Gasparrinia et al. (2010) to describe two dimensions of two independent variables between temperature and lags by using function cross-basis. The cross-basis variables are included in the core model of regression. An advantage of the DLNM model is it allows the user to add variable df and delay effects to provide the estimated effect (Gasparrinia et al., 2010). The example results from the cross-basis function plots in 3D to show RR along with temperature and lags (see in Figure 2-5). Two-dimensions of association between temperature and distributed lag effects can be achieved through a cross-basis function (see in Figure 2-6).

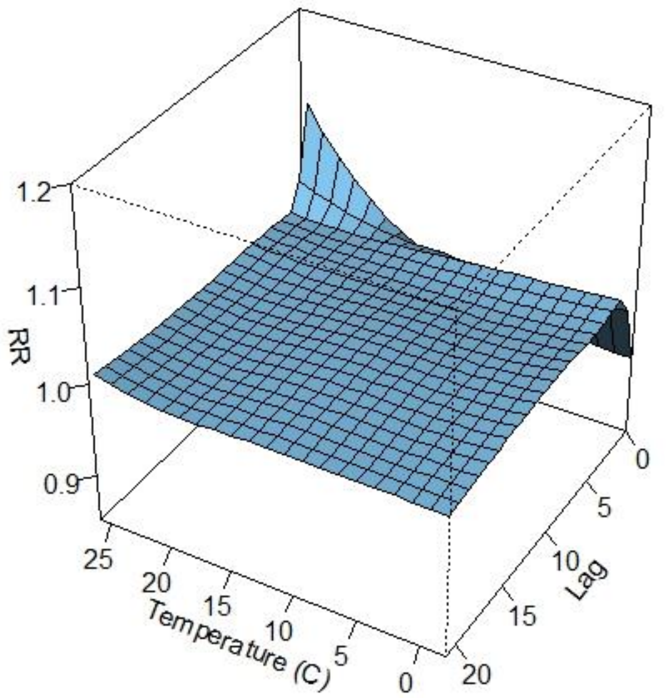

Figure 2-5 RR of ambulance dispatches (999 dispatches) by the temperature and lag days.

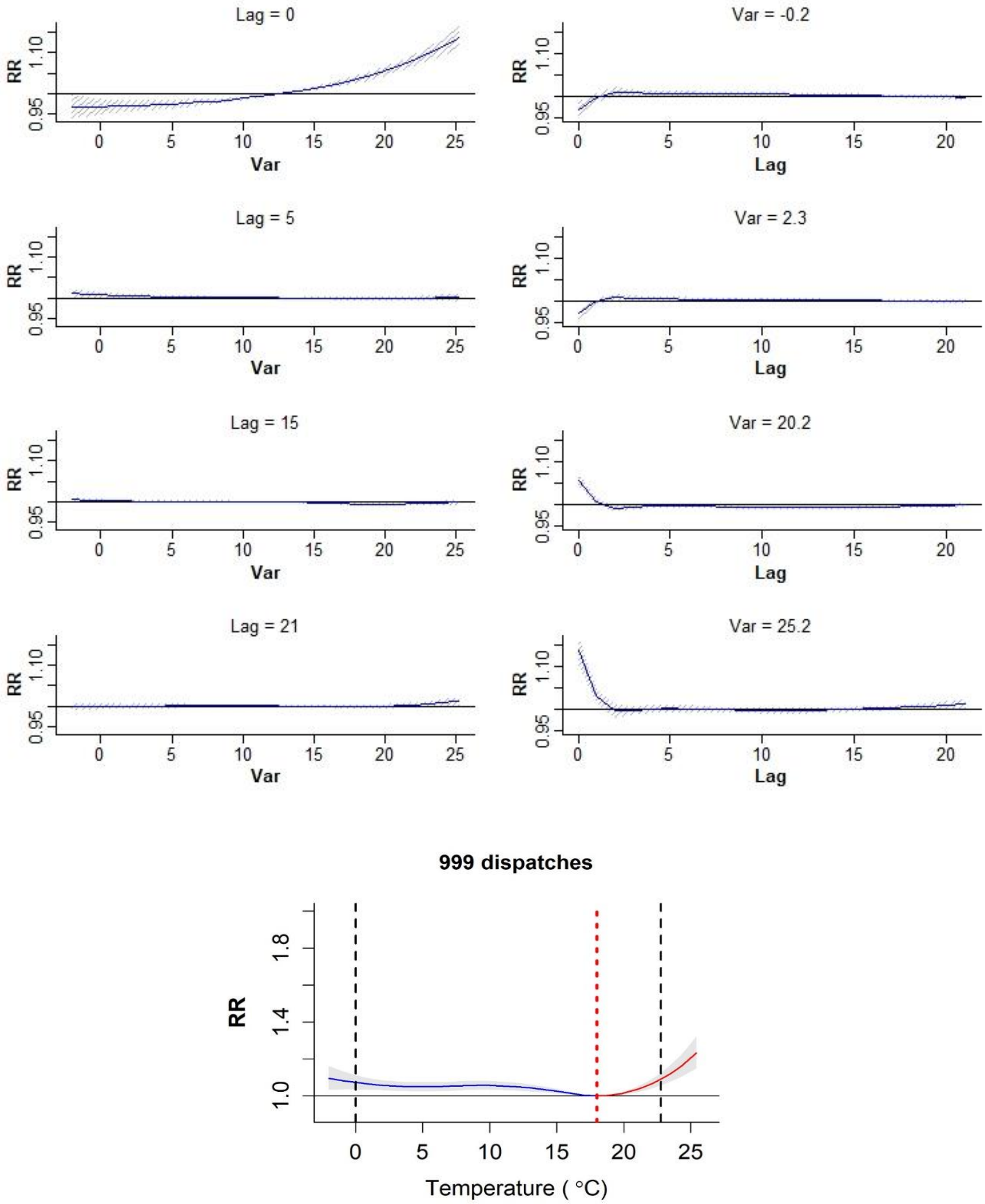

Figure 2-6 RR with 95% confidence interval (CI) of ambulance dispatches (999 dispatches) at different lags (right side) and at different temperatures (°C) as shown in Var variable (left side). The cumulative effect over 21 days was presented (bottom)

In the present study, the DLNM package is used with a regression model. The best model will be chosen by the AIC to obtain an optimal the selected lags and degree of freedom. Some studies have used different lags and df checking for sensitivity analysis.

2.6.2 Case crossover

This method is also used for approaching the effect of environmental factors (e.g. temperature and pollutants) on health outcomes, but it can control the interferences from individual factors such as gender, age and personal behaviour. The method focuses on individual levels rather than the daily event (mortality or morbidity) (Schwartz, 2004). It was designed to compare their own control, known as matched case-control studies, at different times (Jaakkola, 2003). The case-crossover design compares the different exposures among cases whose days have events present (adverse health outcomes) and control, which nearby the day that events occurred, this result in controlling for seasonality (Schwartz, 2004). This method can explain whether a recent exposure has had an impact on health. While time series analysis focuses on time adjustments of the same population under different exposure, case-crossover is an explanation of exposure distribution. Currently, case-crossover design is used for the association between air pollutants and their impact on health (Jaakkola, 2003), especially the association due to a transient change and acute outcomes (Maclure, 2017).

2.6.3 Cohort study

This design is used to examine the association between long term exposure and impacts on health. The unexposed group is followed up at the beginning over a period of time to access the period when health-impacts occurred. This data can be gathered from surveillance or participant records or questionnaires for prospective design while retrospective design data may also be available (Souza Tadano et al., 2012). This study type is suitable for a large sample size and follow-up over a long period (Song and Chung, 2010). The exposure can be a special event (e.g. accumulation of air pollutant) then analysing compared to an unexposed group.

2.7 Decomposition

This is the technique used to determine the three components in time series data, comprising a seasonal component, a trend (long-term trend) and a residual component. In R program, the decompose function can generate three components of time series data (Brownlee, 2017). The residual trend or random in Figure 2-7 is the remain after removing a seasonality and a long-term trend. In the model, we can obtain a residual value from the natural cubic spline function.

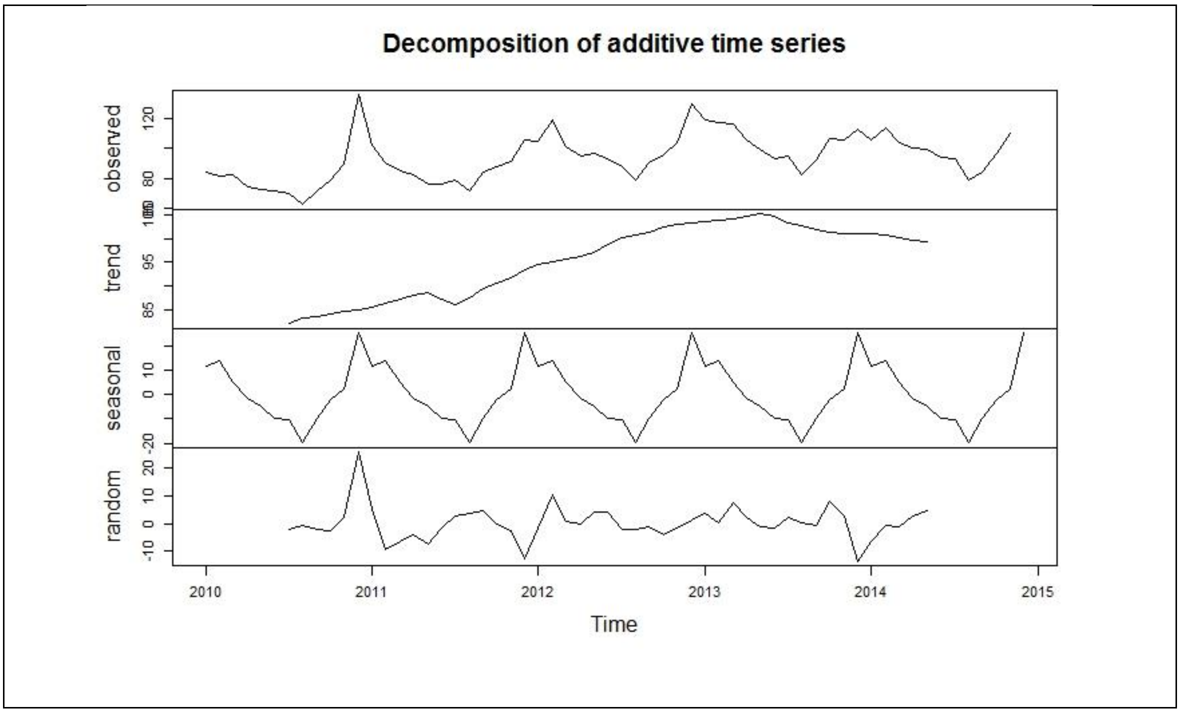

Figure 2-7 The Example of decomposition of ‘generally unwell’ dispatches to remove a long-term trend and a-seasonality

2.8 Sensitivity analyses

The sensitivity analyses check the uncertainty of results from the model when input is changed in different ways. There are many ways to investigate sensitivity analyses, such as, for example, changing the model by removing or adding pollutants, replacing the mean temperature with the maximum temperature and changing the number of delayed effects.

2.9 Harvesting effect or displacement

Exposure to extreme temperature or high pollutant levels can lead to a harvesting effect because of the premature mortality and morbidity of frail individuals by a few days, reducing the number of admissions or deaths later after several days (Carder et al., 2005; Le et al., 2014).

2.10 References

Anomaly, 2015. Extracting Seasonality and Trend from Data: Decomposition Using R [WWW Document]. Anomaly. URL https://anomaly.io/seasonal-trend-decomposition-in-r/ (accessed 12.4.19).

APIS, 2016. Nitrogen Oxides (NOx) | Air Pollution Information System [WWW Document]. URL http://www.apis.ac.uk/overview/pollutants/overview_NOx.htm (accessed 12.17.19).

Baccini, M., Biggeri, A., Accetta, G., Kosatsky, T., Katsouyanni, K., Analitis, A., Anderson, H.R., Bisanti, L., D'Iippoliti, D., Danova, J., Forsberg, B., Medina, S., Paldy, A., Rabczenko, D., Schindler, C., Michelozzi, P., 2008. Heat effects on mortality in 15 European cities. Epidemiology 19, 711–719. https://doi.org/10.1097/EDE.0b013e318176bfcd

Ban, J., Xu, D., He, M.Z., Sun, Q., Chen, C., Wang, W., Zhu, P., Li, T., 2017. The effect of high temperature on cause-specific mortality: A multi-county analysis in China. Environ. Int. 106, 19–26. https://doi.org/10.1016/j.envint.2017.05.019

Basara, J.B., Basara, H.G., Illston, B.G., Crawford, K.C., 2010. The Impact of the Urban Heat Island during an Intense Heat Wave in Oklahoma City. Adv. Meteorol. 2010, 1–10. https://doi.org/10.1155/2010/230365

Basu, R., 2009. High ambient temperature and mortality: A review of epidemiologic studies from 2001 to 2008. Environ. Heal. A Glob. Access Sci. Source 8. https://doi.org/10.1186/1476-069X-8-40

Basu, R., Ostro, B.D., 2008. A multicounty analysis identifying the populations vulnerable to mortality associated with high ambient temperature in California. Am. J. Epidemiol. 168, 632–637. https://doi.org/10.1093/aje/kwn170

Baxter, P.J., Heap, B.J., Rowland, M.G.M.M., Murray, V.S.G.G., 1995. Thetford plastics fire, October 1991: The role of a preventive medical team in chemical incidents. Occup. Environ. Med. 52, 694–698. https://doi.org/10.1136/oem.52.10.694

Bell, M.L., Zanobetti, A., Dominici, F., 2013. Evidence on vulnerability and susceptibility to health risks associated with short-term exposure to particulate matter: a systematic review and meta-analysis. Am. J. Epidemiol. https://doi.org/10.1093/aje/kwt090

Berko, J., Ingram, D.D., Saha, S., Parker, J.D., 2014. Deaths attributed to heat, cold, and other weather events in the United States, 2006–2010. Natl. Health Stat. Report. 2014, 1–15.

Bhaskaran, K., Gasparrini, A., Hajat, S., Smeeth, L., Armstrong, B., 2013. Time series regression studies in environmental epidemiology. Int. J. Epidemiol. 42, 1187–1195. https://doi.org/10.1093/ije/dyt092

Brooke Anderson, G., Bell, M.L., 2011. Heat waves in the United States: Mortality risk during heat waves and effect modification by heat wave characteristics in 43 U.S. communities. Environ. Health Perspect. 119, 210–218. https://doi.org/10.1289/ehp.1002313

Bureau of Labor Statistics, U.S. Department of Labor. 2015. Census of Fatal Occupational Injuries, Occupational Injuries and Illnesses and Fatal Injuries Profiles, 2007-2011. URL https://data.bls.gov/gqt/ InitialPage (accessed 11.10.19).

C2ES, 2014. Extreme Weather and Climate Change [WWW Document]. URL http://www.c2es.org/publications/extreme-weather-and-climate-change (accessed 1.24.20).

Cakmak, S., Dales, R.E., Judek, S., 2006. Do gender, education, and income modify the effect of air pollution gases on cardiac disease? J. Occup. Environ. Med. 48, 89–94. https://doi.org/10.1097/01.jom.0000184878.11956.4b

Carder, M., McNamee, R., Beverland, I., Elton, R., Cohen, G.R., Boyd, J., Agius, R.M., 2005. The lagged effect of cold temperature and wind chill on cardiorespiratory mortality in Scotland. Occup. Environ. Med. 62, 702–710. https://doi.org/10.1136/oem.2004.016394

Cardona, O.D., Van Aalst, M.K., Birkmann, J., Fordham, M., Mc Gregor, G., Rosa, P., Pulwarty, R.S., Schipper, E.L.F., Sinh, B.T., Décamps, H., Keim, M., Davis, I., Ebi, K.L., Lavell, A., Mechler, R., Murray, V., Pelling, M., Pohl, J., Smith, A.O., Thomalla, F., 2012. Determinants of risk: Exposure and vulnerability. Manag. Risks Extrem. Events Disasters to Adv. Clim. Chang. Adapt. Spec. Rep. Intergov. Panel Clim. Chang. 9781107025, 65–108. https://doi.org/10.1017/CBO9781139177245.005

Carmona, R., Díaz, J., Mirón, I.J., Ortíz, C., León, I., Linares, C., 2016. Geographical variation in relative risks associated with cold waves in Spain: The need for a cold wave prevention plan. Environ. Int. 88, 103–111. https://doi.org/10.1016/j.envint.2015.12.027

CCOHS, 2019. Cold Environments - Working in the Cold : OSH Answers [WWW Document]. Can. Cent. Occup. Heal. Saf. URL https://www.ccohs.ca/oshanswers/phys_agents/cold_working.html (accessed 12.11.19).

CCOHS, 2014. Hot Environments - Health Effects and First Aid [WWW Document]. Can. Cent. Occup. Heal. Saf. URL %5Ctwww.ccohs.ca/oshanswers/phys_agents/heat_health.html. (accessed 12.11.19).

CDC, 2019. Precipitation Extremes : Heavy Rainfall, flooding , and Droughts [WWW Document]. URL https://www.cdc.gov/climateandhealth/effects/precipitation_extremes.htm (accessed 1.26.20).

CDC, 2006. Hypothermia-related deaths - United States, 1999-2002 and 2005 [WWW Document]. Morb. Mortal. Wkly. Rep. URL https://www.cdc.gov/mmwr/preview/mmwrhtml/mm5510a5.htm (accessed 12.24.19).

Chen, R., Yin, P., Wang, L., Liu, C., Niu, Y., Wang, W., Jiang, Y., Liu, Y., Liu, J., Qi, J., You, J., Kan, H., Zhou, M., 2018. Association between ambient temperature and mortality risk and burden: Time series study in 272 main Chinese cities. BMJ 363. https://doi.org/10.1136/bmj.k4306

Chen, W., Jiang, Z., Li, L., Yiou, P., 2011. Simulation of regional climate change under the IPCC A2 scenario in southeast China. Clim. Dyn. 36, 491–507. https://doi.org/10.1007/s00382-010-0910-3

Cohen, A.J., Brauer, M., Burnett, R., Anderson, H.R., Frostad, J., Estep, K., Balakrishnan, K., Brunekreef, B., Dandona, L., Dandona, R., Feigin, V., Freedman, G., Hubbell, B., Jobling, A., Kan, H., Knibbs, L., Liu, Y., Martin, R., Morawska, L., Pope, C.A., Shin, H., Straif, K., Shaddick, G., Thomas, M., van Dingenen, R., van Donkelaar, A., Vos, T., Murray, C.J.L., Forouzanfar, M.H., 2017. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. Lancet 389, 1907–1918. https://doi.org/10.1016/S0140-6736(17)30505-6

Czado, C., Pfettner, J., Gschlobi, S., Schiller, F., 2009. Nonnested model comparison of GLM and GAM count regression models for life insurance data.

D'Amato, M., Molino, A., Calabrese, G., Cecchi, L., Annesi-Maesano, I., D'Amato, G., 2018. The impact of cold on the respiratory tract and its consequences to respiratory health. Clin. Transl. Allergy 8, 20. https://doi.org/10.1186/s13601-018-0208-9

Dennekamp, M., Akram, M., Abramson, M.J., Tonkin, A., Sim, M.R., Fridman, M., Erbas, B., 2010. Outdoor air pollution as a trigger for out-of-hospital cardiac arrests. Epidemiology 21, 494–500. https://doi.org/10.1097/EDE.0b013e3181e093db

Department of the Environment and Energy, 2005. Sulfur dioxide (SO2) - Air quality fact sheet [WWW Document]. Aust. Gov. URL https://www.environment.gov.au/protection/publications/factsheet-sulfur-dioxide-so2%0Ahttps://www.environment.gov.au/protection/publications/factsheet-sulfur-dioxide-so2%250Ahttps://www.environment.gov.au/protection/publications/factsheet-sulfur-dioxide-s (accessed 12.17.19).

DHS, 2019. Carbon Dioxide [WWW Document]. URL https://www.dhs.wisconsin.gov/chemical/carbondioxide.htm (accessed 1.26.20).

EEA, 2016. Health effects of exposure to ozone [WWW Document]. URL https://www.eea.europa.eu/publications/TOP08-98/page010.html (accessed 1.26.20).

Ensor, K.B., Raun, L.H., Persse, D., 2013. A case-crossover analysis of out-of-hospital cardiac arrest and air pollution. Circulation 127, 1192–1199. https://doi.org/10.1161/CIRCULATIONAHA.113.000027

Environmental Pollution Centers, 2017. What Is Food Pollution [WWW Document]. URL https://www.environmentalpollutioncenters.org/food/ (accessed 5.18.20).

EPA, 2017. Health Effects of Ozone Pollution For Healthcare Providers [WWW Document]. Us Epa. URL https://www.epa.gov/ground-level-ozone-pollution/health-effects-ozone-pollution (accessed 12.17.19).

EPA, 2016a. Overview of Greenhouse Gases Greenhouse Gas (GHG) Emissions US EPA [WWW Document]. URL https://www.epa.gov/ghgemissions/overview-greenhouse-gases (accessed 12.13.19).

EPA, 2016b. Air Quality and Climate Change Research [WWW Document]. URL https://www.epa.gov/air-research/air-quality-and-climate-change-research (accessed 1.9.20).

EPA, 2015. Health Effects of Ozone in the General Population [WWW Document]. Environ. Prot. Agency. URL http://www.epa.gov/apti/ozonehealth/population.html (accessed 1.27.20).

Fazzo, L., Minichilli, F., Santoro, M., Ceccarini, A., Della Seta, M., Bianchi, F., Comba, P., Martuzzi, M., 2017. Hazardous waste and health impact: A systematic review of the scientific literature. Environ. Heal. A Glob. Access Sci. Source. https://doi.org/10.1186/s12940-017-0311-8

Field, C.B., Barros, V., Stocker, T.F., Dahe, Q., Jon Dokken, D., Ebi, K.L., Mastrandrea, M.D., Mach, K.J., Plattner, G.K., Allen, S.K., Tignor, M., Midgley, P.M., 2012. Managing the risks of extreme events and disasters to advance climate change adaptation: Special report of the intergovernmental panel on climate change, Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change. https://doi.org/10.1017/CBO9781139177245

Follow, J.S., 2019. Signi cance of ACF and PACF Plots In Time Series Analysis [WWW Document]. URL https://towardsdatascience.com/significance-of-acf-and-pacf-plots-in-time-series-analysis-2fa11a5d10a8 (accessed 12.12.19).

Foster, K.G., Ellis, F.P., Doré, C., Exton-smtth, A.N., Weiner, J.S., 1976. Sweat responses in the aged. Age Ageing 5, 91–101. https://doi.org/10.1093/ageing/5.2.91

Galizia, A., Kinney, P.L., 1999. Long-term residence in areas of high ozone: Associations with respiratory health in a nationwide sample of nonsmoking young adults. Environ. Health Perspect. 107, 675–679. https://doi.org/10.1289/ehp.99107675

Garssen, J., Harmsen, C., De Beer, J., 2005. The effect of the summer 2003 heat wave on mortality in the Netherlands. Eurosurveillance 10, 13–14. https://doi.org/10.2807/esm.10.07.00557-en

Gasparrini, A., Armstrong, B., 2010. Time series analysis on the health effects of temperature: Advancements and limitations. Environ. Res. https://doi.org/10.1016/j.envres.2010.06.005

Gasparrini, A., Armstrong, B., Kovats, S., Wilkinson, P., 2011. The effect of high temperatures on cause-specific mortality in England and Wales. Occup. Environ. Med. 69, 56–61. https://doi.org/10.1136/oem.2010.059782

Gasparrini, A., Guo, Y.-L.L.Y., Hashizume, M., Lavigne, E., Zanobetti, A., Schwartz, J., Tobias, A., Tong, S., Rocklöv, J., Forsberg, B., Leone, M., De Sario, M., Bell, M.L., Guo, Y.-L.L.Y., Wu, C.-F., Kan, H., Yi, S.-M., de Sousa Zanotti Stagliorio Coelho, M., Saldiva, P.H.N., Honda, Y., Kim, H., Armstrong, B., De, M., Zanotti, S., Coelho, S., Hilario, P., Saldiva, N., Honda, Y., Kim, H., Armstrong, B., 2015a. Mortality risk attributable to high and low ambient temperature: a multicountry observational study. Lancet 386, 369–375. https://doi.org/10.1016/S0140-6736(14)62114-0

Gasparrini, A., Guo, Y., Hashizume, M., Kinney, P.L., Petkova, E.P., Lavigne, E., 2015b. Temporal Variation in Heat – Mortality Associations : A Multicountry Study. Environ. Health Perspect. 1200, 1200–1207.

Gasparrinia, A., Armstrong, B., Kenward, M.G., 2010. Distributed lag non-linear models. Stat. Med. 29, 2224–2234. https://doi.org/10.1002/sim.3940

Ghirardi, L., Bisoffi, G., Mirandola, R., Ricci, G., Baccini, M., 2015. The impact of heat on an emergency department in Italy: Attributable visits among children, adults, and the elderly during the warm season. PLoS One 10. https://doi.org/10.1371/journal.pone.0141054

Gu, S., Huang, C., Bai, L., Chu, C., Liu, Q., 2016. Heat-related illness in China, summer of 2013. Int. J. Biometeorol. 60, 131–137. https://doi.org/10.1007/s00484-015-1011-0

Guaita, R., Pichiule, M., Mate, T., Linares, C., Diaz, J., 2011. Short-term impact of particulate matter (PM2.5) on respiratory mortality in Madrid. Int. J. Environ. Health Res. 21, 260–274. https://doi.org/10.1080/09603123.2010.544033

Guisan, A., Edwards, T.C., Hastie, T., 2002. Generalized linear and generalized additive models in studies of species distributions: Setting the scene. Ecol. Modell. 157, 89–100. https://doi.org/10.1016/S0304-3800(02)00204-1

Guo, Y., Gasparrini, A., Armstrong, B., Li, S., Tobias, A., Lavigne, E., Sousa, M. De, Stagliorio, Z., 2014. Europe PMC Funders Group Global variation in the effects of ambient temperature on mortality : a systematic evaluation. Epidemiology 25, 781–789. https://doi.org/10.1097/EDE.0000000000000165.Global

Guo, Y., Li, S., Tian, Z., Pan, X., Zhang, J., Williams, G., 2013. The burden of air pollution on years of life lost in Beijing, China, 2004-08: Retrospective regression analysis of daily deaths. BMJ 347. https://doi.org/10.1136/bmj.f7139

Haigh, J., 2017. A brief history of the Earth’s CO2 - BBC News [WWW Document]. URL http://www.bbc.com/news/science-environment-41671770 (accessed 1.26.20).

Hanna, E.G., Kjellstrom, T., Bennett, C., Dear, K., 2011. Climate change and rising heat: Population health implications for working people in Australia. Asia-Pacific J. Public Heal. 23. https://doi.org/10.1177/1010539510391457

Harduar Morano, L., Bunn, T.L., Lackovic, M., Lavender, A., Dang, G.T.T., Chalmers, J.J., Li, Y., Zhang, L., Flammia, D.D., 2015. Occupational heat-related illness emergency department visits and inpatient hospitalizations in the southeast region, 2007-2011. Am. J. Ind. Med. 58, 1114–1125. https://doi.org/10.1002/ajim.22504

Haseena, M., Malik, M., Javed, A., Arshad, S., Asif, N., Zulfiqar, S., Hanif, J., 2017. Water pollution and human health. Water. Air. Soil Pollut. 1, 16–19. https://doi.org/10.4066/2529-8046.100020

He, S., Mazumdar, S., Arena, V.C., 2006. A comparative study of the use of GAM and GLM in air pollution research. Environmetrics 17, 81–93. https://doi.org/10.1002/env.751

He, T., Yang, Z., Liu, T., Shen, Y., Fu, X., Qian, X., Zhang, Y., Wang, Y., Xu, Z., Zhu, S., Mao, C., Xu, G., Tang, J., 2016. Ambient air pollution and years of life lost in Ningbo, China. Sci. Rep. 6. https://doi.org/10.1038/srep22485

Hong, Y.C., Lee, J.T., Kim, H., Ha, E.H., Schwartz, J., Christiani, D.C., 2002. Effects of air pollutants on acute stroke mortality. Environ. Health Perspect. 110, 187–191. https://doi.org/10.1289/ehp.02110187

Iñiguez, C., Ballester, F., Ferrandiz, J., Pérez-Hoyos, S., Sáez, M., López, A., Tempro-Emecas, Ballester, F., Iñíguez, C., Rodríguez, P., Pérez-Hoyos, S., Tenías, J.M., Gómez, F., Molina, R., González-Aracil, J., Medina, S., Patiño, J.A., Bosch, J.L., Peiró, S., Saez, M., Barceló, M.A., Saurina, C., Lertxundi, A., Artacoz, L., Sunyer, J., Plasència, A., Tobías, A., Daponte, A., Gurucelain, J.L., Gutiérrez, P., Maldonado, J.A., Maldonado, J.A., Mayoral, J.M., Ocaña, R., Caro, E., Lopez, P., Toro, S., Aguilera, I., Aguilera, I., Ordóñez, J.M., Aránguez, E., Galán, I., Gandarillas, A.M., López, L., Aragonés, N., Martinez, M., Fernández, R., Arias, P., Brezmes, A., Mantero, F.J., Cambra, K., Alonso, E., Cirarda, F.B., Martínez-Rueda, T., Figueiras, A., Aguiar, M.R., Sixto, C., Sánchez, M.C., Arribas, F., Navarro, M., Martos, C., Rabanaque, M.J., Muniesa, E., Alcalá, J.T., Urraca, J.I., Loarte, M., Bellido, J.B., Arnedo, A., González, F., Felis, C., Herrero, C., Guillén, J.J., Cirera, L., García, L., Jiménez, E., Martínez, M.J., Moreno, S., Navarro, C., Medrano, J., Martínez, M.A., Aguinaga, I., Guillén, F., Floristán, M.Y., Aldaz, F.J., Zuazo, P., Moreno, C., Arrazola, A., Aguinaga, E., Ugarte, M.D., Fernández, A., Serrano, I., Martinez, M.A., Viñes, J.J., Cañada, A., Fernández, C., Fernández, F., García, J. V., Huerta, I., Rodríguez, V., Asturias, E., López, E., 2010. Relation between temperature and mortality in thirteen Spanish cities. Int. J. Environ. Res. Public Health 7, 3196–3210. https://doi.org/10.3390/ijerph7083196

IPCC, 2014. Climate Change 2014 Synthesis Report Summary for Policymakers, IPCC 5th Assessment Report.

Jaakkola, J.J.K., 2003. Case-crossover design in air pollution epidemiology, in: European Respiratory Journal, Supplement. https://doi.org/10.1183/09031936.03.00402703

Kan, H., London, S.J., Chen, G., Zhang, Y., Song, G., Zhao, N., Jiang, L., Chen, B., 2008. Season, sex, age, and education as modifiers of the effects of outdoor air pollution on daily mortality in Shanghai, China: The Public Health and Air Pollution in Asia (PAPA) study. Environ. Health Perspect. 116, 1183–1188. https://doi.org/10.1289/ehp.10851

Kim, K.H., Kabir, E., Kabir, S., 2015. A review on the human health impact of airborne particulate matter. Environ. Int. https://doi.org/10.1016/j.envint.2014.10.005

Knowlton, K., Rotkin-Ellman, M., King, G., Margolis, H.G., Smith, D., Solomon, G., Trent, R., English, P., 2009. The 2006 California heat wave: Impacts on hospitalizations and emergency department visits. Environ. Health Perspect. 117, 61–67. https://doi.org/10.1289/ehp.11594

Kovats, R.S., Hajat, S., Wilkinson, P., 2004. Contrasting patterns of mortality and hospital admissions during hot weather and heat waves in Greater London, UK. Occup. Environ. Med. 61, 893–898.

Le, A., Lefranc, A., Eilstein, D., Declercq, C., Medina, S., Blanchard, M., Chardon, B., Fabre, P., Filleul, L., Jusot, J., Pascal, L., Prouvost, H., Cassadou, S., Ledrans, M., Tertre, A. Le, Lefranc, A., Chardon, B., Jusot, J., Prouvost, H., 2014. Impact of the 2003 Heatwave on All-Cause Mortality in 9 French Cities * Volume Epidemiology Number. Source Epidemiol. 17, 75–79. https://doi.org/10.1097/01.ede.0000187650.36636.lf

Lenine, R., 2016. How air pollution is destroying our health [WWW Document]. World Heal. Organ. URL https://www.who.int/airpollution/news-and-events/how-air-pollution-is-destroying-our-health (accessed 12.17.19).

Löndahl, J., Pagels, J., Swietlicki, E., Zhou, J., Ketzel, M., Massling, A., Bohgard, M., 2006. A set-up for field studies of respiratory tract deposition of fine and ultrafine particles in humans. J. Aerosol Sci. 37, 1152–1163. https://doi.org/10.1016/j.jaerosci.2005.11.004

Maclure, M., 2017. The case-crossover design: A method for studying transient effects on the risk of acute events, American Journal of Epidemiology. https://doi.org/10.1093/aje/kwx105

Marzella, L., Myers, R.A.M., 1986. Carbon monoxide poisoning [WWW Document]. Am. Fam. Physician. URL https://www.nhs.uk/conditions/carbon-monoxide-poisoning/ (accessed 12.17.19).

McKeown, A., & Bugyi, G. (Eds.). (2016). Impact of Water Pollution on Human Health and Environmental Sustainability. IGI Global. http://doi:10.4018/978-1-4666-9559-7

Met Office, 2019. What is climate change? - Met Office [WWW Document]. Https//Www.Epa.Gov/Climate-Indicators/Climate-Change-Indicators-Us-and-Global-Temperature Dl 04062019. https://doi.org/10.1088/1742-6596/909/1/012014

Minnesota Department of Health, 2016. Carbon Monoxide (CO) Poisoning in Your Home.

NASA, 2018. NASA Climate Kids :: What is the greenhouse effect? [WWW Document]. URL https://climatekids.nasa.gov/greenhouse-effect/ (accessed 12.13.19).

NASA, 2015. What is Ozone? [WWW Document]. URL https://ozonewatch.gsfc.nasa.gov/facts/SH.html (accessed 1.26.20).

NHS, 2017. 10 winter illnesses [WWW Document]. URL https://www.nhs.uk/live-well/healthy-body/10-winter-illnesses/ (accessed 12.16.19).

O'Neill, M.S., Hajat, S., Zanobetti, A., Ramirez-Aguilar, M., Schwartz, J., 2005a. Impact of control for air pollution and respiratory epidemics on the estimated associations of temperature and daily mortality. Int. J. Biometeorol. 50, 121–129. https://doi.org/10.1007/s00484-005-0269-z

O'Neill, M.S., Zanobetti, A., Schwartz, J., 2005b. Disparities by race in heat-related mortality in four US cities: The role of air conditioning prevalence. J. Urban Heal. 82, 191–197. https://doi.org/10.1093/jurban/jti043

Oke, T.R., 1982. The energetic basis of the urban heat island. Q. J. R. Meteorol. Soc. 108, 1–24. https://doi.org/10.1002/qj.49710845502

Pachauri, R.K., Meyer, L., Hallegatte France, S., Bank, W., Hegerl, G., Brinkman, S., van Kesteren, L., Leprince-Ringuet, N., van Boxmeer, F., 2014. AR5 Synthesis Report: Climate Change 2014 — IPCC [WWW Document]. Clim. Chang. 2014 Synth. Report. Contrib. Work. Groups I, II III to Fifth Assess. Rep. Intergov. Panel Clim. Chang. URL http://www.ipcc.ch. (accessed 12.13.19).

Pantavou, K.G., Lykoudis, S.P., Nikolopoulos, G.K., 2016. Milder form of heat-related symptoms and thermal sensation: a study in a Mediterranean climate. Int. J. Biometeorol. 60, 917–929. https://doi.org/10.1007/s00484-015-1085-8

Peng, R.D., Chang, H.H., Bell, M.L., McDermott, A., Zeger, S.L., Samet, J.M., Dominici, F., 2008. Coarse particulate matter air pollution and hospital admissions for cardiovascular and respiratory diseases among medicare patients. JAMA - J. Am. Med. Assoc. 299, 2172–2179. https://doi.org/10.1001/jama.299.18.2172

Poupart, A.A., Smargiassi, A., Busque, M.A., Duguay, P., Fournier, M., Zayed, J., Labrèche, F., 2014. Summer outdoor temperature and occupational heat-related illnesses in Quebec (Canada). Environ. Res. 134, 339–344. https://doi.org/10.1016/j.envres.2014.07.018

Pradeau, C., Rondeau, V., Lévèque, E., Guernion, P.Y., Tentillier, E., Thicoip, M., Brochard, P., 2015. Air pollution and activation of mobile medical team for out-of-hospital cardiac arrest. Am. J. Emerg. Med. 33, 367–372. https://doi.org/10.1016/j.ajem.2014.12.007

Public Health England, 2019. Public Health England publishes air pollution evidence review - GOV.UK [WWW Document]. URL https://www.gov.uk/government/news/public-health-england-publishes-air-pollution-evidence-review (accessed 1.26.20).

Roger, P., Francesca, D., 2008. Statistical Methods for Environmental Epidemiology with R, Statistical Methods for Environmental Epidemiology with R. Springer New York. https://doi.org/10.1007/978-0-387-78167-9

Rosenthal, F.S., Kuisma, M., Lanki, T., Hussein, T., Boyd, J., Halonen, J.I., Pekkanen, J., 2013. Association of ozone and particulate air pollution with out-of-hospital cardiac arrest in Helsinki, Finland: Evidence for two different etiologies. J. Expo. Sci. Environ. Epidemiol. 23, 281–288. https://doi.org/10.1038/jes.2012.121

Schinasi, L.H., Hamra, G.B., 2017. A Time Series Analysis of Associations between Daily Temperature and Crime Events in Philadelphia, Pennsylvania. J. Urban Heal. 94, 892–900. https://doi.org/10.1007/s11524-017-0181-y

Schneider, A., Breitner, S., 2016. Temperature effects on health - current findings and future implications [WWW Document]. EBioMedicine. https://doi.org/10.1016/j.ebiom.2016.04.003

Schwartz, J., 2005. Who is sensitive to extremes of temperature? A case-only analysis. Epidemiology 16, 67–72. https://doi.org/10.1097/01.ede.0000147114.25957.71

Schwartz, J., 2004. Air Pollution and Children's Health.

Schwartz, J., 2004. The effects of particulate air pollution on daily deaths: A multi-city case crossover analysis. Occup. Environ. Med. 61, 956–961. https://doi.org/10.1136/oem.2003.008250

Seltenrich, N., 2015. Between extremes: Health effects of heat and cold. Environ. Health Perspect. https://doi.org/10.1289/ehp.123-A275

Shendell, D.G., Alexander, M.S., Lorentzson, L., McCarty, F.A., 2010. Knowledge and awareness of heat-related morbidity among adult recreational endurance athletes. Int. J. Biometeorol. 54, 441–448. https://doi.org/10.1007/s00484-009-0295-3

Silverman, R.A., Ito, K., Freese, J., Kaufman, B.J., De Claro, D., Braun, J., Prezant, D.J., 2010. Association of ambient fine particles with out-of-hospital cardiac arrests in New York city. Am. J. Epidemiol. 172, 917–923. https://doi.org/10.1093/aje/kwq217

Song, J.W., Chung, K.C., 2010. Observational studies: Cohort and case-control studies. Plast. Reconstr. Surg. 126, 2234–2242. https://doi.org/10.1097/PRS.0b013e3181f44abc

Souza Tadano, Y. de, Lie Ugaya, C.M., Teixeira, A., 2012. Methodology to Assess Air Pollution Impact on Human Health Using the Generalized Linear Model with Poisson Regression, in: Air Pollution - Monitoring, Modelling and Health. InTech. https://doi.org/10.5772/33385

Stafoggia, M., Forastiere, F., Agostini, D., Biggeri, A., Bisanti, L., Cadum, E., Caranci, N., De'Donato, F., De Lisio, S., De Maria, M., Michelozzi, P., Miglio, R., Pandolfi, P., Picciotto, S., Rognoni, M., Russo, A., Scarnato, C., Perucci, C.A., 2006. Vulnerability to heat-related mortality: A multicity, population-based, case-crossover analysis. Epidemiology 17, 315–323. https://doi.org/10.1097/01.ede.0000208477.36665.34

Stone, B., Hess, J.J., Frumkin, H., 2010. Urban form and extreme heat events: Are sprawling cities more vulnerable to climate change than compact cities? Environ. Health Perspect. 118, 1425–1428. https://doi.org/10.1289/ehp.0901879

The Met Office, 2019. Heatwave - Met Office [WWW Document]. Heatwave. URL https://www.metoffice.gov.uk/weather/learn-about/weather/types-of-weather/temperature/heatwave (accessed 12.26.19).

Ulrich, A.S., Rathlev, N.K., 2004. Hypothermia and localized cold injuries. Emerg. Med. Clin. North Am. https://doi.org/10.1016/j.emc.2004.01.002

UNFCCC, 2008. Kyoto Protocol - Targets for the first commitment period | UNFCCC [WWW Document]. What is Kyoto Protoc. URL https://unfccc.int/process-and-meetings/the-kyoto-protocol/what-is-the-kyoto-protocol/kyoto-protocol-targets-for-the-first-commitment-period%0Ahttps://unfccc.int/process/the-kyoto-protocol (accessed 12.13.19).

United Nations, 2019. United Nations Climate Change Summit 2019 [WWW Document]. 2019. URL https://www.un.org/en/climatechange/cop24.shtml (accessed 12.13.19).

United Nations, 2018. The Paris Agreement | UNFCCC [WWW Document]. United Nations Framew. Conv. Clim. Chang. URL https://unfccc.int/process/the-paris-agreement/what-is-the-paris-agreement (accessed 12.13.19).

United States Environmental Protection Agency, 2014. Climate Impacts on Human Health [WWW Document]. URL http://www.epa.gov/climatechange/impacts-adaptation/health.html (accessed 12.6.19).

US EPA, 2020. Health Effects of Ozone Pollution.

US EPA, 2019. How Does PM Affect Human Health.

US EPA, 2016. Basic Information about NO2 [WWW Document]. URL https://www.epa.gov/no2-pollution/basic-information-about-no2 (accessed 1.27.20).

WHO, 2018a. Climate change and health [WWW Document]. URL https://www.who.int/news-room/fact-sheets/detail/climate-change-and-health (accessed 1.17.20).

WHO, 2018b. Information and public health advice: heat and health [WWW Document]. World Health Organisation. URL https://www.who.int/globalchange/publications/heat-and-health/en/ (accessed 12.16.19).

WHO, 2018c. Ambient (outdoor) air quality and health [WWW Document]. World Health Organisation. URL http://www.who.int/en/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health (accessed 4.24.18).

WHO, 2017. Review of evidence on health aspects of air pollution – REVIHAAP project: final technical report.

WHO, 2016. Exposure to extreme heat and cold [WWW Document]. World Health Organisation. URL http://www.who.int/sustainable-development/housing/health-risks/extreme-heat-cold/en/ (accessed 12.16.19).

WHO, 2005. Effects of Air Pollution on Children’s Health and Development.

Williams, S., Nitschke, M., Sullivan, T., Tucker, G.R., Weinstein, P., Pisaniello, D.L., Parton, K.A., Bi, P., 2012. Heat and health in Adelaide, South Australia: Assessment of heat thresholds and temperature relationships. Sci. Total Environ. 414, 126–133. https://doi.org/10.1016/j.scitotenv.2011.11.038

Ye, X., Wolff, R., Yu, W., Vaneckova, P., Pan, X., Tong, S., 2012. Ambient temperature and morbidity: A review of epidemiological evidence. Environ. Health Perspect. 120, 19–28.

https://doi.org/10.1289/ehp.1003198

Zeng, Q., Ni, Y., Jiang, G., Li, G., Pan, X., 2017. The short term burden of ambient particulate matters on non-accidental mortality and years of life lost: A ten-year multi-district study in Tianjin, China. Environ. Pollut. 220, 713–719. https://doi.org/10.1016/j.envpol.2016.10.036

Zhang, X.-J., Ma, W.-P., Zhao, N.-Q., Wang, X.-L., 2015. Time series analysis of the association between ambient temperature and cerebrovascular morbidity in the elderly in Shanghai, China OPEN. https://doi.org/10.1038/srep19052

Zhang, Y., Wang, S.G., Ma, Y.X., Shang, K.Z., Cheng, Y.F., Li, X., Ning, G.C., Zhao, W.J., Li, N.R., 2015. Association between ambient air pollution and hospital emergency admissions for respiratory and cardiovascular diseases in Beijing: A time series study. Biomed. Environ. Sci. 28, 352–363. https://doi.org/10.3967/bes2015.049

Zhang, Y., Yan, C., Kan, H., Cao, J., Peng, L., Xu, J., Wang, W., 2014. Effect of ambient temperature on emergency department visits in Shanghai, China: a time series study. https://doi.org/10.1186/1476-069X-13-100

Xiang, J., Hansen, A., Pisaniello, D., Bi, P., 2015. Extreme heat and occupational heat illnesses in South Australia, 2001-2010. Occup. Environ. Med. 72, 580–586. https://doi.org/10.1136/oemed-2014-102706

CHAPTER 3 : STUDY DESIGN AND METHODOLOGY

This chapter explains and provides background to the study population, data collection and data analysis which are presented in chapter 4, chapter 5 and chapter 6.

3.1 Introduction

This thesis is divided into three sections and uses different statistics to achieve the objectives. In chapter 4, systematic review is used to investigate the exposure to pollutants and health outcomes focusing on ambulance dispatches. Chapter 5 examines the relationship between extreme temperatures (low and high) and ambulance dispatches based upon London Ambulance Service (LAS) data. A time-series analysis with Poisson regression is applied in this phase. Chapter 6, a time-series with Poisson regression analysis is applied to Thai ambulance data. The relationship between rainfall and road accidents is conducted and the estimated risk between the Northern and the Southern Thai provinces is compared. The analyses will provide benefit for ambulance services to improve their quality of service, in particular they highlight how ambulance demand change as a function of environmental factors (pollutants, temperature and rainfall). Furthermore, the likely effects under a climate changed future are explored. An overview of the three research sections are shown in Figure 3-1

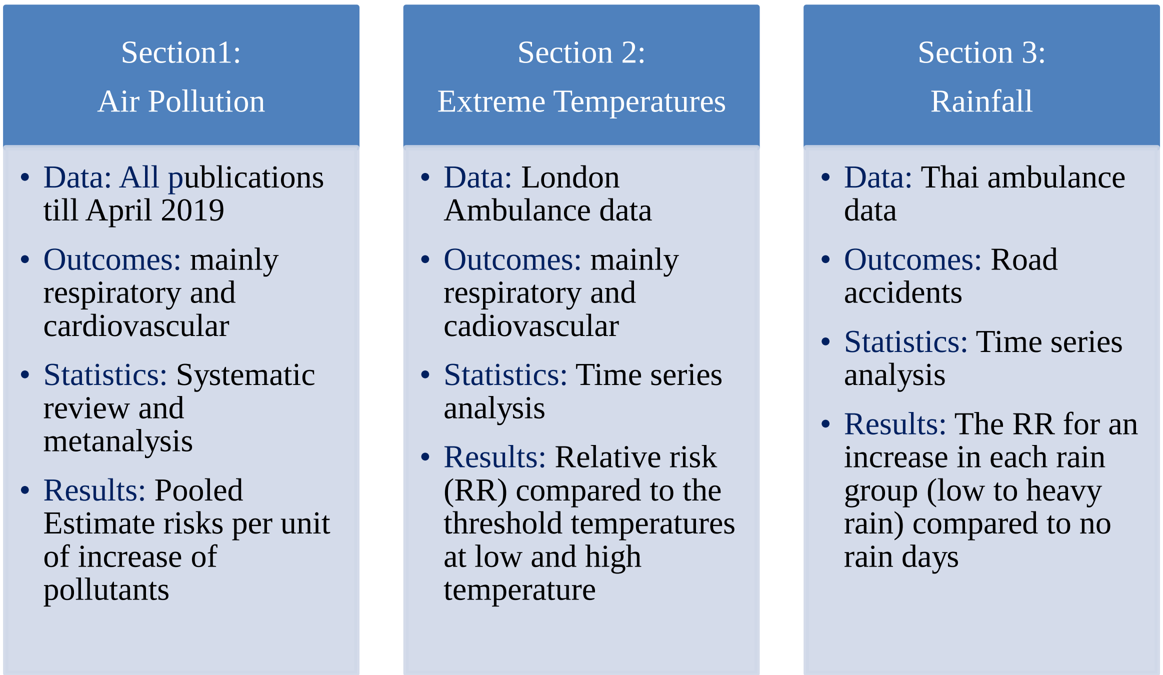

Figure 3-1 The three sections of the study. Chapters 4-6 of this thesis respectively present sections 1-3.

3.2 Study population

3.2.1 The impact of air pollutants on ambulance dispatches: A systematic review and meta-analysis of acute effects

Chapter 4 is a systematic review to study the impact of air pollutants on ambulance dispatches. Data is taken from any study conducted regardless of country; it includes data from the United States, Europe, Asia, and Australia that was published up to April 2019. The PICO approach was used to define the search terms, as shown in Table 3-1. Moreover, the inclusion criteria were set to find articles that focus on ambulance dispatches and report the risk associated with air pollutant exposure.

Table 3-1 The PICO approach for developing a search strategy

P	I	C	O
Population or Problem	Intervention or Exposure	Comparison	Outcome
Publication study focus solely upon ambulance data	Studies have investigated the impact of air pollutants upon health (particulate matter and gases) such as - PM_{10} - $PM_{2.5}$ - Ozone (O_3) - Sulphur dioxide (SO_2) - Nitrogen dioxide (NO_2)	The comparison of intervention or exposures in increment of air pollutants.	Health outcomes, for example, respiratory and cardiovascular diseases, which relate to exposure to air pollutants.

3.2.2 Impact of extreme temperature on ambulance dispatches

Chapter 5 uses data taken between 2010 and 2014 from the London ambulance service (LAS). The LAS serves approximately 8.5 million people, covering a geographical area of 1,570 square kilometres. London is the capital and the biggest city in the United Kingdom. The coordinates for the centre of London are 51° 30' 35.5140" North and 0° 7' 5.1312" West. London has periodically experienced summer heatwaves, for example those in 1976, 2003, 2006, 2018 and 2019. In summer 2019, the highest temperature was recorded as 34.0 °C in London (BBC, 2019).

3.2.3 The association between rainfall and road accidents

Chapter 6 uses ambulance data from Thailand. Thailand is in Southeast Asia consisting of 76 provinces with a total population of 68 million people. Thailand is located in the tropical zone at 5^{O} 37′ North to 20^{O} 27′ North and longitudes 97^{O} 22′ East to 105^{O} 37 ′ East. Thailand can be divided into six parts with different meteorological conditions including the Northern (n=9), the Northeastern (n=20), the Central (n=22), the Eastern (n=7), the Western (n=5) and the Southern (n=14) regions. The climate in Thailand is influenced by the Southwest and Northeast monsoons. The Northeast monsoon can bring the cold and dry air from the anticyclone in China through Thailand especially for the Northern and Northeastern regions. The Northeast monsoon is usually observed in Thailand from October to mid-February. The Southwest monsoon takes warm moist air from the Indian Ocean through Thailand. This brings mild weather and more rainfall across the country, especially on the Eastern coast, this starts from May to October (Meteorological Department, 2015).

Three main seasons in Thailand can be identified:

- Rainy season starts from mid-May to mid-October except the area around Southern Thailand East coast which still has rainfall until the end of year. This is an effect of Southwest monsoon.
- Winter season is the period from mid-October to mid-February. This season is influenced by Northeast monsoon.
- Summer season corresponds to mid-February to mid-May. The weather is warmer in Northern Thailand and the hottest month is April.

3.3 The rationale for including areas and studies

3.3.1 The impact of air pollutants on ambulance dispatches: A systematic review and meta-analysis of acute effects

Ambulance services provide emergency transport to help patients from the scene of their debilitation to hospitals. At present, there are only two systematic reviews about ambulance data that investigate the impact of air pollutants on adverse health (Teng et al., 2014; Zhao et al., 2017). Both these previous works studied outcomes for cardiac arrest while this study focuses upon multiple health outcomes including cardiac arrest. Variations of health outcomes in this study are related to cardiovascular and respiratory diseases or symptoms. Moreover, pooled estimated risks are stratified by the way health outcome classification is collected following either telephone interview, paramedic assessment or physician diagnosis. The results will be useful to improve the quality of ambulance service under exposure to air pollution, hence effective emergency services/hospital services can increase survival rates and reduction of cost.

3.3.2 Impact of extreme temperature on ambulance dispatches

Up to now, few studies have reported/investigated the association between temperature and health outcomes, with a focus on ambulance dispatches. Most previous studies investigate the relationship between temperature and health impacts on mortality and morbidity data. WHO (2009) and Turner et al. (2012) suggested ambulance calls can be used to study the association between weather and health data because the data collected is real-time and most sensitive to hot weather. During the heatwave on 19th of June 2017, the number of calls increased by 41 % (6,613 calls) compared to the week before (4,695 calls) with fainting and collapsing symptoms common. Under heatwave conditions, older people and people with who had pre-existing medical conditions experience higher (London Ambulance Service, 2017a). In the UK, the number of ambulance dispatches has increased every year for which records have been recorded. For example during 2017 and 2018, the total number of 999 calls was 1.9 million while in 2016/2017 there were 1.8 million of emergency calls (London Ambulance Service, 2017b, 2019). LAS dispatches increased by 5.5 percent during that time.

3.3.3 The association between rainfall and road accidents

The Northern and Southern provinces of Thailand were selected for study because of the contrasting geographies and meteorological conditions. The Northern region has higher temperatures (a maximum temperature was 44.5 °C) compared to the regions in the summer months. The Southern region is wetter in the rainy season than other regions. From 1981 to 2010, some provinces in the Southern region received 4,500 mm of rainfall annually, compared to a mean annual rainfall for the whole of Thailand of less than 1,200 mm over the same period (Meteorological Department, 2015).

Ambulance dispatches for road accidents in Thailand have increased every year between 2012 and 2018. Road accidents represent the category with the highest number of callouts for ambulance dispatches. Hence, this part of the thesis focused upon the association between road accidents and rainfall levels, since a better understanding of this environmental health factor has the best potential for saving lives and reducing morbidity.

3.4 Data

3.4.1 The impact of air pollutants on ambulance dispatches: A systematic review and meta-analysis of acute effects

Previous publications, published up to April 2019, were retrieved from web-databases including Web of Science, PubMed and the Cochrane Library . Three keyword strings 'ambulance service', 'air pollution' and 'human health' were used to search the literature systematically. Moreover, inclusion and exclusion criteria are used to screen the results.

3.4.2 Impact of extreme temperature on ambulance dispatches

Chapter 5 uses data from distinct databases. The health outcomes are obtained from the London Ambulance Service (LAS) as accessed by through patients or their intermediaries dialling 999. The time period studied was 2010 to 2014, and 14 categories from 103 possible categories were studied (Sangkharat et al., 2020). The health outcomes studied related to respiratory, cardiovascular and non-cardiorespiratory categories. The categories chosen were informed by previous studies suggested (Alessandrini et al., 2011; Basu and Samet, 2002; Mahmood et al., 2017). Ambulance dispatches might be misclassification in some cases depending on the method that was used for collecting ambulance data including telephone call taker, paramedic assessment or physician diagnoses. Hence, the results need to be interpreted carefully.

Daily meteorological data for mean temperature, relative humidity and wind speed were obtained from The British Atmospheric Data Centre (BADC) (http://www.badc.nerc.ac.uk) for the St James Park meteorological station, which is located in central London. When the missing data was observed from the station, the average mean of meteorological data replaced that missing data when clearly sensible.

Air pollution data was collected from daily data, and was obtained from the Automatic Urban and Rural Network (AURN: https://uk-air.defra.gov.uk/) by average daily data from the seven urban background stations located in London. If there were missing values from some stations, it was not usually a problem because daily air pollution data was calculated from daily mean of seven urban background stations sites in London which are London Bloomsbury, London Haringey Priory Park South, London Hillingdon, London N. Kensington, London Teddington Bushy Park, London Harrow Stanmore and London Westminster.

3.4.3 The association between rainfall and road accidents

In chapter 6, daily data ambulance dispatches using the telephone number 1699 in Thailand (similar to 999 in the U.K.) was obtained from the National Institute for Emergency Medicine (NIEM) for 76 provinces. This study collected ambulance dispatches only for the Northern (n =9) and the Southern Provinces (n=14). The Thai ambulance service uses a protocol dispatch tool named Criteria Based Dispatch (CBD) as a guideline to assess the direction of treatment. Thai ambulance dispatches use 25 categories as shown in Table 3-2. For data cleaning, for each province there was no missing data on that period. However, there can be a data density problem in terms of some dispatches are few in number so data would be overdispersed. Hence, a dispersion statistic was considered to manage erroneous conclusions.

Table 3-2 List of symptoms for ambulance dispatches in Thailand

Symptoms
01:Abdominal/Back/Groin Pain
02:Anaphylaxis/Allergic Reaction

Symptoms
03:Infectious Disease
04:Bleeding (Non-traumatic)
05:Breathing Difficulty
06:Cardiac arrest
07:Chest Pain/Discomfort/Heart Problems
08:Choking
09:Diabetic
10: Environmental/Toxic Exposure
11: Medical Knowledge (Medical Facility Only)
12:Head/Neck
13:Mental/Emotional/Psychological
14:Overdose/Poisoning
15:Pregnancy/Childbirth/Gyn.
16:Seizures
17:Sick (Unknown)/Other
18:Stroke (CVA)
19:Unconscious/Unresponsive/Syncope
20:Pediatric Emergencies
21:Assault/Trauma
22:Burns - Thermal/Electrical/Chemical
23:Drowning/Near Drowning/Diving or Water-related Injury
24:Falls/Accidents/Pain
25:Road accidents

Daily meteorological data for temperature, relative humidity and rainfall were obtained from the Thai Meteorological Department (www.tmd.go.th) for each province. The monitoring sites located in urban areas were selected to be the representative sites.

3.5 Methodology

3.5.1 The impact of air pollutants on ambulance dispatches: A systematic review and meta-analysis of acute effects

In chapter 4, a systematic review method is used to collect secondary data from publication as shown. First, a search term, inclusion and exclusion criteria are created. Second, the search term is used to get eligible studies that met these criteria from online databases. Third, eligible studies from the previous stage are extracted by two reviewers to get relevant details. Fourth, the quality of the data from publications is assessed by using the Newcastle-Ottawa Scale (NOS). Finally, all included studies are analysed and combined (meta-analysis) for reducing the variation between individual studies (Yang et al., 2018).

When results are pooled together in a meta-analysis, the heterogeneity (I^2) can be explained the variation between studies. Heterogeneity, defined using of Cochran's Q statistics test following equations (1), (2) and (3), was used to interpret results (Harrer et al., 2019). If the I^2 value is greater than or equal to 25, or the p-value is less than 0.1, this indicates that heterogeneity is present (have heterogeneity among the effect size). The method for random-effect is applied if results is observed high heterogeneity. The problem of high heterogeneity leads to difficulty in interpreting pooled estimates. The narrative review or investigation of the cause are designed to deal with high heterogeneity (Borenstein et al., 2011). In contrast, if heterogeneity is low, a fixed method is appropriate.

3.5.1.1 Cochran's Q statistics can generate from equation (1)

$$Q = \sum_{k=1}^{K} \omega_k \left(\hat{\theta}_k - \frac{\sum_{k=1}^{K} \omega_k \hat{\theta}_k}{\sum_{k=1}^{K} \omega_k}\right)^2 \tag{1}$$

In equation (1), k is number of individual studies in meta-analysis, K is all studies in meta-analysis, $\hat{\theta}_k$ is the estimated effect of k with a variance of $\hat{\sigma}_k^2$ and ω_k is a weight of each study with calculate from inverse of variance, $\omega_k = \frac{1}{\hat{\sigma}_k^2}$.

3.5.1.2 Heterogeneity (I^2) is the percentage of variability which calculated from equation (2) (Higgins and Thompson 2002)

$$I^2 = \max\left\{0, \frac{Q-(K-1)}{Q}\right\} \tag{2}$$

3.5.1.3 In a random effect method, the variation among the study variance is called Tau-squared τ^2. Tau-squared is a variance of the effect size across studies (Riley et al., 2011)

$$\hat{\tau}^2 = \frac{Q-(n-1)}{\sum \omega_i - \frac{\sum \omega_i^2}{\sum \omega_i}} \tag{3}$$

3.5.1.4 Sensitivity analysis is the way to repeat the analysis involving a different decision to check the robustness of the results. There are many different ways of conducting sensitivity analysis. Typically, in the first round, all analyses are included and the second round removes certain studies. Only studies that met the inclusion or exclusion criteria such as characteristics of a participant, time point of studies and methodological criteria are included (Higgins and Green, 2011). For instance, only publication that was published before 2010 is analysed or removing individual study from whole studies. If the second result remains consistent with the prior results, the results are deemed to be robust, otherwise careful interpretation is required (Joanna Briggs Institute, 2019).

3.5.2 Impact of extreme temperature on ambulance dispatches

Chapter 5 explains the effect of temperature upon 14 health outcomes as measured by ambulance dispatch frequency in London between 2010 and 2014. A Poisson regression with time-series study was conducted to estimate the cold and hot effects from exposure to extreme low and extreme high temperature at the 1^{st} (0.0°C) and 99^{th} (22.8°C) percentile of London temperature. The distributed lag non-linear model (DLNM) which is recommended by Gasparrini et al. (2015) was used with adding a cross basis for two-dimension between temperature and delay effect for 21 days (Guo et al., 2018). Estimated risks were reported with 95% confidence intervals (CIs) with relative risk (RR). Firstly, the threshold temperature which has the lowest estimated risk is examined for each category. Secondly, investigation the estimated risk for the extreme low and extreme high temperature compared with the threshold temperature then reported the relative risk for a single lag (e.g. lag 0 = lag of same day, lag 1 = lag one day prior) and cumulative lags for lag 0-2 days (average of same-day through two days prior), lag 0-14 days and lag 0-21 days.

3.5.3 The association between rainfall and road accidents

Chapter 6 demonstrates how to investigate the effect of rainfall on road accidents. Firstly, A Poisson regression by using a time series analysis design was conducted as previous studies (Guo et al., 2012; Onozuka et al., 2018). A distributed lag non-linear model (DLNM) was applied to study non-linear and delay effects which combining between rain groups and lags (Guo et al., 2012). The DLNM model was used to estimate the relative risk (RR) with 95% CI for each rain group compared with no rain days. Temperature, relative humidity, day of week, public holiday, seasonality and a long-term trend were adjusted in the model. Secondly, a meta-analysis was applied to summarise the estimate effect of rain groups stratified the Northern and Southern parts. Pooled estimate risks and heterogeneity which referred the variation between studies were reported.

3.6 References

Alessandrini, E., Zauli Sajani, S., Scotto, F., Miglio, R., Marchesi, S., Lauriola, P., 2011. Emergency ambulance dispatches and apparent temperature: A time series analysis in Emilia-Romagna, Italy. Environ. Res. 111, 1192–1200. https://doi.org/10.1016/j.envres.2011.07.005

Basu, R., Samet, J.M., 2002. Relation between elevated ambient temperature and mortality: a review of the epidemiologic evidence. Epidemiol. Rev. 24, 190–202. https://doi.org/10.1093/epirev/mxf007

BBC, 2019. UK weather: Hottest day of the year, says Met Office [WWW Document]. BBC News. URL https://www.bbc.co.uk/news/uk-48810170 (accessed 1.19.20).

Borenstein, M., Hedges, L., 2007. Meta-Analysis Fixed effect vs. random effects.

Centre for Environmental data analysis, n.d. CEDA Data Server, Index of /badc/ukcp09/data/gridded-land-obs/gridded-land-obs-averages-5km/grid/ascii/sunshine/1981-2010/ [WWW Document]. URL http://data.ceda.ac.uk/badc/ukcp09/data/gridded-land-obs/gridded-land-obs-averages-5km/grid/ascii/sunshine/1981-2010/ (accessed 12.14.18).

Department for Environment, F. and R.A. (Defra) webmaster@defra. gsi. gov. u., n.d. Home-Defra, UK [WWW Document]. URL https://uk-air.defra.gov.uk/ (accessed 12.14.18).

Gasparrini, A., Guo, Y., Hashizume, M., Kinney, P.L., Petkova, E.P., Lavigne, E., 2015. Temporal Variation in Heat – Mortality Associations : A Multicountry Study. Environ. Health Perspect. 1200, 1200–1207.

Guo, Y., Li, S., Zhang, Y., Armstrong, B., Jaakkola, J.J.K., Tong, S., Pan, X., 2012. Extremely cold and hot temperatures increase the risk of ischaemic heart disease mortality: epidemiological evidence from China. https://doi.org/10.1136/heartjnl-2012

Guo, Y., Ma, Y., Ji, J., Liu, N., Zhou, G., Fang, D., Huang, G., Lan, T., Peng, C., Yu, S., 2018. The relationship between extreme temperature and emergency incidences: a time series analysis in Shenzhen, China. Environ. Sci. Pollut. Res. 25, 36239–36255. https://doi.org/10.1007/s11356-018-3426-8

Harrer, M., Cuijpers, P., Furukawa, T.A., Ebert, D.D., 2019. Doing Meta-Analysis in R: A Hand- on Guide. https://bookdown.org/MathiasHarrer/Doing_Meta_Analysis_in_R/. DOI 10.5281/zenodo.2551803. https://doi.org/10.5281/zenodo.2551803

Higgins, J.P.T., Green, S., 2011. 9.7 Sensitivity analyses [WWW Document]. Cochrane Handb. Syst. Rev. Interv. URL http://handbook.cochrane.org/chapter_9/9_7_sensitivity_analyses.htm (accessed 12.27.19).

Joanna Briggs Institute, 2019. Sensitivity analysis in meta-analysis [WWW Document]. URL https://wiki.joannabriggs.org/display/MANUAL/3.3.8+Sensitivity+analysis+in+meta-analysis (accessed 1.20.20).

London Ambulance Service, 2019. Annual Report 2017 - 2018 [WWW Document]. URL https://www.londonambulance.nhs.uk/document-search/annual-report-2017-2018/ (accessed 12.26.19).

London Ambulance Service, 2017a. Thousands more emergency calls during hottest week of the year - London Ambulance Service NHS Trust [WWW Document]. URL https://www.londonambulance.nhs.uk/2017/06/21/thousands-emergency-calls-hottest-week-year/ (accessed 12.26.19).

London Ambulance Service, 2017b. Annual Report 2016-17 [WWW Document]. URL https://www.londonambulance.nhs.uk/document-search/annual-report-2016-17/ (accessed 2.18.18).

Mahmood, M.A., Thornes, J.E., Pope, F.D., Fisher, P.A., Vardoulakis, S., 2017. Impact of Air Temperature on London Ambulance Call-Out Incidents and Response Times. Climate 5, 61.

Meteorological Department, 2015. The Climate of Thailand.

Onozuka, D., Nishimura, K., Hagihara, A., 2018. Full moon and traffic accident-related emergency ambulance transport: A nationwide case-crossover study. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2018.07.053

Riley, R.D., Higgins, J.P.T., Deeks, J.J., 2011. Interpretation of random effects meta-analyses. BMJ 342, d549. https://doi.org/10.1136/bmj.d549

Sangkharat, K., Mahmood, M.A., Thornes, J.E., Fisher, P.A., Pope, F.D., 2020. Impact of extreme temperatures on ambulance dispatches in London, UK. Environ. Res. 182. https://doi.org/10.1016/j.envres.2019.109100

Teng, T.-H.K., Williams, T.A., Bremner, A., Tohira, H., Franklin, P., Tonkin, A., Jacobs, I., Finn, J., 2014. A systematic review of air pollution and incidence of out-of-hospital cardiac arrest. J. Epidemiol. Community Health 68, 37–43. https://doi.org/10.1136/jech-2013-203116

Turner, L.R., Connell, D., Tong, S., 2012. Exposure to hot and cold temperatures and ambulance attendances in Brisbane, Australia: A time-series study. BMJ Open 2. https://doi.org/10.1136/bmjopen-2012-001074

WHO, 2009. Improving public health responses to extreme EuroHEAT.

Yang, B.Y., Qian, Z., Howard, S.W., Vaughn, M.G., Fan, S.J., Liu, K.K., Dong, G.H., 2018. Global association between ambient air pollution and blood pressure: A systematic review and meta-analysis. Environ. Pollut. 235, 576–588. https://doi.org/10.1016/j.envpol.2018.01.001

Zhao, R., Chen, S., Wang, W., Huang, J., Wang, K., Liu, L., Wei, S., 2017. The impact of short-term exposure to air pollutants on the onset of out-of-hospital cardiac arrest: A systematic review and meta-analysis. Int. J. Cardiol. 226, 110–117. https://doi.org/10.1016/j.ijcard.2016.10.053

CHAPTER 4 : THE IMPACT OF AIR POLLUTANTS ON AMBULANCE DISPATCHES: A SYSTEMATIC REVIEW AND META-ANALYSIS OF ACUTE EFFECTS

The work presented in Chapter 4, most of the material was published or under process in following journals:

References:

Sangkharat, K., Fisher, P., Thomas, G.N., Thornes, J. and Pope, F.D., 2019. The impact of air pollutants on ambulance dispatches: A systematic review and meta-analysis of acute effects. Environmental Pollution.

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Kamolrat Sangkharat: Designed for study design, collected data, analysed data and wrote the manuscript;

Paul Fisher: Collected data, reviewed, edited and revised the manuscript;

Neil Thomas: Reviewed, edited and revised the manuscript;

John Thrones: Reviewed, edited and revised the manuscript;

Francis Pope: Reviewed, edited and revised the manuscript

4.1 Abstract

A number of systematic reviews have investigated the association between air pollutants and health impacts, these mostly focus on morbidity and mortality from hospital data. Previously, no reviews focused solely on ambulance dispatch data. These data sets have excellent potential for environmental health research. For this review, publications up to April 2019 were identified using three main search categories covering: ambulance services including dispatches; air pollutants; and health outcomes. From 308 studies initially identified, 275 were excluded as they did not relate to ambulance service dispatches, did not report the air pollutant association, and/or did not study ambient air pollution. The main health outcomes in the remaining 33 studies were cardiac arrest (n = 14), cardiovascular (n = 11) and respiratory (n = 10) dispatches. Meta-analyses were performed to summarise pooled relative risk (RR) of pollutants: particulate matter less than 2.5 and 10 µm ($PM_{2.5}$, PM_{10}), the fraction between PM_{10} and $PM_{2.5}$ (coarse) and suspended particulate matter (SPM) per 10 µg/m^3 increase, carbon monoxide (CO) per 1 ppm increase and of sulphur dioxide (SO_2), nitrogen dioxide (NO_2), and ozone (O_3) per 10 ppb increment and ambulance dispatches. Statistically significant associations were found for ambulance dispatch data for all-respiratory and $PM_{2.5}$ at 1.03 (95% CI:1.02-1.04) and at 1.10 (95% CI:1.00-1.21) for asthma and NO_2 associations. For dispatches with subsequent paramedic assessment for cardiac arrest with $PM_{2.5}$, CO and coarse dispatches at 1.05 (95% CI:1.03-1.08), 1.10 (95% CI:1.02-1.18) and 1.04 (95% CI:1.01-1.06) respectively. For dispatches with subsequent physician diagnosis for all-respiratory and $PM_{2.5}$ at 1.02 (95% CI:1.01-1.03). In conclusion, air pollution was significantly associated with an increase in ambulance dispatch data, including those for cardiac arrest, all-respiratory, and asthma dispatches. Ambulance services should plan accordingly during pollution events. Furthermore, efforts to improve air quality should lead to decreases in ambulance dispatches.

Keywords: ambulance dispatches, emergency services, air pollution, pollutants, health impacts

4.2 Introduction

The World Health Organization (WHO), states that ambient air pollution increases the incidence of stroke, heart disease, lung cancer and respiratory disease, and it is one of the leading causes of death and disability worldwide. Air pollutants reported to adversely impact on health include: particulate matter with aerodynamic diameters less than 2.5 ($PM_{2.5}$) and 10 micrometres (PM_{10}); carbon monoxide (CO); ozone (O_3); nitrogen dioxide (NO_2); and sulphur dioxide (SO_2) (WHO, 2018).

Emission of most pollutants in Europe have decreased substantially over the last twenty years, but continue to cause significant mortality and morbidity (European Energy Agency, 2015). Estimates vary, but the WHO has stated over 4.2 million premature deaths worldwide from cardiovascular and respiratory diseases in 2016 (WHO, 2018) and the Lancet Commission reported nine million premature deaths due to ambient air pollution globally in 2015 or approximately 16% of all deaths (Landrigan et al., 2017). These relationships have been summarised in previous systematic reviews, examining the association between health impacts and short-term exposure to $PM_{2.5}$, PM_{10}, SO_2, NO_2 and O_3 (Aunan and Pan, 2004; Kan et al., 2005; Lai et al., 2013; Shang et al., 2013), with most finding a positive association between air pollution and health outcomes, especially for respiratory and cardiovascular mortality and morbidity.

Ambulance (also known as paramedic or emergency medical service) dispatches involve assessment and possible pre-treatment of patients requiring an urgent medical response outside medical centres**.** The recording of ambulance data in each country has different systems and guidelines dependent on country and region. Three categories of ambulance data can be observed: 1) ambulance dispatches, identified from telephone interviews by ambulance service operators. 2) Dispatches with paramedics assessment made in situ via physical examination and clinical history at the scene (Johnston et al., 2019). 3) Dispatches diagnosis is clarified by physicians or emergency medical doctor after patients are delivered to hospitals (Michikawa et al., 2015a; Tasmin et al., 2016). Hence ambulance dispatch studies might be sensitive to which of these three methods are used.

There are few studies investigating the association between ambulance dispatches and air pollution. Most study the association between out-of-hospital cardiac arrest (OHCA) and have found significant positive relationships (Pradeau et al., 2015; Straney et al., 2014; Wichmann et al., 2013). However, some have not reported any significant associations (Salimi et al., 2017; Youngquist et al., 2016). The inconsistency in these results may be due to the variation of geographical data, air pollutant levels, characteristics of the population and misclassification of diagnosis (Ichiki et al., 2016; Yang et al., 2018). Until now, two systematic reviews covering the short-term association between air pollution and health outcomes have included ambulance dispatch data (Teng et al., 2014; Zhao et al., 2017). However, both studies focus only on OHCA cases, which include but are not limited to ambulance dispatch data. Of these two, only Zhao et al. (2017) undertook a meta-analysis and they found PM_{10}, $PM_{2.5}$, NO_2 and O_3, but not SO_2 or CO, were significantly associated with OHCA.

Ambulance dispatch data can be used for surveillance systems. These data are particularly useful as they can provide information in real time and give the location of the health event rather than the patient's residential address (Salimi et al., 2017). This systematic review fills a gap in this important research area. The results will be of particular interest to ambulance services and public health officials, enabling them to improve the effectiveness of planning during pollutant incidents, which can inform air quality policy, especially in low and middle income countries.

4.3 Methods

Details of the protocol for this systematic review were registered on PROSPERO, reference number: CRD42018112705

4.3.1 Search strategy

This study used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to summarise and assimilate the results (http://prisma-statement.org/Protocols/Default.aspx). The PRISMA checklist can be found in the supplementary data, Table 4-9. Web of Science, PubMed and the Cochrane Library were used for searching the association between air pollutants and health outcomes. We used the following keywords in the three overarching search terms ‘ambulance services’, ‘air pollution’ and ‘human health’:

- To identify ambulance service terms, the relevant words were “ambulance” or “out of hospital” or “Emergency call*” or “Emergency medical dispatch*” or “Emergency services*” or “emergency medical service*” or “paramedic*”
- To identify air pollution terms, the relevant words were “air pollut*” or “*fine partic*” or “ozone” or “O_3” or “particulate matter” or “PM_{10}” or “$PM_{2.5}$” or “smoke” or “forest fire” or “dust”
- To identify human health terms, the relevant words were “health” or “cardiac” or “cardio*” or “stroke” or “breathing difficult*” or “mortality” or “morbidity” or

“respiratory disease*” or “asthma” or “COPD” or “chronic obstructive pulmonary disease*” or “chest pain”

The “AND” function was used to combine the three groups of keywords, and articles had to be published, worldwide, by April 2019. A search strategy for each database can be found Table 4-1. Inclusion criteria were: (1) the health outcome in the study was ambulance dispatches, (2) studied the short-term health impacts of exposure to ambient outdoor air pollutants, and (3) the results were reported in relative risk (RR), odds ratios (OR), excess risk (ER), and/or hazard ratios (HR) per unit of air pollution with their corresponding 95% confidence intervals (CIs). The definition of ambulance dispatch data in this study covered services for patients with life-threatening or serious conditions. The outcome data may be informed by the telephone call to the ambulance dispatch centre, or through in situ paramedic assessment or physician at a hospital. No language limits were applied. Exclusion criteria were: (1) pre- or out-of-hospitals data that was not broken down by ambulance dispatches; emergency department data; any hospital; and/or mortality data; (2) studies that did not report risk estimates as RR, OR, ER or HR, or where these could not be readily calculated; (3) studies that did not focus on ambient air pollution; (4) studies that did not have results from daily exposure; (5) systematic reviews, case reports or editorials; and (6) if two articles used the same data source and studied the same pollutants and health outcomes the oldest published article was excluded.

Table 4-1 Search Strategies for each database

Database	Search Strategies	Results
Web of Science	TOPIC:(Ambulance or "out of hospital" or "Emergency call*" or "Emergency medical dispatche*" or "Emergency services*") AND TOPIC: ("air pollut*" or "*fine partic*" or ozone or O3 or "particulate matter" or "PM10" or PM2.5 or "smoke" or "forest fire" or "dust") AND TOPIC: (health or	194

Database	Search Strategies	Results
	cardiac or cardio* or stroke or " breathing difficult* " or mortality or morbidity or "respiratory disease*" or asthma or COPD or "chronic obstructive pulmonary disease*" or “chest pain”)	
Pubmed	(((Ambulance[Title/Abstract] OR "out of hospital"[Title/Abstract] OR "Emergency call*"[Title/Abstract] OR "Emergency medical dispatche*"[Title/Abstract] OR "Emergency services*"[Title/Abstract])) AND ("air pollut*"[Title/Abstract] OR "*fine partic*"[Title/Abstract] OR ozone[Title/Abstract] OR O3[Title/Abstract] OR "particulate matter"[Title/Abstract] OR "PM10"[Title/Abstract] OR PM2.5[Title/Abstract] OR "smoke"[Title/Abstract] OR "forest fire"[Title/Abstract] OR "dust"[Title/Abstract])) AND (health[Title/Abstract] OR cardiac[Title/Abstract] OR cardio*[Title/Abstract] OR stroke[Title/Abstract] OR " breathing difficult* "[Title/Abstract] OR mortality[Title/Abstract] OR morbidity[Title/Abstract] OR "respiratory disease*"[Title/Abstract] OR asthma[Title/Abstract] OR COPD[Title/Abstract] OR "chronic obstructive pulmonary disease*"[Title/Abstract] OR “chest pain”[Title/Abstract])	99
Cochrane Library	(Ambulance or "out of hospital" or "Emergency call*" or "Emergency medical dispatche*" or "Emergency services*") and ("air pollut*" or "*fine partic*" or ozone or O3 or "particulate matter" or "PM10" or PM2.5 or "smoke" or "forest fire" or "dust") and (health or cardiac or cardio* or stroke or " breathing difficult* " or mortality or morbidity or "respiratory disease*" or asthma or COPD or "chronic obstructive pulmonary disease*" or "chest pain")	71
Summary	Total	364
	Duplicated paper	82
	Total without duplicates	282

4.3.2 Study selection

This study used two independent reviewers to screen articles for eligibility by inspecting all abstracts and titles. When there was disagreement between the two initial reviewers (KS and PF), a third senior reviewer (FDP) was employed to adjudicate. After review, studies were included depending on the exclusion and inclusion criteria. In the next stage, the full text of eligible studies were accessed against the relevant criteria.

4.3.3 Data extraction

Following the two stages of screening, the data from all remaining articles were extracted by the two reviewers separately into a Microsoft Excel spreadsheet. The details of each study were recorded, including: author; location; study period; study design; health outcome; pollutant; adjustment factors; measure/ exposure unit; lagged days; and risk result with 95% confidence intervals. Health outcomes in ambulance studies are generally grouped into major conditions such as 'cardiac arrest', 'all-respiratory dispatches', 'all-cardiovascular dispatches' or 'total dispatches'. Where articles were missing the relevant data, a personal e-mail to the first or corresponding authors was sent to obtain these data.

If there were multiple results for the same outcome measure (for example different lag effects) only one estimate was selected. Results for whole populations were chosen over sub-groups by age, gender or other factors. Results for whole days were chosen over parts of the the day. For multiple lag estimates, the lag measure was selected using the following priorities: (1) the lag that the author focused on in the abstract or stated a priori (2) the most statistically significant lag (positive or negative); and (3) the largest effect estimate was selected (Atkinson et al., 2012). Where possible, the same lag was selected for all the pollutants for a given paper.

If there were results for both single-pollutant and multi-pollutant models, only the single pollutant results were extracted.

4.3.4 Risk of bias assessment

The Newcastle-Ottawa Scale (NOS) for time series analyses was adapted to evaluate the quality of the observational data publications. This scale consists of three domains: selection of study groups; comparability of groups; and ascertainment of outcomes as shown below (Wells et al., 2013). Publications were investigated for the quality of studies on a 10-point scale, with scores of 0-2 being poor quality, 3-7 fair quality and 8-10 good quality (Modesti et al., 2016).

Newcastle - Ottawa Quality Assessment Scale

Selection: (Maximum 5 stars)

1) Representativeness of the sample:

a) Truly representative of the average in the target population. * (all subjects or random sampling)

b) Somewhat representative of the average in the target population. * (non-random sampling)

c) Selected group of users.

d) No description of the sampling strategy.

2) Sample size:

a) Justified and satisfactory. *

b) Not justified.

3) Non-respondents:

a) Comparability between respondents and non-respondents characteristics is established, and the response rate is satisfactory. *

b) The response rate is unsatisfactory, or the comparability between respondents and non-respondents is unsatisfactory.

c) No description of the response rate or the characteristics of the responders and the non-responders.

4) Ascertainment of the exposure (risk factor):

a) Validated measurement tool. **

b) Non-validated measurement tool, but the tool is available or described.*

c) No description of the measurement tool.

Comparability: (Maximum 2 stars)

1) The subjects in different outcome groups are comparable, based on the study design or analysis. Confounding factors are controlled.

a) The study controls for the most important factor (select one). *

b) The study control for any additional factor. *

Outcome: (Maximum 3 stars)

1) Assessment of the outcome:

a) Independent blind assessment. **

b) Record linkage. **

c) Self report. *

d) No description.

2) Statistical test:

a) The statistical test used to analyse the data is clearly described and appropriate, and the measurement of the association is presented, including confidence intervals and the probability level (p value). *

b) The statistical test is not appropriate, not described or incomplete.

4.3.5 Meta-analysis

Meta-analysis was performed to integrate the associations between specific air pollutants and ambulance dispatches, where appropriate (for example if there were at least two papers in a sub-group (Lai et al., 2013)). This was done because reporting pooled effects can reduce the variation associated with using individual papers (Yang et al., 2018). Different study designs (such as time series and/or case-crossover studies) were combined when there was a standard estimation of risk. The pooled effect for $PM_{2.5}$, PM_{10}, coarse particles and SPM which are small particles of solid or liquid suspended in the air such as fine dust, fly ash and smoke were standardized for a 10 µg/m^3 increase, an increment of 10 parts per billion (ppb) was used for O_3, SO_2 and NO_2, and 1 part per million (ppm) for CO. All pooled effects were reported in RR. Results were converted to RR, from other metrics, if necessary.

The original results were used to generate the effect size regardless of whether these were in RR, OR or HR (Lu et al., 2015). This approach is typical for these types of studies as the outcome measures will be similar (Nhung et al., 2017). Estimate risk values were calculated following formula (1) (Sun et al., 2017). A generic inverse variance technique was carried out to get a variance between studies (Deeks et al., 2004). RR values were standardised to increments of pollutants assuming the association between pollutants and health outcomes was linear. Non-transformed RRs were standardised for a 10 µg/m^3 or 10 ppb increment as shown in formula (2) (Yang et al., 2018; Shah et al., 2013). If the studies did not report a standard error (SE), the SE was computed from 95% confidence intervals (CI) (Deeks et al., 2004).

$$\text{Excess risk (\%)} = (\text{RR}-1) \times 100\% \tag{1}$$

$$\text{RR}_{(\text{standardized})} = \text{original RR}^{\text{Increment (10) / Increment (original)}} \tag{2}$$

Sub-group meta-analyses were undertaken to investigate the impact of different designs (time-series and case-crossover), geographical areas (USA, Europe, Asia and Australia) and whether results had been adjusted or not. Unadjusted and adjusted results were collected during data extraction when studies reported quantitative data adjusted for temperature and relative humidity. A sensitivity analysis was also undertaken by removing each study in turn to see whether there was a dominant publication influence.

Tests of heterogeneity statistic for meta-analysis were reported base on Cochran's Q test at a critical level of significance of 0.10 (10%). Heterogeneity among studies was reported by I^2 statistics (Higgin's I^2 test statistic), calculated from the weighted sum of squared differences. Where there was an I^2 of more than 50%, this was taken as an indication of high heterogeneity. An I^2 of 0-30 and 30-50 were classed as low and moderate, respectively (Atkinson et al., 2014).

Pooled effects of relative risk were reported by forest plot. Meta-analysis of estimated relative risks with 95% confidence intervals were calculated using a random effect which incorporated both within and between study heterogeneity (Shah et al., 2013; Zheng et al., 2015). Funnel plots were produced to visualise potential publication bias at alpha level 0.1 (Egger et al., 1997). All statistical analyses were carried out using R program.

4.4 Results

4.4.1 Study characteristics

A total of 308 publications were found in the initial search. After screening by abstract and title, 249 studies were excluded. Of these excluded studies: 178 were not based on ambulance dispatch results; 39 did not study the association between air pollution and health outcomes; 16 publications did not study ambient air pollution; nine studies were systematic reviews or case reports; and seven other studies did not report risk estimate results for the association between air pollution and health outcomes. The full texts of the remaining 59 studies were read by both reviewers. From these studies, 20 studies were excluded because they examined hospital admissions data or mortality data, five studies did not report results for the association between air pollutants and health outcomes and one study was an editorial. The selection process is illustrated in a flowchart (see Figure 4-1).

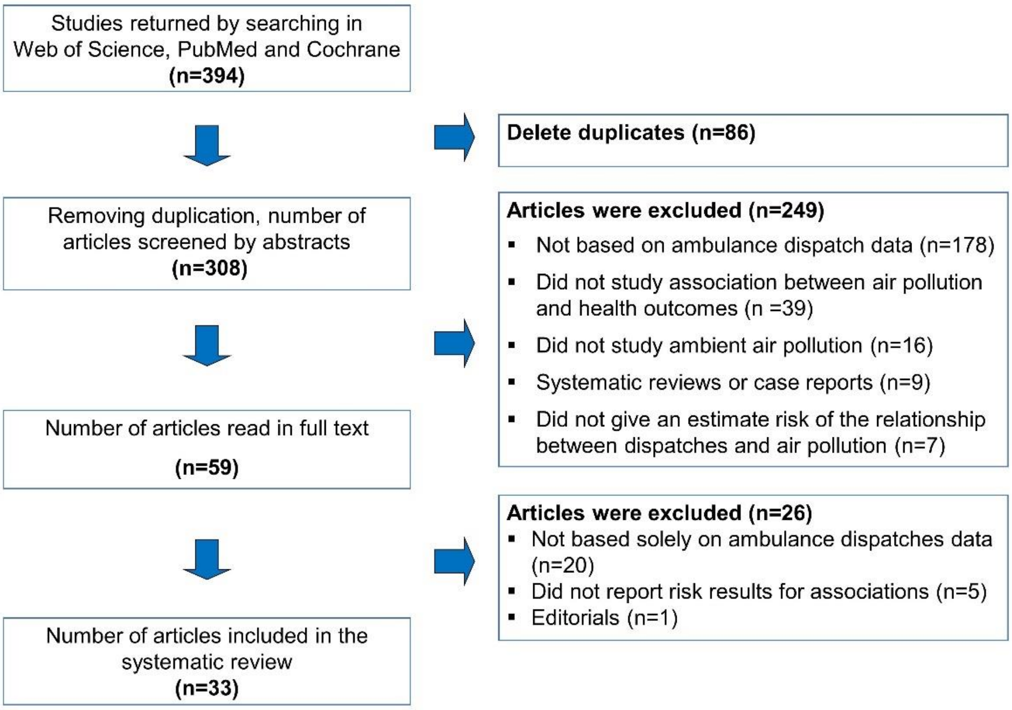

Figure 4-1 Flow diagram of relevant study selection process.

Summary data from the 33 studies that met the inclusion criteria are described in Table 4-2 (for studies based solely on ambulance dispatch data), Table 4-3 (dispatch data with subsequent paramedic assessment) and Table 4-4 (dispatch data with subsequent physician diagnosis). 10 studies were based solely on ambulance dispatch data and physician diagnosis at the hospital and 13 were informed by paramedic assessment on scene. 12 studies were conducted in Asia, seven in Western Europe, five in both the United States and Australia and four in Eastern Europe. Most studies used a case-crossover design (20 studies), 12 studies used time series analysis and one study used both case-crossover and time series. Considering health outcomes, most of the studies focused on cardiac arrest (n = 14), all-cardiovascular dispatches (n = 11), all-respiratory dispatches (n = 10) and six publications focused on total dispatches. Some studies assessed more than one category of dispatches. Most studies examined multiple pollutants with the most common being $PM_{2.5}$, PM_{10}, NO_2, SO_2, O_3 and CO with 21, 15, 15, 14, 13 and 13 studies, respectively. Other pollutants included: suspended particulate matter (SPM) where particles were less than 7 μm in diameter; ultrafine particles (UFP) where particles were less than 0.1 μm; coarse particles (the PM_{10} fraction minus $PM_{2.5}$ fraction); accumulation mode particulate (greater than 0.32 μm in diameter) and black smoke which gives a relative value for the soot content of the sample.

Most studies attempted to adjust the results for a variety of confounding factors. Temperature (n = 30) and relative humidity (n = 27) were the most commonly adjusted for variables. In particular, temperature is known to have a strong effect on certain ambulance dispatch categories (Mahmood et al., 2017). Other factors considered were day of week (n = 21), a long-term trend (n = 20), seasonality (n = 19), and holidays (n = 12) (see Table 4-5).

Within the primary research, statistically significant positive associations with air pollutants and ambulance dispatches were found in 28 of the papers. These included: cardiac arrest (for $PM_{2.5}$, PM_{10}, coarse particles, CO, NO_2, SO_2 and O_3); all-cardiovascular ($PM_{2.5}$, PM_{10}, SPM, Asian dust and black smoke); all-respiratory ($PM_{2.5}$, PM_{10} and SPM); asthma attack (CO, $PM_{2.5}$, NO_2 and O_3); hypertension (CO and UFP); COPD ($PM_{2.5}$); croup ($PM_{2.5}$); and total dispatches ($PM_{2.5}$, Asian dust and SPM). Of the remaining five papers, positive associations that were not statistically significant were found in four papers and negative associations that were not statistically significant were found in the one remaining paper. There were no statistically significant negative association reported in any of the papers.

These original results were reported as relative risks (11 papers), odds ratios (12 papers), excess risk (9 papers) and hazard ratios (1 paper). For relative risk the magnitude of significant results ranged from 1.12 (95% CI: 1.07-1.17) for asthma dispatches and NO_2 to 1.0012 (95% CI: 1.0002-1.0022) for total dispatches and $PM_{2.5}$. For odds ratios, the range was 1.37 (95% CI: 1.09-1.74) for other cardiac dispatches and O_3 to 1.001 (95% CI: 1.000-1.002) for cardiorespiratory dispatches and black smoke. For excess risk the range was 20.8% (95% CI: 3.5-40.9%) for cardiovascular dispatches and SPM to 0.86% (95% CI: 0.61-1.10%) for non-traumatic dispatches and PM_{10}. Finally, for hazard ratios, the only result was not significant 1.02 (95% CI: 0.94-1.11) for cardiac arrest and $PM_{2.5}$. A variety of lagged effects were examined from 0-14 days but the majority of the papers (n=20) looked at lag 0, 0-1 and/or 1 day. For the analysis of quality, NOS scores were ‘good’ for 30 studies (with scores of 9 for 25 studies and a score of 10 for seven studies) and ‘fair’ for one study (with a score of 6).

Table 4-2 Characteristics and results of included studies (ambulance dispatches)

No	Author	Location	Study period	Study design	Health outcome	Pollutant	Adjustment factor	Measure/ exposure unit	Lagged days	Risk results with 95%CI	NOS
1	Carracedo-Martinez et al., 2008	Vigo, Spain	1996-1999	time-series	**CV, R, CR**	**SO_2, BS**	A,B,C,D,G,H	OR/	0-3		10
								10 μg/m^3	**Lag 0**	CV, SO_2: 1.003 (0.997-1.009)	
								10 μg/m^3	**Lag 0**	CV, BS: 1.002 (1.001-1.003)*	
								10 μg/m^3	**Lag 0**	R, SO_2: 0.992 (0.981-1.003)	
								10 μg/m^3	**Lag 0**	R, BS: 1.001 (0.999-1.002)	
								10 μg/m^3	**Lag 0**	CR, SO_2 1.002 (0.996-1.007)	
								10 μg/m^3	**Lag 0**	CR, BS 1.001 (1.000-1.002)*	
2	Rosenthal et al., 2008	Indianapolis, Indiana, USA	2002-2006	case-crossover	**CA**	**$PM_{2.5}$**	A,B,H	HR/	0-7		9
								10 μg/m^3	**Lag 0**	CA, $PM_{2.5}$: 1.02 (0.94-1.11)	
3	Franck et al., 2011	Leipzig, Germany	2002-2003	time-series	**HT**	**UFP, PM_{10}, $PM_{2.5}$**	A,B,C,D	OR/	0-10		9
								1000 particles/cm^3,	**Lag 2**	HT, UFP: 1.06 (1.02-1.10)*	
								1 μg/m^3	**Lag 2**	HT, PM_{10}: 0.98 (0.95-1.00)[a]	
								1 μg/m^3	**Lag 2**	HT, $PM_{2.5}$: 1.01 (0.97-1.04)[a]	
4	Laurent et al., 2012	Strasbourg, France	2000-2005	case-crossover	**AA**	**PM_{10}, NO_2, SO_2**	N/A	OR/	N/A		6
								10 μg/m^3		AA, PM_{10}: 1.035 (0.997-1.075)	
								10 μg/m^3		AA, NO_2: 1.025 (0.990-1.062)	
								10 μg/m^3		AA, SO_2: 1.056 (0.979-1.139)	
5	Neuberger et al., 2013	Graz and Linz, Austria	1990-2007	case-crossover	**CPN, CV, R, Unclear**	**PM_{10}, $PM_{2.5}$, NO_2**	A,B,C,E, F,G,H	ER%/	0-14		9
								10 μg/m^3	**Lag 0**	CPN, PM_{10}: 1.7% (1.0-2.3%)*	
								10 μg/m^3	**Lag 0**	CPN, $PM_{2.5}$: 6.1% (4.3-7.8%)*	
								10 μg/m^3	**Lag 0**	CPN, NO_2: 2.0% (0.8-3.2%)*	
								10 μg/m^3	**Lag 0**	CV, PM_{10}: 1.3% (0.9-2.6%)*	
								10 μg/m^3	**Lag 0**	CV, $PM_{2.5}$: 7.1% (4.7-9.4%)*	
								10 μg/m^3	**Lag 0**	CV, NO_2: 1.2% (-0.4-2.8%)	
								10 μg/m^3	**Lag 0**	R, PM_{10}: 2.7% (1.2-4.2%)*	

No	Author	Location	Study period	Study design	Health outcome	Pollutant	Adjustment factor	Measure/ exposure unit	Lagged days	Risk results with 95%CI	NOS
								10 μg/m^3	**Lag 0**	R, $PM_{2.5}$: 2.1% (-2.1-6.3%)	
								10 μg/m^3	**Lag 0**	R, NO_2: 2.3% (-0.5-5.1%)	
								10 μg/m^3	**Lag 0**	Unclear, NO_2: 3.4% (1.2-5.6%)*	
								10 μg/m^3	**Lag 0**	Unclear, $PM_{2.5}$: 3.7% (0.4-7.0%)*	
								10 μg/m^3	**Lag 0**	Unclear, PM_{10}: 1.6% (0.9-3.3%)*	
6	Raun et al., 2014	Houston, USA	2004-2011	case-crossover	**AA**	**$PM_{2.5}$, CO, NO_2 SO_2, O_3**	A,D,G	RR/	0-3		9
								6 μg/m^3	**Lag 0**	AA, $PM_{2.5}$: 1.02 (0.99-1.05)	
								155 ppb	**Lag 0**	AA, CO: 1.05 (1.02-1.08)*	
								8 ppb	**Lag 0**	AA, NO_2: 1.12 (1.07-1.17)*	
								20 ppb	**Lag 0**	AA, O_3: 1.04 (1.01-1.07)*	
								2 ppb	**Lag 0**	AA, SO_2: 1.03 (0.97-1.08)	
7	Sajani et al., 2014	Emilia-Romagna, Italy	2002-2006	time-series	**CV, R, NT**	**PM_{10}**	A,C,D,E, F,G,I	ER%/			9
								10 μg/m^3	**Lag 0-1**	CV, PM_{10}: 0.31% (-0.13-0.75%)	
								10 μg/m^3	**Lag 0-1**	R, PM_{10}: 0.44% (-0.02-0.91%)	
								10 μg/m^3	**Lag 0-1**	NT, PM_{10}: 0.86% (0.61-1.10%)*	
8	Youngquist et al., 2016	Utah, USA	2009-2012	case-crossover		**$PM_{2.5}$**	N/A	RR/	0-21		9
								10 μg/m^3	**Lag 0**	Abdominal pain, $PM_{2.5}$: 0.997 (0.976-1.018)	
								10 μg/m^3	**Lag 0**	Consciousness, $PM_{2.5}$: 0.996 (0.978-1.014)	
								10 μg/m^3	**Lag 0**	Behavioural disorder, $PM_{2.5}$: 0.988 (0.973-1.003)	
								10 μg/m^3	**Lag 0**	CA, $PM_{2.5}$: 0.991 (0.949-1.033)	
								10 μg/m^3	**Lag 0**	Cardiac rhythm disturbance, $PM_{2.5}$: 1.015 (0.977-1.055)	
								10 μg/m^3	**Lag 0**	CP, $PM_{2.5}$: 0.989 (0.970-1.008)	
								10 μg/m^3	**Lag 0**	Diabetic, $PM_{2.5}$ 1.034: (1.000-1.068)	
								10 μg/m^3	**Lag 0**	Respiratory arrest, $PM_{2.5}$: 0.962 (0.874-1.058)	
								10 μg/m^3	**Lag 0**	Respiratory distress, $PM_{2.5}$: 0.986 (0.968-1.005)	
								10 μg/m^3	**Lag 0**	Seizure, $PM_{2.5}$: 1.008 (0.985-1.031)	
								10 μg/m^3	**Lag 0**	Stroke/CVA, $PM_{2.5}$: 1.009 (0.970- 1.049)	
								10 μg/m^3	**Lag 0**	Syncope/fainting, $PM_{2.5}$: 1.034 (1.009-1.061)*	

No	Author	Location	Study period	Study design	Health outcome	Pollutant	Adjustment factor	Measure/ exposure unit	Lagged days	Risk results with 95%CI	NOS
								10 μg/m^3	**Lag 0**	Traumatic injury, $PM_{2.5}$: 1.002 (0.991-1.013)	
								10 μg/m^3	**Lag 0**	Other, $PM_{2.5}$: 1.006 (0.988-1.025)	
9	Ichiki et al., 2016	Japan	2010	case-crossover	**CV**	**$PM_{2.5}$**	A,B,E,F,J	RR/ 1 μg/m^3	**0-6**	CV, $PM_{2.5}$: 1.00 (0.99-1.00)	10
10	Salimi et al., 2017	Sydney, Australia	2004-2015	time-series	**CA, R, CP, OHP, S**	**$PM_{2.5}$**	A,B,C,D, E,F,G,J	RR/	0-3		9
								10 μg/m^3	**Lag 0**	CA, $PM_{2.5}$: 1.03 (1.00-1.06)	
								10 μg/m^3	**Lag 0**	R, $PM_{2.5}$: 1.03 (1.02-1.04)*	
								10 μg/m^3	**Lag 0**	CP, $PM_{2.5}$: 1.01 (1.00-1.02)	
								10 μg/m^3	**Lag 0**	OHP, $PM_{2.5}$: 0.99 (0.97-1.01)[a]	
								10 μg/m^3	**Lag 0**	S, $PM_{2.5}$: 1.00 (0.98-1.02)[a]	

Table 4-3 Characteristics and results of included studies (ambulance dispatches with paramedic assessments)

No	Author	Location	Study period	Study design	Health outcome	Pollutant	Adjustment factor	Measure/ exposure unit	Lagged day	Risk result with 95%CI	NOS
1	Levy et al., 2001	Washington, USA	1988-1994	case-crossover	**CA**	**PM_{10}, CO, SO_2**	C,E,F,J	RR/	0-5		9
								19.3 μg/m^3	**Lag 1**	CA, PM_{10}: 0.87 (0.74-1.01)	
								-	**Lag 1**	CA, CO: 0.99 (0.83-1.18)[b]	
								-	**Lag 1**	CA, SO_2: 0.87 (0.76-1.00)[b]	
2	Silverman et al., 2010	New York, USA	2002-2006	**time-series** and case-crossover	**CA**	**$PM_{2.5}$, CO, NO_2, SO_2, O_3**	A,C,F	RR/	0-3		9
								10 μg/m^3	**Lag 0-1**	CA, $PM_{2.5}$: 1.06 (1.02-1.10) *	
								0.3 ppm	**Lag 0-1**	CA, CO: 0.99 (0.95-1.04)[a]	
								11 ppb	**Lag 0-1**	CA, NO_2: 1.02 (0.98-1.08)[a]	
								6 ppb	**Lag 0-1**	CA, SO_2: 1.00 (0.95-1.05)[a]	
								22 ppb	**Lag 0-1**	CA, O_3: 1.05 (0.99-1.12)[a]	
3	Dennekamp et al., 2010	Melbourne, Australia	2003-2006	case-crossover	**CA**	**Coarse, PM_{10}, $PM_{2.5}$, CO,**	A,B,C,E,F	ER%/	0-3		9
								6.07 μg/m^3	**Lag 0-1**	CA, Coarse: 1.32% (-1.49-4.21%)	
								9.66 μg/m^3	**Lag 0-1**	CA, PM_{10}: 3.17% (0.55-5.85%)*	

No	Author	Location	Study period	Study design	Health outcome	Pollutant	Adjustment factor	Measure/ exposure unit	Lagged day	Risk result with 95%CI	NOS
						NO_2, SO_2, O_3		4.26 μg/m^3	**Lag 0-1**	CA, $PM_{2.5}$: 3.61% (1.29-5.99%)*	
								0.25 ppm	**Lag 0-1**	CA, CO: 3.09% (0.25-6.02%)*	
								6.64 ppb	**Lag 0-1**	CA, NO_2: 2.99% (-2.57-8.86%)	
								0.76 ppb	**Lag 0-1**	CA, SO_2: -0.05% (-4.93-5.07%)	
								8.02 ppb	**Lag 0-1**	CA, O_3: 2.94% (-2.42-8.59%)	
4	Raza et al., 2014	Stockholm, Sweden	2000-2010	case-crossover	**CA**	**Coarse, $PM_{2.5}$, NO_2, NO_x, O_3**	A,B	OR/	0-3		9
								10 μg/m^3	**Lag 24 h**	CA, Coarse: 0.98 (0.92-1.05)[a]	
								10 μg/m^3	**Lag 24 h**	CA, $PM_{2.5}$: 1.00 (0.95-1.07)[a]	
								10 μg/m^3	**Lag 24 h**	CA, NO_2: 0.95 (0.91-0.99)[a]	
								10 μg/m^3	**Lag 24 h**	CA, NO_x: 0.98 (0.95-1.00)[a]	
								10 μg/m^3	**Lag 24 h**	CA, O_3: 1.04 (1.01-1.07)* [a]	
5	Rosenthal et al., 2013	Helsinki, Finland	1998-2006	case-crossover	**CA, MI, OC**	**UFP, Acc, Coarse, PM_{10}, $PM_{2.5}$, CO, NO_2, NO, SO_2, O_3**	A,B	OR/	0-7		10
								10,624/cm^3	**Lag 0**	CA, UFP: 0.96 (0.86-1.07)	
								1007 cm^3	**Lag 0**	CA, Acc: 1.04 (0.97-1.12)	
								7.0 μg/m^3	**Lag 0**	CA, Coarse: 1.02 (0.96-1.09)	
								14.0 μg/m^3	**Lag 0**	CA, PM_{10}: 1.06 (0.99-1.13)	
								7.7 μg/m^3	**Lag 0**	CA, $PM_{2.5}$: 1.07 (1.00-1.15)*	
								33.2 μg/m^3	**Lag 0**	CA, O_3: 1.09 (0.95-1.24)	
								5.2 μg/m^3	**Lag 0**	CA, NO: 1.01 (0.98-1.04)	
								0.21 mg/m^3	**Lag 0**	CA, CO: 1.03 (0.94-1.13)	
								20.0 μg/m^3	**Lag 0**	CA, NO_2: 0.95 (0.84-1.07)	
								3.5 μg/m^3	**Lag 0**	CA, SO_2: 0.99 (0.93-1.05)	
								10,624/cm^3	**Lag 0**	MI, UFP: 1.27 (1.05-1.54)*	
								1007 cm^3	**Lag 0**	MI, Acc: 1.19 (1.04-1.35)*	
								7.0 μg/m^3	**Lag 0**	MI, Coarse: 1.06 (0.95-1.19)	
								14.0 μg/m^3	**Lag 0**	MI, PM_{10}: 1.11 (0.98-1.25)	
								7.7 μg/m^3	**Lag 0**	MI, $PM_{2.5}$: 1.17 (1.03-1.33)*	
								33.2 μg/m^3	**Lag 0**	MI, O_3: 0.86 (0.67-1.11)	
								5.2 μg/m^3	**Lag 0**	MI, NO: 1.07 (1.01-1.13)*	

No	Author	Location	Study period	Study design	Health outcome	Pollutant	Adjustment factor	Measure/ exposure unit	Lagged day	Risk result with 95%CI	NOS
								0.21 mg/m^3	**Lag 0**	MI, CO: 1.07 (0.91-1.25)	
								20.0 µg/m^3	**Lag 0**	MI, NO_2: 1.11 (0.94-1.40)	
								3.5 µg/m^3	**Lag 0**	MI, SO_2: 1.00 (0.89-1.12)	
								10,624/cm^3	**Lag 0**	OC, UFP: 0.86 (0.75-0.98)	
								1007 cm^3	**Lag 0**	OC, Acc: 0.98 (0.90-1.07)	
								7.0 µg/m^3	**Lag 0**	OC, Coarse: 1.01 (0.93-1.09)	
								14.0 µg/m^3	**Lag 0**	OC, PM_{10}: 1.03 (0.95-1.12)	
								7.7 µg/m^3	**Lag 0**	OC, $PM_{2.5}$: 1.04 (0.98-1.11)	
								33.2 µg/m^3	**Lag 0**	OC, O_3: 1.37 (1.09-1.74) *	
								5.2 µg/m^3	**Lag 0**	OC, NO: 0.94 (0.90-0.98)	
								0.21 mg/m^3	**Lag 0**	OC, CO: 1.01 (0.91-1.13)	
								20.0 µg/m^3	**Lag 0**	OC, NO_2: 0.88 (0.76-1.02)	
								3.5 µg/m^3	**Lag 0**	OC, SO_2: 0.98 (0.92-1.05)	
6	Wichmann et al., 2013	Copenhagen, Denmark	2000-2010	case-crossover	**CA**	**PM_{10}, $PM_{2.5}$, Coarse**, CO, NO_2, **NO_x**, O_3	A,B,D,E,F	ER%/	0-4		9
								7.22 µg/m^3	**Lag 3**	CA, PM_{10}: 4.7% (0.7-8.8%)*	
								4.69 µg/m^3	**Lag 3**	CA, $PM_{2.5}$: 4.4% (0.2-8.8%)*	
								3.74 µg/m^3	**Lag 3**	CA, Coarse: 3.5% (-0.3-7.4%)	
								8.50 ppb	**Lag 3**	CA, NO_x: 3.4% (-0.9-7.9%)	
7	Straney et al., 2014	Perth, Western Australia	2000-2010	case-crossover	**CA**	**PM_{10}, $PM_{2.5}$, CO, NO_2, SO_2, O_3**	A,B	OR/	0-1		9
								11.10 µg/m^3	**Lag 0-24 h**	CA, PM_{10}: 1.002 (0.998-1.006)	
								5.08 µg/m^3	**Lag 0-24 h**	CA, $PM_{2.5}$: 1.009 (1.002-1.016) *	
								14.50 ppb	**Lag 0-24 h**	CA, O_3: 1.002 (0.997-1007)	
								0.16 ppm	**Lag 0-24 h**	CA, CO: 1.058 (0.938-1.192)	
								7.10 ppb	**Lag 0-24 h**	CA, NO_2: 0.997 (0.990-1.004)	
								0.80 ppb	**Lag 0-24 h**	CA, SO_2: 0.991 (0.967-1.016)	
8	Dennekamp et al., 2015	Melbourne, Australia	2006-2007	case-crossover	**CA**	**PM_{10}, $PM_{2.5}$, CO,** NO_2, SO_2, O_3	A,B,C,E,F	ER%/	0-2		9
								13.7 µg/m^3	**Lag 0-48 h**	CA, PM_{10}: 4.0% (-2.4-10.8%)	
								6.1 µg/m^3	**Lag 0-48 h**	CA, $PM_{2.5}$: 4.4% (0.2-8.7%)*	
								0.3 ppm	**Lag 0-48 h**	CA, CO: 5.6% (-1.6-13.2%)	

No	Author	Location	Study period	Study design	Health outcome	Pollutant	Adjustment factor	Measure/ exposure unit	Lagged day	Risk result with 95%CI	NOS
9	Liu et al., 2017	Chengdu area, China	2013-2015	time-series	**CV, R TD**	**$PM_{2.5}$**	A,B,C, D,E,J	RR/	0-3		9
								10 μg/m^3	**Lag 0**	TD, $PM_{2.5}$: 1.0012 (1.0002-1.0022)*	
								10 μg/m^3	**Lag 0**	R, $PM_{2.5}$: 1.0051 (1.0021-1.0089) *	
								10 μg/m^3	**Lag 0**	CV, $PM_{2.5}$: 1.0041 (1.0009-1.0074)*	
10	Vencloviene et al., 2017a	Kaunas city, Lithuania	2009-2011	Time-series	**AF**	**PM_{10}, CO**	A,B,C, H,J,K	RR/	0-7		9
								7.31 μg/m^3	**Lag 2**	AF, PM_{10}: 1.06 (1.01-1.10)*	
								0.333 mg/m^3	**Lag 2-3**	AF, CO: 1.06 (1.00-1.14)	
11	Vencloviene et al., 2017b	Kaunas city, Lithuania	2009-2011	Time-series	**HT**	**PM_{10}, CO, O_3**	A,B,C, H,K	RR/	0-7		9
								18.3 μg/m^3	**Lag 1**	HT, PM_{10}: 1.02 (1.00-1.04)	
								0.367 mg/m^3	**Lag 1**	HT, CO: 1.03 (1.01-1.05)*	
								26.1 μg/m^3	**Lag 0**	HT, O_3: 0.96 (0.92-0.99)	
12	Xia et al., 2017	Beijing, China	2013-2015	case-crossover	**CA**	**$PM_{2.5}$, Coarse, CO, NO_2, SO_2, O_3**	A,B,C,E,F,J	OR/	0-5		9
								10 μg/m^3	**Lag 1**	CA, $PM_{2.5}$: 1.07 (1.04-1.10)*	
								10 μg/m^3	**Lag 1**	CA, Coarse: 1.05 (1.03-1.07)*	
								0.9 mg/m^3	**Lag 1**	CA, CO: 1.08 (0.94-1.22)[a]	
								10 μg/m^3	**Lag 1**	CA, NO_2: 1.05 (0.98-1.11)	
								10 μg/m^3	**Lag 1**	CA, SO_2: 1.05 (0.82-1.08)	
								10 μg/m^3	**Lag 1**	CA, O_3: 0.95 (0.88-1.02)[a]	
13	Johnston et al., 2019	Victoria, New South Wales and Tasmania, Australia	2009-2014	case-crossover		**$PM_{2.5}$**	A,B,C,E,F	OR/	0-2		9
								10 μg/m^3	**Lag 1**	AR, $PM_{2.5}$: 1.02 (0.99-1.06)	
								10 μg/m^3	**Lag 1**	HF, $PM_{2.5}$: 1.05 (1.00-1.10)	
								10 μg/m^3	**Lag 1**	FA, $PM_{2.5}$: 1.04 (0.99-1.08)	
								10 μg/m^3	**Lag 1**	ACS, $PM_{2.5}$: 1.00 (0.97-1.03)	
								10 μg/m^3	**Lag 1**	AN, $PM_{2.5}$: 1.04 (0.99-1.09)	
								10 μg/m^3	**Lag 1**	S, $PM_{2.5}$: 1.00 (0.95-1.04)	
								10 μg/m^3	**Lag 1**	TIA, $PM_{2.5}$: 0.96 (0.90-1.02)	
								10 μg/m^3	**Lag 1**	AS, $PM_{2.5}$: 1.06 (1.01-1.11)*	
								10 μg/m^3	**Lag 1**	COPD, $PM_{2.5}$: 1.07 (1.01-1.13)*	
								10 μg/m^3	**Lag 1**	LRI, $PM_{2.5}$: 1.02 (0.99-1.05)	

No	Author	Location	Study period	Study design	Health outcome	Pollutant	Adjustment factor	Measure/ exposure unit	Lagged day	Risk result with 95%CI	NOS
								10 μg/m^3	**Lag 1**	CRO, $PM_{2.5}$: 1.09 (1.02-1.17)*	

Table 4-4 Characteristics and results of included studies (ambulance dispatches with physician diagnoses)

No	Author	Location	Study period	Study design	Health outcome	Pollutant	Adjustment factor	Measure/ exposure unit	Lagged day	Risk result with 95%CI	NOS
1	Ueda et al., 2012	Nagasaki, Japan	2003-2007	case-crossover	**CV, R, TD**	**SPM,** NO_2, SO_2, O_x	A,B,C,E,F	ER%/	0-3		10
								10 μg/m^3	**Lag 0-3**	CV, SPM: 20.8% (3.5-40.9%)*[c]	
									Lag 0-3	R, SPM: 10.3% (-11.5-37.5%)[c]	
									Lag 0-3	TD, SPM: 12.1% (2.3-22.9%)* [c]	
2	Kashima et al., 2014	Okayama, Japan	2006-2010	time-series	**CV, TD, CeV, P**	**SPM, AD**	A,B,C,D,E,G	RR/	0-3		10
								20.7 μg/m^3	**Lag 0**	CV, AD: 1.016 (1.001-1.032)*	
								20.7 μg/m^3	**Lag 0**	TD, AD: 1.009 (1.002-1.017)*	
								20.7 μg/m^3	**Lag 0**	CeV, AD: 1.028 (1.007-1.049)*	
								20.7 μg/m^3	**Lag 0**	P, AD: 1.005 (0.986-1.025)	
								17.8 μg/m^3	**Lag 0**	CV, SPM: 1.027 (1.000-1.055)	
								17.8 μg/m^3	**Lag 0**	TD, SPM: 1.014 (1.002-1.027)*	
								17.8 μg/m^3	**Lag 0**	CeV, SPM: 1.039 (1.001-1.077)*	
								17.8 μg/m^3	**Lag 0**	P, SPM: 1.019 (0.986-1.053)	
3	Yang et al., 2014	Guangzhou, China	2008-2012	time-series	**HF**	**PM_{10}, NO_2, SO_2**	A,B,C,D,E,F	ER%/	0-3		9
								10 μg/m^3	**Lag 0**	HF, PM_{10}: 3.54% (1.35-5.74%)*[d]	
								10 μg/m^3	**Lag 0**	HF, NO_2: 4.34% (1.71-6.97%)* [d]	
								10 μg/m^3	**Lag 0**	HF, SO_2: 5.29% (2.28-8.30%)* [d]	
4	Michikawa et al., 2015a	Fukuoka, Japan	2005-2010	case-crossover	**CV, R, TD**	**$PM_{2.5}$**	A,B,E,F,J	OR/	0-14		10
								10 μg/m^3	**Lag 0-1**	CV, $PM_{2.5}$:1.002 (0.987-1.016)	
								10 μg/m^3	**Lag 0-1**	R, $PM_{2.5}$: 1.027 (1.007-1.048)*	
								10 μg/m^3	**Lag 0-1**	TD, $PM_{2.5}$: 1.008 (1.002-1.014)*	

No	Author	Location	Study period	Study design	Health outcome	Pollutant	Adjustment factor	Measure/ exposure unit	Lagged day	Risk result with 95%CI	NOS
5	Michikawa et al., 2015b	Fukuoka, Japan	2005-2010	case-crossover	**CV, R, TD**	**Coarse**	A,B,D,E,F,G, J	OR/	0-6		10
								10 μg/m^3	**Lag 0-1**	CV, Coarse: 0.998 (0.974-1.022)	
								10 μg/m^3	**Lag 0-1**	R, Coarse: 1.028 (0.995-1.063)	
								10 μg/m^3	**Lag 0-1**	TD, Coarse: 1.006 (0.996-1.016)	
6	Pradeau et al., 2015	Bordeaux, France	2007-2012	case-crossover	**CA**	PM_{10}, **$PM_{2.5}$, O_3**	A,B	OR/	0-7		9
								10.5 μg/m^3	**Lag 8 h**	CA, $PM_{2.5}$: 1.11 (1.02-1.19)*	
								27.6 μg/m^3	**Lag 1**	CA, O_3: 1.13 (1.03-1.22)*	
7	Kang et al., 2016	Seoul, Korea	2006-2013	time-series	**CA**	**PM_{10}, $PM_{2.5}$, Coarse CO, NO_2, SO_2, O_3**	A,B,C,E,F,H, J	ER%/	0-5		9
								10 μg/m^3	**Lag 1**	CA, PM_{10}: 0.21% (0.22-0.64%)*	
								10 μg/m^3	**Lag 1**	CA, $PM_{2.5}$: 0.94% (-0.05-1.94%)	
								10 μg/m^3	**Lag 1**	CA, Coarse PM: 0.07% (-0.57-0.70%)	
								10 ppb	**Lag 1**	CA, O_3: 0.96% (-0.25-2.18%)	
								0.1 ppm	**Lag 1**	CA, CO: 0.91% (0.23-1.59%)*	
								10 ppb	**Lag 1**	CA, NO_2: 1.31% (0.08-2.54%)*	
								1 ppb	**Lag 1**	CA, SO_2: 0.98% (0.23-1.73%)*	
8	Tasmin et al., 2016	Japan	2007-2011	time-series	**CV, R, AI**	**SPM**	A,B,C,D, E,F,G	RR/	0-3		9
								10 μg/m^3	**Lag 0-1**	CV, SPM: 1.000 (0.996-1.005)	
								10 μg/m^3	**Lag 0-1**	R, SPM: 1.018 (1.013-1.023)*	
								10 μg/m^3	**Lag 0-1**	AI, SPM: 1.008 (1.007-1.010)*	
9	Phung et al., 2018	8 cities, Japan	2007-2011	time-series	**TD, CV, R, NP, CeV**	**$PM_{2.5}$**	A,B,C,D,E,F, G	ER%/	0-7		9
								10 μg/m^3	**Lag 0**	TD, $PM_{2.5}$: 1.24% (0.92-1.56%)*	
								10 μg/m^3	**Lag 0**	CV, $PM_{2.5}$: 0.36% (-1.30-2.05%)	
								10 μg/m^3	**Lag 0**	R, $PM_{2.5}$: 1.88% (1.00-2.76%)*	
								10 μg/m^3	**Lag 0**	NP, $PM_{2.5}$: 1.48% (0.69-2.28%)*	
								10 μg/m^3	**Lag 0**	CeV, $PM_{2.5}$: 0.24% (-0.62-1.11%)	

No	Author	Location	Study period	Study design	Health outcome	Pollutant	Adjustment factor	Measure/ exposure unit	Lagged day	Risk result with 95%CI	NOS
10	Chen et al., 2019	Chengdu area, China	2013-2017	case-crossover	**AS**	**CO, NO_2, SO_2, O_3**	A,B,C,E,F,H	OR	0-7		9
								498 μg/m^3	**Lag 1**	AS, CO: 1.031 (1.003-1.059)*	
								17 μg/m^3	**Lag 1**	AS, NO_2: 1.065 (0.988-1.148)	
								13 μg/m^3	**Lag 1**	AS, SO_2: 1.065 (0.955-1.187)	
								74 μg/m^3	**Lag 1**	AS, O_3: 1.053 (0.943-1.177)	

Characteristics in bold relate to the risk results displayed in this table. *Risk results had significant association ($p < 0.05$) and ** risk results had significant association ($p < 0.01$).For example, often many pollutants were mentioned but results shown only for a limited number of pollutants. If there were multiple variations of a given risk result (for example different lag days) only the option in bold text has been displayed.

[a] estimated value from figures

[b] no details of pollutant exposure units

[c] reported only heavy Asian dust days

[d] population from elderly who age more than 65 years

Abbreviations:

NA: No available relevant data; 95% CI, 95% of confidence intervals; A, temperature; AA, asthma attacks; Acc, accumulation mode particulate; ACS, acute coronary syndrome; AD, asian dust; AI, acute illness; AN, Angina; AR, Arrhythmia; AS,Asthma; AF, atrial fibrilation; B , relative humidity; BS, black smoke; C, day of week; CA, cardiac arrest; Cev, cerebrovascular; COPD, chronic obstructive pulmonary disease; CP, chest pain; CPN, cardiopulmonary; CR, cardiorespiratory; CRO, Croup; CV, all-cardiovascular; D, holiday; E, long-trend; ER, excess risk; F, seasonality; FA, Faint; G,Influenza; H, atmospheric pressure; HF, heart failure; HT, hypertension; HR, hazard ratio; I,age; IQR, An interquartile range; J, other pollutants; K, other meteorological; LRI, lower respiratory infections; MI, myocardial infarction; NOS, Newcastle-Ottawa scale; NP, neuropsychological; NT, non-traumatic; OC, other cardiac; OHP, other heart problems; OR, odds ratio; P, pulmonary; R, all-respiratory; RR, relative risk; S, stroke; TIA, Transient ischemic attack; TD, total dispatches

Table 4-5 Summary of included studies by regions, study design, health outcomes, air pollutants, adjusted variables and exposure units in each ambulance data source

	All studies (n=33)		Ambulance dispatches (n=10)		Paramedic assessment (n=13)		Physician diagnosis (n=10)	
Topics	**Number of studies**	**%**	**Number of studies**	**%**	**Number of studies**	**%**	**Number of studies**	**%**
Regions								
United States : *America (6)*	5	15.2%	3	30.0%	2	15.4	-	-
Western Europe : *France(2), Italy, Finland, Denmark, Germany, Spain*	7	21.2%	4	40.0%	2	15.4	1	10.0%
Eastern Europe : *Sweden, Austria, Lithuania*	4	12.1%	1	10.0%	3	23.1	-	-
Asia : *Japan (7), Korea (1), China (3)*	12	36.4%	1	10.0%	2	15.4	9	90.0%
Australia, New Zealand : *Australia (4)*	5	15.2%	1	10.0%	4	30.8	-	-
Study designs								
Case-crossover	20	60.6%	6	60.0%	9	69.2	5	50.0%
Time series	12	36.4%	4	40.0%	3	23.1	5	50.0%
Mixed case-crossover and time series	1	3.0%	-	-	1	7.7	-	-
Health outcomes								
Cardiac arrest dispatches: CA	14	42.4%	3	30.0%	9	69.2%	2	20.0%
All-cardiovascular dispatches: CV	11	33.3%	4	40.0%	1	7.7%	6	60.0%
All-respiratory dispatches: R	10	30.3%	4	40.0%	1	7.7%	5	50.0%
Total dispatches: TD	6	18.2%	-	-	1	7.7%	5	50.0%
Asthma: AS	2	6.1%			1	7.7%	1	10.0%
Asthma attack: AA	2	6.1%	2	20.0%	-	-	-	-
#VALUE!Angina: AN	1	3.0%	-	-	1	7.7%	-	-
Atrial fibrillation: AF	1	3.0%	-	-	1	7.7%	-	-
Arrhythmia: AR	1	3.0%	-	-	1	7.7%	-	-
Acute coronary syndrome: ACS	1	3.0%	-	-	1	7.7%	-	-
Heart failure: HF	2	6.1%	-	-	1	7.7%	1	10.0%
Chest pain: CP	2	6.1%	2	20.0%	-	-	-	-
Cerebrovascular:CeV	2	6.1%	-	-	-	-	2	20.0%
Chronic obstructive pulmonary disease: COPD	1	3.0%	-	-	1	7.7%	-	-
Croup: CRO	1	3.0%	-	-	1	7.7%	-	-
Neuropsychology:NP	1	3.0%	-	-	-	-	1	10.0%
Hypertension: HT	2	6.1%	1	10.0%	1	7.7%	-	-
Cardiorespiratory: CR	1	3.0%	1	10.0%	-	-	-	-
Cardiopulmonary: CPN	1	3.0%	1	10.0%	-	-	-	-
Non-traumatic: NT	1	3.0%	1	10.0%	-	-	-	-
Faint: FA	1	3.0%	-	-	1	7.7%	-	-
Lower respiratory infections: LRI	1	3.0%	-	-	1	7.7%	-	-

	All studies (n=33)		Ambulance dispatches (n=10)		Paramedic assessment (n=13)		Physician diagnosis (n=10)	
Topics	**Number of studies**	**%**	**Number of studies**	**%**	**Number of studies**	**%**	**Number of studies**	**%**
Transient ischemic attack: TIA	1	3.0%	-	-	1	7.7%	-	-
Other heart problems: OHP	1	3.0%	1	10.0%	-	-	-	-
Stroke: S	1	3.0%	1	10.0%	1	7.7%	-	-
Myocardial infarction: MI	1	3.0%	-	-	1	7.7%	-	-
Other cardiac: OC	1	3.0%	-	-	1	7.7%	-	-
Acute illness: AI	1	3.0%	-	-	-	-	1	10.0%
Pulmonary: P	1	3.0%	-	-	-	-	1	10.0%
Other/unclear	1	3.0%	1	10.0%	-	-	-	-
Air pollutants								
Suspended particulate matter: SPM	3	9.1%	-	-	-	-	3	30.0%
Total suspended particles: TSP	-	-	-	-	-	-	-	-
Ultrafine particles: UFP	2	6.1%	1	10.0%	1	7.7%	-	-
Accumulation mode: Acc	1	3.0%	-	-	1	7.7%	-	-
145.563.600.018.300. 0black smoke: BS	1	3.0%	1	10.0%	-	-	-	-
Asian dust: AD	1	3.0%	-	0.0%	-	-	1	10.0%
PM_{10}	15	45.5%	4	40.0%	8	61.5%	3	30.0%
$PM_{2.5}$	21	63.6%	7	70.0%	10	76.9%	4	40.0%
PM_{10} - $PM_{2.5}$: Coarse	7	21.2%	-	-	5	38.5%	2	20.0%
CO	13	39.4%	1	10.0%	10	76.9%	2	20.0%
NO_2	15	45.5%	3	30.0%	8	61.5%	4	40.0%
NO_x	3	9.1%	-	0.0%	3	23.1%	-	-
SO_2	14	42.4%	3	30.0%	7	53.8%	4	40.0%
O_3	13	39.4%	1	10.0%	9	69.2%	3	30.0%
O_x	1	3.0%	-	-	-	-	1	10.0%
Adjusted variables								
A, temperature	30	90.9%	8	80.0%	12	92.3%	10	100.0%
B, relative humidity	27	81.8%	6	60.0%	11	84.6%	10	100.0%
C, day of week	21	63.6%	5	50.0%	9	69.2%	7	70.0%
D, holiday;	12	36.4%	5	50.0%	2	15.4%	5	50.0%
E, long-trend	20	60.6%	4	40.0%	7	53.8%	9	90.0%
F, seasonality	19	57.6%	4	40.0%	7	53.8%	8	80.0%
G, Influenza	9	27.3%	5	50.0%	-	-	4	40.0%
H, Atmospheric pressure	7	21.2%	3	30.0%	2	15.4%	2	20.0%
I, age	1	3.0%	1	10.0%	-	-	-	-
J, other pollutants other	9	27.3%	2	20.0%	4	30.8%	3	30.0%
K, meteorological variables	2	6.1%	-	-	2	15.4%	-	-
Exposure units								
RR	11	33.3%	4	40.0%	5	38.5%	2	20.0%
OR	12	36.4%	3	30.0%	5	38.5%	4	40.0%
PC	9	27.3%	2	20.0%	3	23.1%	4	40.0%
HR	1	3.0%	1	10.0%	-	-	-	-

4.4.2 Meta-analysis

The estimated RR at 95% CI were computed when there were two or more papers reporting the association between the same pollutants within the same grouping of either (1) ambulance dispatch data (2) ambulance dispatch with paramedic assessments and (3) ambulance dispatch with physician diagnoses (Deeks et al., 2004) (see Table 4-6). For ambulance dispatch data, eight meta-analyses were carried out. Statistically significant relationships were found between all-respiratory and $PM_{2.5}$ (RR=1.03, 95% CI: 1.02-1.04) and asthma dispatches and NO_2 (RR=1.10, 95% CI: 1.00-1.21). For paramedic assessment data, the pooled RRs for cardiac arrest dispatches showed a significant positive association for $PM_{2.5}$ (RR = 1.05, 95% CI: 1.03-1.08), CO (RR = 1.10, 95% CI: 1.02-1.18) and coarse particulate (RR = 1.04, 95% CI: 1.01-1.06). The relationship between cardiac arrest dispatches was not statistically significant at the 95% level for the exposure to other pollutants including PM_{10}, SO_2, O_3 and NO_2. For physician diagnosis data, $PM_{2.5}$ exposure was significantly associated with all-respiratory (RR = 1.02, 95% CI: 1.01-1.03).

Six forest plots are presented for the significant associations between: all-respiratory and $PM_{2.5}$ and asthma and NO_2 for the ambulance dispatch data and reported as I^2 = 0.00% and 78.69% respectively (Figure 4-2). The association between cardiac arrest and $PM_{2.5}$, CO and coarse particulates for the paramedic datasets are reported I^2 = 59.60%, 0.00% and 25.37% respectively (Figure 4-3). The association between all-respiratory and $PM_{2.5}$ for physician diagnosis data was reported a heterogeneity at 0.00% (Figure 4-4). The forest plots for the 13 non-significant associations are shown Figure 4-4 – Figure 4-6, with ambulance dispatches (Figure 4-5) for data with paramedic assessments (Figure 4-6) and for data with subsequent hospital physician diagnosis (Figure 4-7).

Funnel plots for examing publication bias can be seen in Figure 4-8. There is some evidence of publication bias as highlighted by the asymmetrical spread of points with more points to the right of the funnel.

Table 4-6 Combined estimates of RR at 95% CI for a 10 μg/m^3 increase in $PM_{2.5}$, PM_{10}, Coarse and SPM, 1 ppm of CO, and 10 ppb of SO_2, NO_2 and O_3 are presented based on data sources: ambulance dispatches, paramedic assessments and physician diagnoses

Pollutants	**Ambulance dispatch data**				
	Cardiac arrest	**All-respiratory**	**All-cardiovascular**	**Asthma**	**Chest pain**
$PM_{2.5}$	1.02 (0.99-1.05) [3]	**1.03 (1.02-1.04)* [2]**	1.04 (0.98-1.10) [2]	N/A	1.00 (0.98-1.02) [2]
PM_{10}	N/A	1.01 (0.99-1.04) [2]	1.01 (1.00-1.02) [2]	N/A	
SO_2	N/A	N/A	N/A	1.16 (0.99-1.35) [2]	N/A
NO_2	N/A	N/A	N/A	**1.10 (1.00-1.21)* [2]**	N/A
Pollutants	**Paramedic assessment data**				
$PM_{2.5}$	**1.05 (1.03-1.08)* [8]**	N/A	N/A	N/A	N/A
PM_{10}	1.02 (1.00-1.05) [6]	N/A	N/A	N/A	N/A
CO	**1.10 (1.02-1.18)* [6]**	N/A	N/A	N/A	N/A
SO_2	1.03 (0.94-1.12) [5]	N/A	N/A	N/A	N/A
NO_2	1.00 (0.96-1.04 [6]	N/A	N/A	N/A	N/A
O_3	1.02 (1.00-1.05) [6]	N/A	N/A	N/A	N/A
Coarse	**1.04 (1.01-1.06)* [5]**	N/A	N/A	N/A	N/A
Pollutants	**Physician diagnosis data**				
$PM_{2.5}$	N/A	**1.02 (1.01-1.03)* [2]**	1.00 (0.99-1.01) [2]	N/A	N/A
SPM	N/A	N/A	1.01 (0.99-1.02) [2]	N/A	N/A
O_3	1.02 (0.99-1.06) [2]	N/A	N/A	N/A	N/A

*Significant at the 95% CI level.

Values in [ ] are number of papers.

NA: Fewer than two eligible papers therefore meta-analysis not undertaken

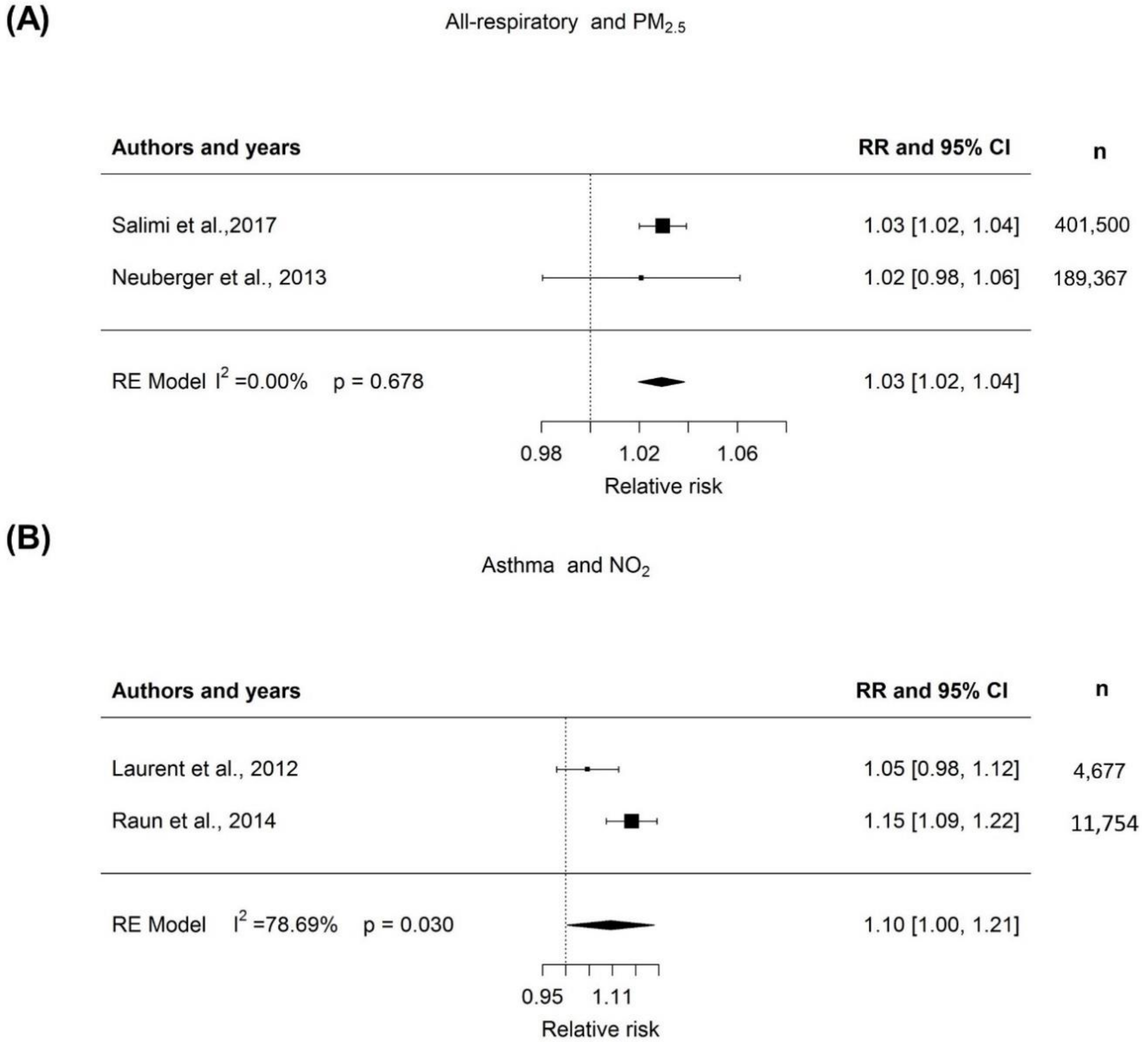

Figure 4-2 Forest plots for all-respiratory dispatches and $PM_{2.5}$ (A) and asthma dispatches and NO_2 (B) from ambulance dispatches. Relative risks (RR) are increment per 10 µg/m3 of $PM_{2.5}$, and 10 ppb of NO_2.

The I^2 statistic (Higgins's I^2 test statistic) is an explanation of the inconsistency of publications from heterogeneity by showing the proportion of percentage of variation. I^2 = 0-30%, ≥30-50% and ≥50% were defined as low, moderated and high heterogeneity respectively. The p-value from Cochran's Q test was report a significant level at 0.10 (10%). Abbreviations: n = the sample size

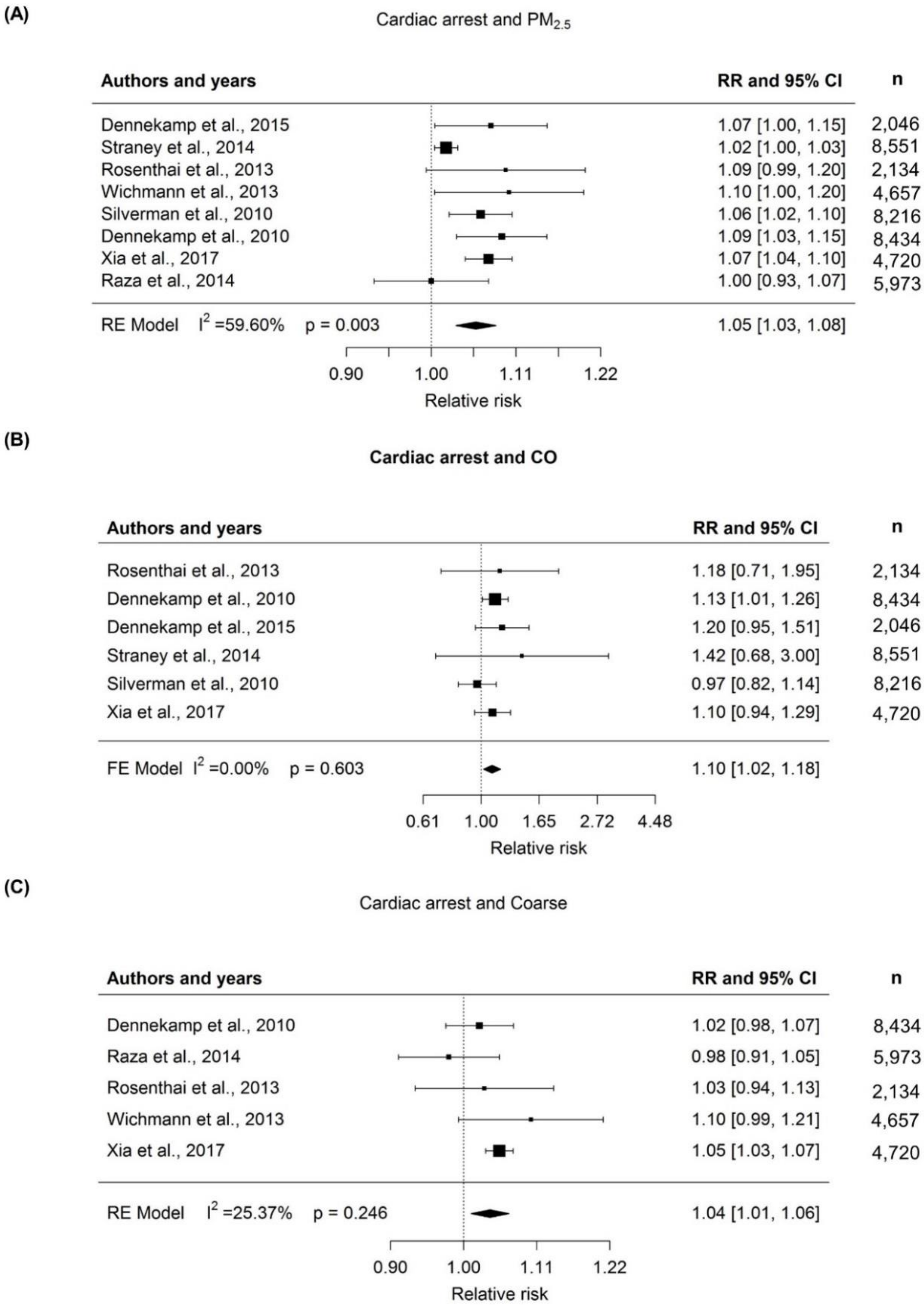

Figure 4-3 Forest plots for cardiac arrest dispatches and $PM_{2.5}$ (A), CO (B) and Coarse (C) from paramedic assessments. Relative risks (RR) are increment per 10 µg/m^3 of $PM_{2.5}$ and Coarse, 1 ppm of CO.

The I^2 statistic (Higgins's I^2 test statistic) is an explanation of the inconsistency of publications from heterogeneity by showing the proportion of percentage of variation. I^2 =

0-30%, ≥30-50% and ≥50% were defined as low, moderated and high heterogeneity respectively. The p-value from Cochran's Q test was report a significant level at 0.10 (10%). Abbreviations: n = the sample size

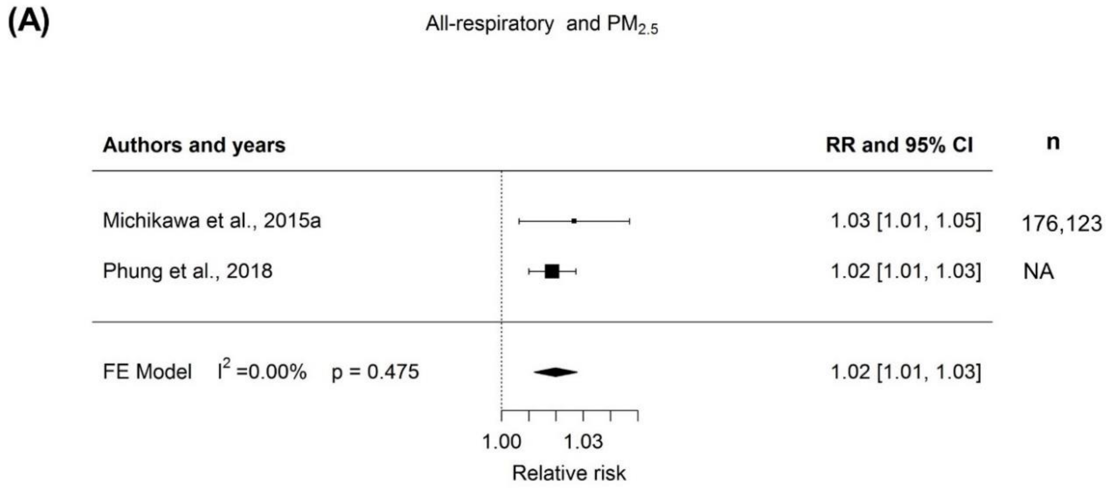

Figure 4-4 Forest plots for all-respiratory dispatches and $PM_{2.5}$ from physician diagnoses. Relative risks (RR) are increment per 10 µg/m^3 of $PM_{2.5}$.

The I^2 statistic (Higgins's I^2 test statistic) is an explanation of the inconsistency of publications from heterogeneity by showing the proportion of percentage of variation. I^2 = 0-30%, ≥ 30-50% and ≥ 50% were defined as low, moderated and high heterogeneity respectively. The p-value from Cochran's Q test was report a significant level at 0.10 (10%).
Abbreviations: NA: No available relevant data; n = the sample size

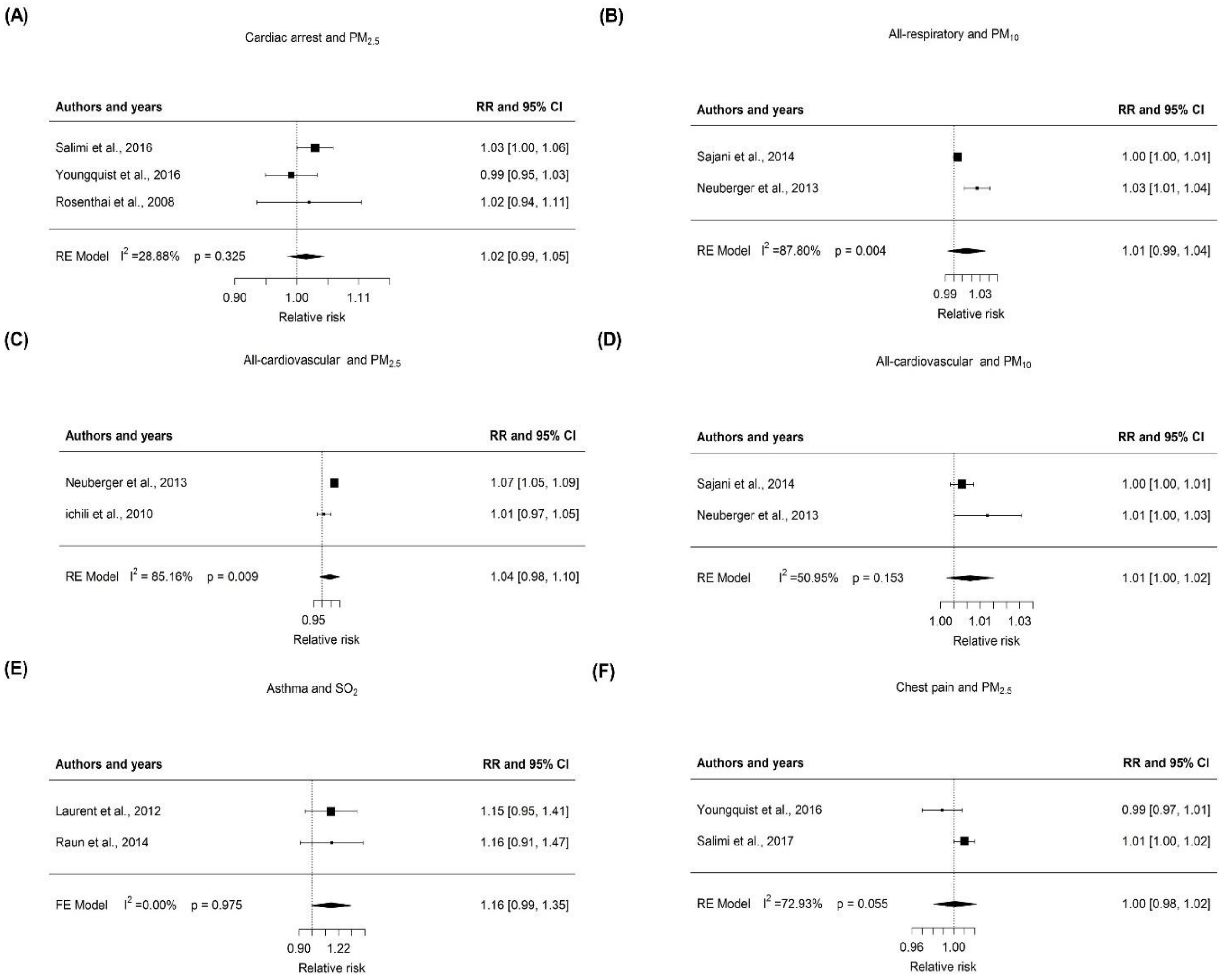

Figure 4-5 Forest plots for cardiac arrest dispatches and $PM_{2.5}$ (A), all-respiratory dispatches and PM_{10} (B), all-cardiovascular and $PM_{2.5}$ (C), all-cardiovascular and PM_{10} (D) and asthma dispatches and SO_2 (E), chest pain dispatches and $PM_{2.5}$ (F) for data with ambulance dispatches

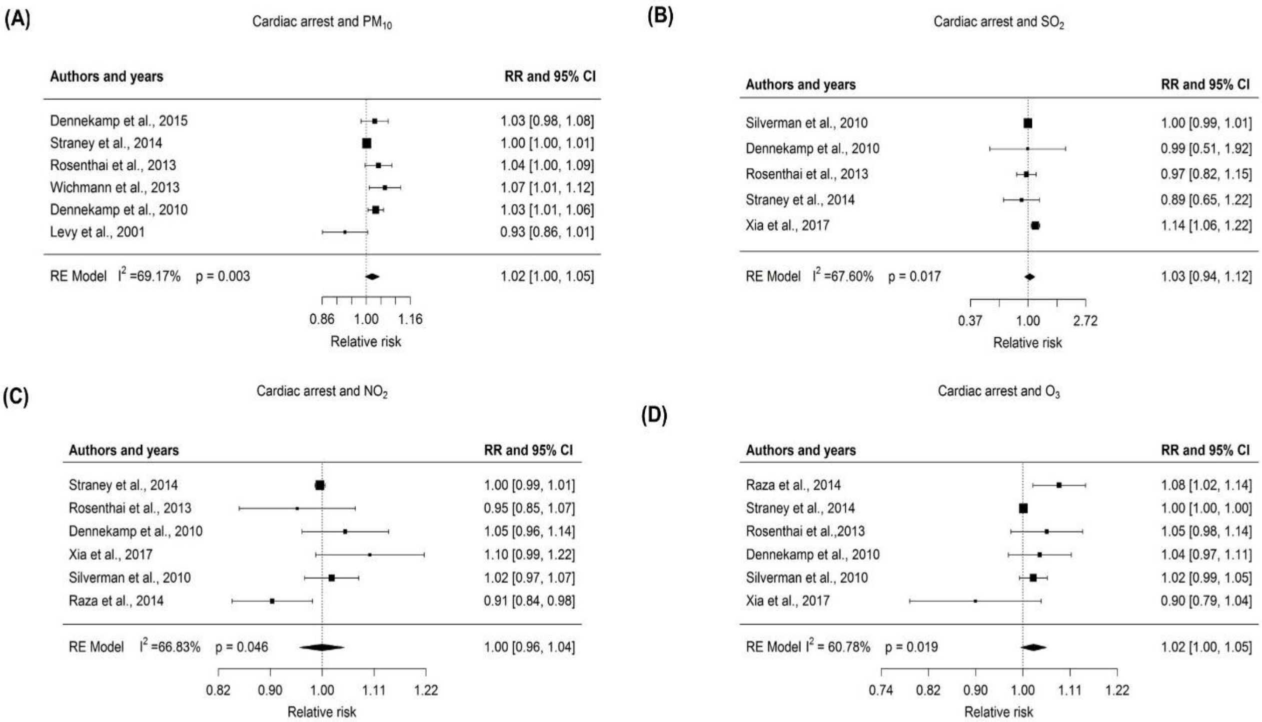

Figure 4-6 Forest plots for cardiac arrest dispatches and PM_{10} (A), cardiac arrest dispatches and SO_2 (B), cardiac arrest dispatches and NO_2 (C) and cardiac arrest dispatches and O_3 (D) for data with paramedic assessments

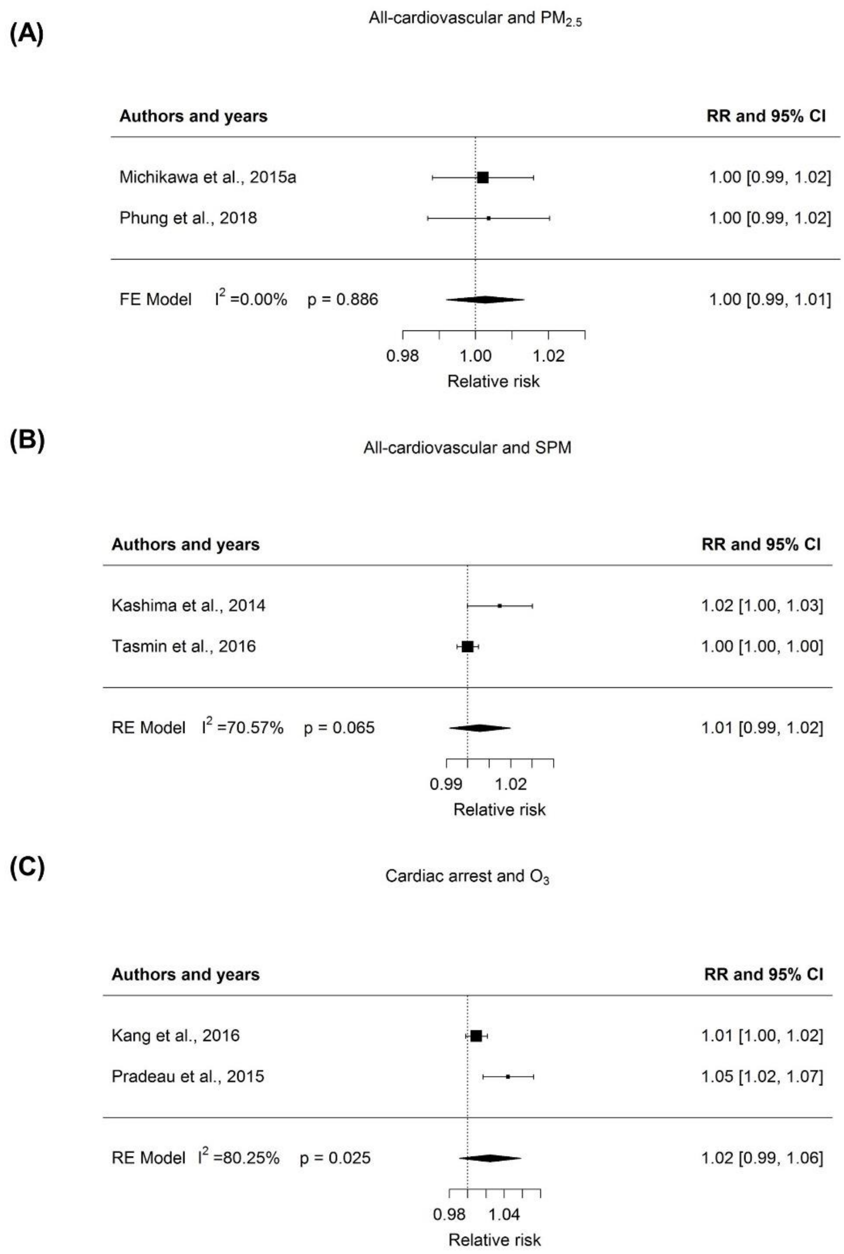

Figure 4-7 Forest plots for all-cardiovascular dispatches and $PM_{2.5}$ (A), all-cardiovascular dispatches and SPM (B) and cardiac arrest dispatches and O_3 (C) for data with subsequent hospital physician diagnosis

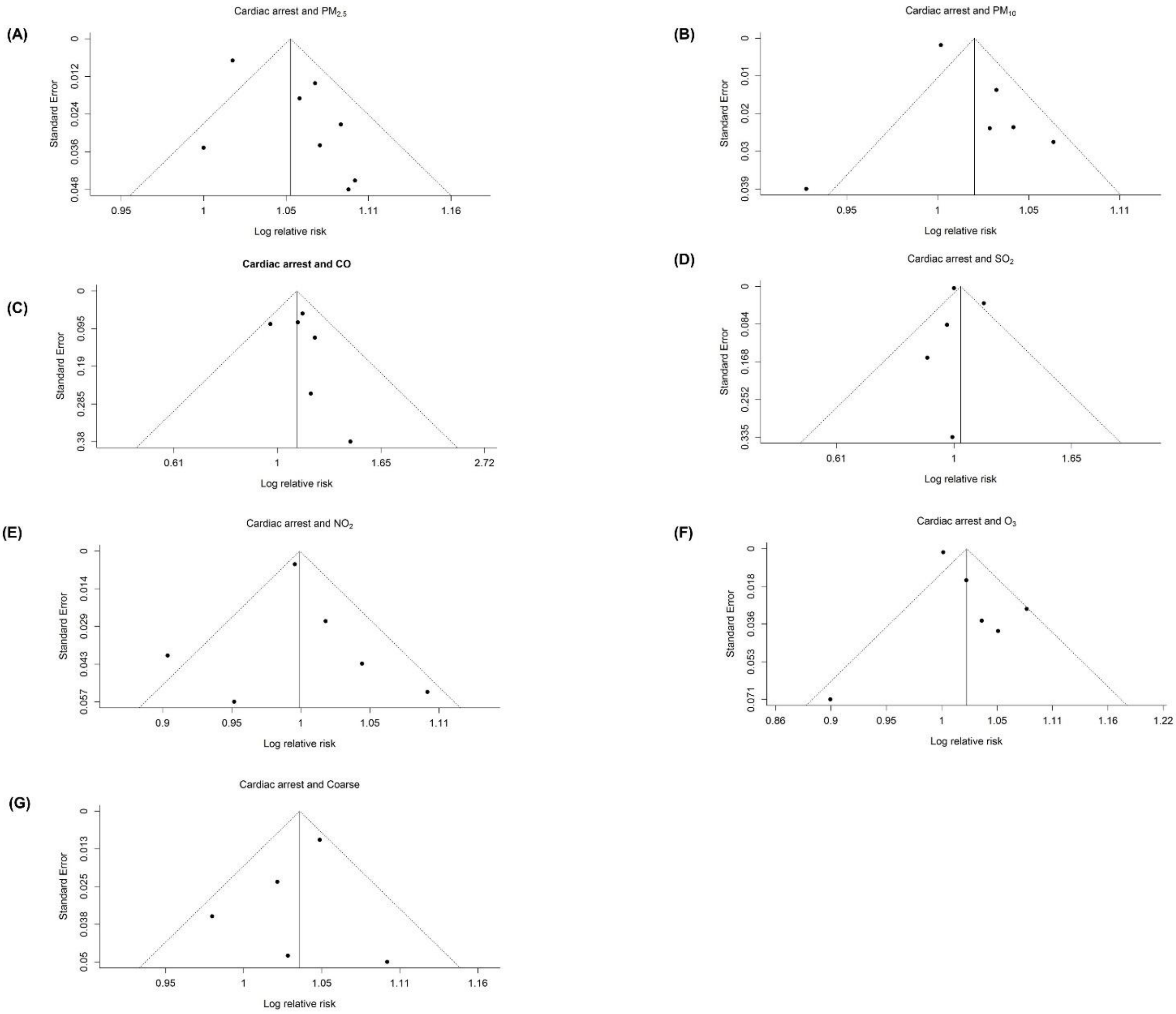

Figure 4-8 Funnel plots of cardiac arrest dispatches and $PM_{2.5}$ (A), cardiac arrest dispatches and PM_{10} (B), cardiac arrest dispatches and CO (C), cardiac arrest dispatches and SO_2 (D), cardiac arrest dispatches and NO_2 (E), cardiac arrest dispatches and O_3 (F), and cardiac arrest dispatches and coarse (G)

4.4.3 Sensitivity analyses

To assess the robustness of results, each individual study was removed from the group, and the pooled estimate re-analysed to identify the impact upon heterogeneity. These results are displayed in Table 4-7.

For the ambulance dispatch meta-analyses, cardiac arrest and $PM_{2.5}$ result was significant (RR=1.03, 95% CI: 1.00-1.06) when Youngquist et al. (2016) was removed, this also reduced the heterogeneity. For the dispatches that subsequently had paramedic assessment, there was a consistent significant pooled RR regardless of the paper removed for cardiac arrest and $PM_{2.5}$ and I^2 remained high regardless of whichever paper was removed in the analysis except when removing Straney et al. (2014), I^2 was decreased to 0.00%. For cardiac arrest and PM_{10} the result became significant when Levy et al. (2001) or Straney et al. (2014) were removed as RR = 1.03 (95% CI: 1.01-1.05), I^2 = 0.37%, p-value = 0.075 and RR = 1.03 (95% CI: 1.00-1.05), I^2 = 65.64%, p-value = 0.007. The pooled result remained significant when all papers except Dennekamp et al. (2010) was removed for cardiac arrest and CO, RR = 1.08 (95% CI: 0.97-1.20), I^2 = 8.57%, p-value = 0.522. For cardiac arrest and both SO_2 and NO_2 the result remained non-significant regardless of whichever paper was removed. For cardiac arrest and O_3 the result became significant when Straney et al. (2014) was removed, RR = 1.03 (95% CI: 1.01-1.06), I^2 = 18.29%, p-value = 0.156. For cardiac and coarse particulates the result became non-significant when either Wichmann et al. (2013) or Xia et al. (2017) were removed. Sensitivity analysis could not be undertaken for the physician diagnosis results as all groups had only two papers.

Table 4-7 Sensitivity analysis of the association between air pollution and ambulance dispatches (when remove publications)

Remove publications	Pooled RR (95% CI)	I^2 (p-value)
Ambulance dispatches		
Cardiac arrest-$PM_{2.5}$		
Salimi et al.,2016	1.00 (0.96-1.03)	0.00% (p=0.548)
Youngquist et al., 2016	1.03 (1.00-1.06)*	0.00% (p=0.830)
Rosenthal et al., 2008	1.01 (0.98-1.05)	55.50% (p=0.134)
All	1.02 (0.99-1.05)	28.88% (p=0.325)
Paramedic assessment		
Cardiac arrest-$PM_{2.5}$		
Dennekamp et al., 2015	1.05 (1.03-1.08)*	63.76% (p=0.003)
Straney et al., 2014	1.07 (1.05-1.09)*	0.00% (p=0.574)
Rosenthai et al,2013	1.05 (1.03-1.08)*	62.86% (p=0.003)

Remove publications	Pooled RR (95% CI)	I^2 (p-value)
Wichmann et al., 2013	1.05 (1.03-1.08)*	62.36% (p=0.003)
Silverman et al., 2010	1.05 (1.02-1.08)*	63.22% (p=0.003)
Dennekamp et al., 2010	1.05 (1.02-1.08)*	59.66% (p=0.007)
Xia et al.,2017	1.05 (1.02-1.08)*	55.26% (p=0.022)
Raza et al., 2014	1.06 (1.03-1.09)*	62.38% (p=0.003)
All	1.05 (1.03-1.08)*	59.60% (p=0.004)
Cardiac arrest-PM_{10}		
Dennekamp et al., 2015	1.02 (0.99-1.05)	79.96% (p=0.003)
Straney et al., 2014	1.03 (1.01-1.05)*	0.37% (p=0.075)
Rosenthai et al,2013	1.02 (0.99-1.05)	76.33% (p=0.005)
Wichmann et al., 2013	1.01 (0.99-1.04)	63.58% (p=0.013)
Dennekamp et al., 2010	1.02 (0.98-1.05)	72.30% (p=0.012)
Levy et al., 2001	1.03 (1.00-1.05)*	65.64% (p=0.007)
All	1.02 (1.00-1.05)	69.17% (p=0.003)
Cardiac arrest-CO		
Rosenthai et al,2013	1.10 (1.02-1.18)*	0.00% (p=0.468)
Dennekamp et al., 2010	1.08 (0.97-1.20)	8.57% (p=0.522)
Dennekamp et al., 2015	1.09 (1.00-1.18)*	2.11% (p=0.554)
Straney et al., 2014	1.10 (1.02-1.18)*	0.00% (p=0.530)
Silverman et al., 2010	1.14 (1.04-1.23)*	0.00% (p=0.949)
Xia et al., 2017	1.10 (1.01-1.19)*	16.49% (p=0.458)
All	1.10 (1.02-1.18)*	0.00% (p=0.603)
Cardiac arrest-SO_2		
Silverman et al., 2010	1.04 (0.91-1.19)	44.56% (p=0.200)
Dennekamp et al., 2010	1.03 (0.94-1.13)	74.13% (p=0.007)
Rosenthai et al,2013	1.04 (0.93-1.16)	75.37% (p=0.008)
Straney et al., 2014	1.04 (0.95-1.14)	73.38% (p=0.009)
Xia et al., 2017	1.00 (0.99-1.01)	0.00% (p=0.893)
All	1.03 (0.94-1.12)	67.60% (p=0.017)
Cardiac arrest-NO_2		
Straney et al., 2014	1.00 (0.94-1.07)	66.10% (p=0.025)
Rosenthai et al,2013	1.01 (0.96-1.06)	74.76% (p=0.031)
Dennekamp et al., 2010	0.99 (0.94-1.04)	72.40% (p=0.041)
Xia et al.,2017	0.99 (0.95-1.03)	58.29% (p=0.091)
Silverman et al., 2010	1.00 (0.94-1.05)	71.77% (p=0.032)
Raza et al., 2014	1.01 (0.99-1.01)	22.57% (p=0.223)
All	1.00 (0.96-1.04)	66.83% (p=0.046)
Cardiac arrest-O_3		
Raza et al., 2014	1.01 (0.99-1.03)	28.59% (p=0.159)
Straney et al., 2014	1.03 (1.01-1.06)*	18.29% (p=0.156)
Rosenthai et al,2013	1.02 (0.99-1.05)	66.37% (p=0.018)
Dennekamp et al., 2010	1.02 (0.99-1.06)	69.87% (p=0.014)
Silverman et al., 2010	1.03 (0.99-1.07)	60.03% (p= 0.020)
Xia et al., 2017	1.03 (1.00-1.06)	66.61% (p=0.022)
All	1.02 (1.00-1.05)	60.78% (0.019)

Remove publications	Pooled RR (95% CI)	I^2 (p-value)
Cardiac arrest-Coarse		
Dennekamp et al., 2010	1.04 (1.00-1.08)*	33.25% (p=0.206)
Raza et al., 2014	1.05 (1.03-1.06)*	0.00% (p=0.549)
Rosenthai et al,2013	1.04 (1.01-1.07)*	37.09% (p=0.148)
Wichmann et al., 2013	1.03 (1.00-1.06)	38.27% (p=0.220)
Xia et al.,2017	1.02 (0.99-1.06)	0.04% (p=0.338)
All	1.04 (1.01-1.06)*	25.37% (p=0.246)

* Statistically significant result at 95% CI level

4.4.4 Subgroup analyses

A subgroup analysis was conducted to calculate the risk of bias in the studies by region, by study design and by adjusted or unadjusted confounding factors. Consistent, statistically significant results were found in most of subgroup analyses. However, in the analysis by region, the pooled RR was not significant when only European paramedic papers were analyzed for cardiac arrest and $PM_{2.5}$, but became significant for PM_{10} and O_3. For analysis by study design all the results remained consistently significant or insignificant with the original results. For analysis by confounding factor the result for cardiac arrest and $PM_{2.5}$ became significant (RR = 1.03, 95% CI: 1.00-1.06) when only adjusted variables were used. In these studies the I^2 value was reduced suggesting the characteristics of the subgroups influences the role of pollution upon the subgroup by region (Table 4-8)

Table 4-8 Subgroup analysis of the association between air pollution and ambulance dispatches (where have more two paper in each subgroup and not for all paper in the same subgroup)

Subgroups	Categories	Studies (n)	Pooled RR (95% CI)	I^2 (p-value)
Ambulance dispatch				
Cardiac arrest-$PM_{2.5}$	**Region**			
	United States	2	1.00 (0.96-1.03)	0.00% (p=0.548)
	Europe	-	-	-
	Asia	-	-	-
	Australia	1	-	-
	Study design			

Subgroups	Categories	Studies (n)	Pooled RR (95% CI)	I^2 (p-value)
	Case-crossover	2	1.00 (0.96-1.03)	0.00% (p=0.548)
	Time series	1	-	-
	Adjusted variable			
	Adjusted[a]	2	1.03 (1.00-1.06)*	0.00% (p=0.830)
	Unadjusted	1	-	-
Paramedic assessment				
Cardiac arrest-$PM_{2.5}$	**Region**			
	United States	1	-	-
	Europe	3	1.05 (0.99-1.12)	45.09% (p=0.167)
	Asia	1	-	-
	Australia	3	1.05 (1.00-1.10)*	69.61% (p=0.024)
Cardiac arrest-PM_{10}	**Region**			
	United States	1	-	-
	Europe	2	1.05 (1.02-1.09)*	0.00% (p=0.539)
	Asia	-	-	-
	Australia	3	1.02 (0.99-1.04)	65.43% (p=0.045)
Cardiac arrest-CO	**Region**			
	United States	1	-	-
	Europe	1	-	-
	Asia	1	-	-
	Australia	3	1.15 (1.04-1.27)*	0.00% (p=0.765)
Cardiac arrest-SO_2	**Region**			
	United States	1	-	-
	Europe	1	-	-
	Asia	1	-	-
	Australia	2	0.91 (0.69-1.21)	0.00% (p=0.774)
Cardiac arrest-NO_2	**Region**			
	United States	1	-	-
	Europe	2	0.92 (0.87-0.98)	0.00% (0.487)
	Asia	1	-	-
	Australia	2	1.00 (0.99-1.01)	22.13% (p=0.257)
Cardiac arrest-O_3	**Region**			
	United States	1	-	-
	Europe	2	1.07 (1.02-1.12)*	0.00% (p=0.589)
	Asia	1	-	-

Subgroups	Categories	Studies (n)	Pooled RR (95% CI)	I^2 (p-value)
	Australia	2	1.00 (1.00-1.01)	4.07% (p=0.307)
Cardiac arrest-$PM_{2.5}$	**Study design**			
	Case-crossover	7	1.05 (1.02-1.08)*	63.22% (p=0.003)
	Time series	1	-	-
Cardiac arrest-CO	**Study design**			
	Case-crossover	5	1.14 (1.04-1.23)*	0.00% (p=0.949)
	Time series	1	-	-
Cardiac arrest-SO_2	**Study design**			
	Case-crossover	4	1.04 (0.91-1.19)	44.56% (p=0.200)
	Time series	1	-	-
Cardiac arrest-NO_2	**Study design**			
	Case-crossover	5	1.00 (0.94-1.05)	71.77% (p=0.032)
	Time series	1	-	-
Cardiac arrest-O_3	**Study design**			
	Case-crossover	5	1.03 (0.99-1.07)	60.03% (p=0.020)
	Time series	1	-	-

[a] The adjusted variables were temperature or relative humidity
* Statistically significant results at 95% CI level

4.5 Discussion

This study is the first systematic review and meta-analysis to focus solely on the association between outdoor air pollutants and health impacts as measured by ambulance dispatches. 33 relevant publications were identified and used to summarise the research in this field. 10 studies were based solely on ambulance dispatch data and physician diagnosis at the hospital, 13 were also informed by paramedic assessment on scene. There were four main categories of dispatches in the studies: cardiac arrest (n=14), all-cardiovascular dispatches (n=11), all-respiratory dispatches (n=10) and total dispatches were analysed in only 6 publications of the studies.

In total, 19 meta-analyses were undertaken to calculate the pooled health risks of exposure to 10 μg/m^3 of $PM_{2.5}$, PM_{10}, coarse particulates and SPM, 1 ppm of CO, and 10 ppb of SO_2, NO_2 and O_3 which six meta-analyses showed significant positive associations. For ambulance dispatch data, statistically significant relationships were found between all-respiratory and $PM_{2.5}$ (RR=1.03, 95% CI: 1.02-1.04) and asthma dispatches and NO_2 (RR=1.10, 95% CI: 1.00-1.21). For paramedic assessment data, the pooled RRs for cardiac arrest dispatches showed a significant positive association for $PM_{2.5}$ (RR = 1.05, 95% CI: 1.03-1.08), CO (RR = 1.10, 95% CI: 1.02-1.18) and coarse particulates (RR = 1.04, 95% CI: 1.01-1.06). For physician diagnosis data, $PM_{2.5}$ exposure was significantly associated with all-respiratory (RR = 1.02, 95% CI: 1.01-1.03). Of the remaining 13 meta-analyses, all found positive associations but did not reach statistical significance.

Consistent, statistically significant results were found in the three subgroup analyses that were performed: by region (United States, Europe, Asia and Australia); by study designs (time-series and case-crossover); and by adjusted or unadjusted results. There was high heterogeneity in most of the meta-analyses which is typical in this field of study. This may be driven by a number of factors such as differences in study design, demographic factors, meteorological factors, location and different chemical composition of particulate matter from different cities. This was, in general, reduced when subgroup analysis was undertaken as would be expected as you are likely to be reducing the heterogeneity if you limit the group to just studies from, for example, one study design or one continent. Interestingly, for ambulance dispatch data, the result for cardiac arrest and $PM_{2.5}$ became significant (RR=1.03 95%CI: 1.00-1.06) when only adjusted variables were used. For the paramedic data by region, the pooled RR for cardiac arrest became significant when only European papers were analysed for PM_{10} and O_3. The stronger consistency in subgroup analysis of European studies has also been found by Kunzil et al. (2000) and Xu et al. (2017) when they limited their analysis to European studies of the association between all-cardiovascular dispatches and $PM_{2.5}$.

These findings are generally consistent with Zhao et al. (2017) who included 15 studies in a meta-analysis of out-of-hospital cardiac arrest (OHCA) and air pollutants. They reported an increase in OHCA with a 10 μg/m^3 of PM_{10}, $PM_{2.5}$, NO_2 and O_3. However, our results differ from theirs as they found a significant association with PM_{10}, NO_2 and O_3 whereas our results were in the same direction and magnitude but not statistically significant. This may be due to the fact that our results were derived from a smaller number of studies (PM_{10} = 6, NO_2 = 6 and O_3 = 6) as we only included ambulance dispatch data, which may have underpowered our results (Shang et al., 2013). The pooled estimate RR for the association between cardiac arrest dispatches and exposure to CO was similar to a systematic review of air pollution and heart failure (Shah et al., 2013). This reported an increment of 1 ppm was associated with an increase in heart failure 3.52 % (95% CI: 2.52-4.54%).

Interestingly, given the evidence of the impact of air pollution on all-respiratory disease, only ten of the 33 primary studies analysed the effect of exposure to $PM_{2.5}$ (n = 5), PM_{10} (n = 2), SPM (n = 2), coarse (n = 1), BS (n = 1), NO_2 (n = 1) and SO_2 (n = 1). The meta-analysis of $PM_{2.5}$ exposure and all-respiratory dispatches was significantly associated both for data with ambulance dispatches and physician diagnosis assessments (RR = 1.03, 95% CI: 1.02-1.04) and (RR = 1.02, 95% CI: 1.01-1.03) respectively. This is consistent with other studies such as between exposure to $PM_{2.5}$ and acute lower respiratory infections (ALRI) (Mehta et al., 2013). The finding may be explained that $PM_{2.5}$ has a greater risk than a larger particle because $PM_{2.5}$ can be inhaled and penetrate deeply into the lung where it irritates the alveolar wall and lung function resulting in acute and chronic lung diseases (Jeong et al., 2019; Lin et al., 2016; Xing et al., 2016).

Results did not find a significant association between respiratory and PM_{10}. It has been suggested, the results for respiratory-particulate matter associations might not be consistent because of different particulate matter composition in different studies (Nhung et al., 2017, Lin et al., 2016). The literature shows a clear size effect of PM upon its health effects (Perez et al., 2009). The Lin et al. (2016) study found chemical constituents including organic carbon, elemental carbon, sulfate, nitrate and ammonium were associated with mortality due to cardiovascular diseases. The level of sulfate has also been associated with cardiovascular mortality (Mar et al., 2000). However, some studies could not find a significant association between sulfate and cardiovascular (Cao et al., 2012; Qiao et al., 2014). In general, the literature is unclear about the role of PM composition upon health. It might be expected that certain components would be more toxic, for example metals and organic acids, but the multicomponent nature of PM makes health associations difficult to discern. In the future, studies should examine the role of PM component and health outcomes to clarify the pattern of associations.

This study did not find significant associations between all-cardiovascular categories and pollutants. However, some studies based on mortality data have reported significant associations between pollutants and all-cardiovascular dispatches. For example, Shang et al. (2013) undertook meta-analysis from 33 publications for associations between air pollution and health impacts and they found for a 10 $\mu g/m^3$ increase of PM_{10}, the cardiovascular mortality excess risk was 0.36% (95%CI: 0.09-0.62%). The lack of association found in our study may be due to the classification of a wide variety of health outcomes into a broad all-cardiovascular category, which could have limited the chance of finding a statistically significant result (Johnston et al., 2019).

The results of the meta-analyses for the association between asthma dispatches and ambulance dispatches were significant for NO_2 (RR = 1.10, 95% CI: 1.00-1.21) but not significant for SO_2 (RR = 1.16, 95% CI: 0.99-1.35). The impact of NO_2 on increasing emergency visits for asthma has been recorded in previous research (Sunyer et al., 1997; Chauhan et al., 2003; Gauderman et al., 2005; Latza et al., 2009). This factor can be explained in terms of exposure to NO_2 is sensitive to inhaled allergens especially for those who have asthma as a pre existing condition. Moreover, exposure to NO_2 leads to decreasing function of alveolar macrophages and epithelial cells (Lee et al., 2006; Weinmayr et al., 2010). Our results for SO_2 was consistent with Sunyer et al. (1997) and Strickland et al. (2010) which also found a non-significant relationship.

This study has a number of limitations. Despite conducting a high-quality systematic review, the quality of the primary studies can impact on the interpretation of the findings. For example, where individual studies are poorly powered, even subsequent meta-analysis of the data may still provide an underpowered estimate potentially resulting in false negatives (type II error). However, this is a well-recognised and accepted limitation of this approach and a meta-analysis provides a more accurate estimate of the associated risk relative to the original studies, even where studies were adequately powered.

These results might underestimate the effects of air pollution as only the short-term acute exposure to air pollution was measured, but the ambulance dispatch data could be influenced by long-term chronic exposure to air pollution, as well as the additive temporal effects. Another limitation is the focus in these studies on single pollutants in isolation which ignores the potential synergistic effects of multiple pollutants and meteorological variables.

Furthermore, PM, NO_2 and SO_2 are not necessarily independent variables due to their partly common sources. There are also many possible reasons, other than changes in air pollution, for differences observed in ambulance dispatches other than those controlled for in the original studies such as gender, age, geographical areas (Clougherty, 2010), and different time lags including cumulative lags (Yang et al., 2018).

The significant meta-analysis results reported high heterogeneity for two of the six meta-analyses (although the I^2 reduces considerably with the removal of individual papers in the sensitivity analysis, whilst the RR remained similar). This indicates there was a lot of variability between the individual articles and therefore pooling them may not led to robust conclusions. In general, systematic reviews of these types of ecological studies have reported significant heterogeneity across all air pollutants due to differences in demographics, sample size and exposure misclassification. This is likely because of the low accuracy of point source measurements rather than personal monitoring (Shah et al., 2013). In the future, the association between pollutants and ambulance dispatches should be investigated in a more standardized fashion, for example by ensuring all studies examine, as a minimum, $PM_{2.5}$ with a 1 day lag, with results expressed as relative risk to enable meta-analysis with more homogeneous results.

There is also an issue with misclassification bias both for exposure and outcome misclassification. As is typical with these types of studies, air pollution exposures at the individual level are assumed from a small number of stationary air monitoring sites that are used to represent a whole city. This is not an ideal approach, but given the resource implications of the alternatives, it is the standard approach for this type of research. This may, though, underestimate the exposure in individuals in more polluted areas, for example those who live by busy road junctions. Furthermore, the category a dispatch is placed in is dependent on the information provided by the caller and the training of the call taker. For example, a ‘breathing difficulty’ dispatch might be classified as a heart attack by the paramedics when they collect more information at the scene and then will be further refined once more diagnostic testing is done at the hospital and an ICD-10 code attributed to the admission at a later date. Hence, the findings of this study will need to be interpreted carefully and this is why we have split the analysis into studies that (1) use ambulance dispatch data only (2) use ambulance dispatch data clarified by paramedic assessments on the scene and (3) ambulance dispatch data confirmed by physician diagnoses at the hospital. Future studies need more research to clarify the impact of air pollution on health outcomes for both short and long term exposure, especially in developing countries.

Comparison of the findings for short term exposure to air pollutants and health impacts from ambulance dispatch data were consistent with hospital or mortality data especially cardiac arrest dispatches. This fact highlights the robustness of this data which is often not captured elsewhere in the health dataset as many patients are treated by paramedics at the scene and then not subsequently transported to another healthcare setting.

The results of ambulance data studies can also be fed back to the public to potentially change behaviour (for example, by highlighting to key patient groups when increased dispatches for their conditions are likely so they can limit their exposure by not travelling) and to ambulance services for improved emergency and capacity planning. Public health policymakers should consider the impact of air pollution on adverse health outcomes and enable the provision of functional surveillance and early warning systems for air pollution reduction. This can lead to reductions in the burden of disease from exposure to air pollution, thereby increasing survival rates and reducing treatment costs.

4.6 Conclusion

Ambulance service data represent a significant signal in the health economy with some cities, such as London, experiencing over a million dispatches annually. These dispatches are an underused resource for researching the impacts of the environment on population health. A key environmental risk factor is ambient air pollution, as it is one of the leading causes of death and disability worldwide (WHO, 2018). Our meta-analyses show that increases in ambient air pollution, as measured by $PM_{2.5}$, CO, NO_2 and coarse particulate matter, are associated with increases in cardiac arrest, all-respiratory and asthma dispatches. To better understand these associations in some of the more polluted areas of the world, more studies are required in Low- and Middle-Income Countries. The outcomes from this study provide evidence that ambulance dispatches show similar associations to air pollutants to mortality or hospital data, especially the association between cardiac arrest and the exposure to $PM_{2.5}$, suggesting that ambulance dispatch data can capture out-of-care effects related to air pollution. In addition, this study will benefit ambulance services by highlighting statistically robust impacts of air pollutants on increasing in ambulance dispatches. This could support environmental policies to control pollutants around the world, especially particulate matter. In particular, this could allow for effective ambulatory planning during high air pollution episodes.

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4.9 Conflicts of interest

None.

4.10 References

Adar, S.D., Filigrana, P.A., Clements, N., Peel, J.L., 2014. Ambient Coarse Particulate Matter and Human Health: A Systematic Review and Meta-Analysis. Curr. Environ. Heal. Reports 1, 258–274. https://doi.org/10.1007/s40572-014-0022-z

Atkinson, R.W., Cohen, A., Mehta, S., Anderson, H.R., 2012. Systematic review and meta-analysis of epidemiological time-series studies on outdoor air pollution and health in Asia. Air Qual. Atmos. Heal. 5, 383–391. https://doi.org/10.1007/s11869-010-0123-2

Atkinson, R.W., Kang, S., Anderson, H.R., Mills, I.C., Walton, H.A., 2014. Epidemiological time series studies of PM2. 5 and daily mortality and hospital admissions: a systematic review and meta-analysis. Thorax thoraxjnl-2013-204492.

Aunan, K., Pan, X.C.C., 2004. Exposure-response functions for health effects of ambient air pollution applicable for China - A meta-analysis. Sci. Total Environ. 329, 3–16. https://doi.org/10.1016/j.scitotenv.2004.03.008

Cao, J., Xu, H., Xu, Q., Chen, B., Kan, H., 2012. Fine Particulate Matter Constituents and Cardiopulmonary Mortality in a Heavily Polluted Chinese City. Environ. Health Perspect. 120, 373–378. https://doi.org/10.1289/ehp.1103671

Carracedo-Martinez, E., Sanchez, C., Taracido, M., Saez, M., Jato, V., Figueiras, A., 2007. Original article: Effect of short-term exposure to air pollution and pollen on medical emergency calls: a case-crossover study in Spain. Allergy 63, 347–353. https://doi.org/10.1111/j.1398-9995.2007.01574.

Chauhan, A., Inskip, H.M., Linaker, C.H., Smith, S., Schreiber, J., Johnston, S.L., Holgate, S.T., 2003. Personal exposure to nitrogen dioxide (NO2) and the severity of virus-induced asthma in children. Lancet 361, 1939–1944. https://doi.org/10.1016/S0140-6736(03)13582-9

Checkoway, H., Levy, D., Sheppard, L., Kaufman, J., Koenig, J., Siscovick, D., 2000. A case-crossover analysis of fine particulate matter air pollution and out-of-hospital sudden cardiac arrest. Res. Rep. Health. Eff. Inst. 5-28; discussion 29-32.

Chen, R., Huang, W., Wong, C.-M., Wang, Z., Thach, T.Q., Chen, B., Kan, H., 2012a. Short-term exposure to sulfur dioxide and daily mortality in 17 Chinese cities: The China air pollution and health effects study (CAPES). https://doi.org/10.1016/j.envres.2012.07.003

Chen, R., Samoli, E., Wong, C.M., Huang, W., Wang, Z., Chen, B., Kan, H., 2012b. Associations between short-term exposure to nitrogen dioxide and mortality in 17 Chinese cities: The China Air Pollution and Health Effects Study (CAPES). Environ. Int. 45, 32–38. https://doi.org/10.1016/j.envint.2012.04.008

Chen, J., Jiang, X., Shi, C., Liu, R., Lu, R., Zhang, L., 2019. Association between gaseous pollutants and emergency ambulance dispatches for asthma in Chengdu, China: a time-stratified case-crossover study. https://doi.org/10.1186/s12199-019-0773-0

Clougherty, J.E., 2010. A growing role for gender analysis in air pollution epidemiology. Environ. Health Perspect. 118, 167–176. https://doi.org/10.1289/ehp.0900994

Deeks JJ, Higgins, JPT, A.D., 2004. Cochrane reviewers' handbook 4.2.2 [updated March 2004] [WWW Document]. Cochrane Libr. https://doi.org/10.1038/sj.ijo.0801229

Dennekamp, M., Akram, M., Abramson, M.J., Tonkin, A., Sim, M.R., Fridman, M., Erbas, B., 2010. Outdoor air pollution as a trigger for out-of-hospital cardiac arrests. Epidemiology 21, 494–500. https://doi.org/10.1097/EDE.0b013e3181e093db

Dennekamp, M., Straney, L.D., Erbas, B., Abramson, M.J., Keywood, M., Smith, K., Sim, M.R., Glass, D.C., Del Monaco, A., Haikerwal, A., Tonkin, A.M., 2015. Forest fire smoke exposures and out-of-hospital cardiac arrests in Melbourne, Australia: A case-crossover study. Environ. Health Perspect. 123, 959–964. https://doi.org/10.1289/ehp.1408436

Egger, M., Davey Smith, G., Schneider, M., Minder, C., 1997. Bias in meta-analysis detected by a simple, graphical test. BMJ 315, 629–34. https://doi.org/10.1136/BMJ.315.7109.629

European Energy Agency, 2015. Air pollution — European Environment Agency [WWW Document]. URL https://www.eea.europa.eu/themes/air/intro (accessed 4.25.18).

Franck, U., Odeh, S., Wiedensohler, A., Wehner, B., Herbarth, O., 2011. The effect of particle size on cardiovascular disorders - The smaller the worse. Sci. Total Environ. 409, 4217–4221. https://doi.org/10.1016/j.scitotenv.2011.05.049

Gauderman, W.J., Avol, E., Lurmann, F., Kuenzli, N., Gilliland, F., Peters, J., Mcconnell, R., 2005. Childhood Asthma and Exposure to Traffic and Nitrogen Dioxide. Source Epidemiol. 16, 737–743. https://doi.org/10.1097/01.ede.0000181308.51440.75

Grant, R.L., 2014. Converting an odds ratio to a range of plausible relative risks for better communication of research findings 7450, 1–7. https://doi.org/10.1136/bmj.f7450

Ichiki, T., Onozuka, D., Kamouchi, M., Hagihara, A., 2016. An association between fine particulate matter (PM2.5) levels and emergency ambulance dispatches for cardiovascular diseases in Japan. Int. Arch. Occup. Environ. Health 89, 1329–1335. https://doi.org/10.1007/s00420-016-1168-9

Jeong, S., Park, S.A., Park, I., Kim, P., Cho, N.H., Hyun, J.W., Hyun, Y.M., 2019. PM2.5 Exposure in the Respiratory System Induces Distinct Inflammatory Signaling in the Lung and the Liver of Mice. J. Immunol. Res. 2019. https://doi.org/10.1155/2019/3486841

Johnston, F.H., Salimi, F., Williamson, G.J., Henderson, S.B., Yao, J., Dennekamp, M., Smith, K., Abramson, M.J., Morgan, G.G., 2019. Ambient Particulate Matter and Paramedic Assessments of Acute Diabetic, Cardiovascular, and Respiratory Conditions. Epidemiology 30, 11–19. https://doi.org/10.1097/EDE.0000000000000929

Kan, H.-D., Chen, B.-H., Chen, C.-H., Wang, B.-Y., Fu, Q.-Y., 2005. Establishment of exposure-response functions of air particulate matter and adverse health outcomes in China and worldwide. Biomed. Environ. Sci. 18, 159–63.

Kang, S.H., Heo, J., Oh, I.Y., Kim, J., Lim, W.H., Cho, Y., Choi, E.K., Yi, S.M., Do Shin, S., Kim, H., Oh, S., 2016. Ambient air pollution and out-of-hospital cardiac arrest. Int. J. Cardiol. 203, 1086–1092. https://doi.org/10.1016/j.ijcard.2015.11.100

Kashima, S., Yorifuji, T., Suzuki, E., 2014. Asian dust and daily emergency ambulance calls among elderly people in Japan. J. Occup. Environ. Med. 56, 1277–1283. https://doi.org/10.1097/JOM.0000000000000334

Künzli, N., Kaiser, R., Medina, S., Studnicka, M., Chanel, O., Filliger, P., Herry, M., Horak, F., Puybonnieux-Texier, V., Quénel, P., Schneider, J., Seethaler, R., Vergnaud, J.-C., Sommer, H., 2000. Public-health impact of outdoor and traffic-related air pollution: a European assessment. Lancet 356, 795–801. https://doi.org/10.1016/S0140-6736(00)02653-2

Lai, H.-K., Tsang, H., Wong, C.-M., 2013. Meta-analysis of adverse health effects due to air pollution in Chinese populations. BMC Public Health 13, 360. https://doi.org/10.1186/1471-2458-13-360

Landrigan, P.J., Fuller, R., Acosta, N.J.R., Adeyi, O., Arnold, R., Basu, N., Baldé, A.B., Bertollini, R., Bose-O'Reilly, S., Boufford, J.I., Breysse, P.N., Chiles, T., Mahidol, C., Coll-Seck, A.M., Cropper, M.L., Fobil, J., Fuster, V., Greenstone, M., Haines, A., Hanrahan, D., Hunter, D., Khare, M., Krupnick, A., Lanphear, B., Lohani, B., Martin, K., Mathiasen, K. V., McTeer, M.A., Murray, C.J.L., Ndahimananjara, J.D., Perera, F., Potočnik, J., Preker, A.S., Ramesh, J., Rockström, J., Salinas, C., Samson, L.D., Sandilya, K., Sly, P.D., Smith, K.R., Steiner, A., Stewart, R.B., Suk, W.A., van Schayck, O.C.P., Yadama, G.N., Yumkella, K., Zhong, M., 2017. The Lancet Commission on pollution and health. Lancet 391, 462–512. https://doi.org/10.1016/S0140-6736(17)32345-0

Latza, U., Gerdes, S., Baur, X., 2009. Effects of nitrogen dioxide on human health: Systematic review of experimental and epidemiological studies conducted between 2002 and 2006. Int. J. Hyg. Environ. Health 212, 271–287. https://doi.org/10.1016/J.IJHEH.2008.06.003

Laurent, O., Benichou, J., Pedrono, G., Segala, C., Filleul, L., Deguen, S., Schillinger, C., Rivière, E., Bard, D., 2012. Estimating the short-term health impacts of air pollution in populations of divergent socioeconomic deprivation levels: A methodological challenge. Environnement, Risques et Sante 11, 52–60. https://doi.org/10.1684/ers.2012.0511

Lee, S.L., Wong, W.H.S., Lau, Y.L., 2006. Association between air pollution and asthma admission among children in Hong Kong, Clinical and Experimental Allergy. https://doi.org/10.1111/j.1365-2222.2006.02555.x

Levy, D., Sheppard, L., Checkoway, H., Kaufman, J., Lumley, T., Koenig, J., Siscovick, D., 2001. A case-crossover analysis of particulate matter air pollution and out-of-hospital primary cardiac arrest. Epidemiology 12, 193–199. https://doi.org/10.1097/00001648-200103000-00011

Lin, H., Tao, J., Du, Y., Liu, T., Qian, Z., Tian, L., Di, Q., Rutherford, S., Guo, L., Zeng, W., Xiao, J., Li, X., He, Z., Xu, Y., Ma, W., 2016. Particle size and chemical constituents of ambient particulate pollution associated with cardiovascular mortality in Guangzhou, China. Environ. Pollut. 208, 758–766. https://doi.org/10.1016/J.ENVPOL.2015.10.056

Liu, R., Zeng, J., Jiang, X., Chen, J., Gao, X., Zhang, L., Li, T., 2017. The relationship between airborne fine particle matter and emergency ambulance dispatches in a southwestern city in Chengdu, China. Environ. Pollut. 229, 661–667. https://doi.org/10.1016/j.envpol.2017.06.098

Lu, F., Xu, D., Cheng, Y., Dong, S., Guo, C., Jiang, X., Zheng, X., 2015. Systematic review and meta-analysis of the adverse health effects of ambient PM2.5and PM10pollution in the Chinese population. Environ. Res. 136, 196–204. https://doi.org/10.1016/j.envres.2014.06.029

Mahmood, M., Thornes, J., Pope, F., Fisher, P. and Vardoulakis, S., 2017. Impact of air temperature on London ambulance call-out incidents and response times. Climate, 5(3), p.61. https://doi.org/10.3390/cli5030061

Mar, T.F., Norris, G.A., Koenig, J.Q., Larson, T. V, 2000. Associations between air pollution and mortality in Phoenix, 1995-1997. Environ. Health Perspect. 108, 347–353. https://doi.org/10.1289/ehp.00108347

Mehta, S., Shin, H., Burnett, R., North, T., Cohen, A.J., 2013. Ambient particulate air pollution and acute lower respiratory infections: a systematic review and implications for estimating the global burden of disease. Air Qual. Atmos. Heal. 6, 69–83. https://doi.org/10.1007/s11869-011-0146-3

Michikawa, T., Ueda, K., Takeuchi, A., Kinoshita, M., Hayashi, H., Ichinose, T., Nitta, H., 2015a. Impact of short-term exposure to fine particulate matter on emergency ambulance dispatches in Japan. J. Epidemiol. Community Health 69, 86–91. https://doi.org/10.1136/jech-2014-203961

Michikawa, T., Ueda, K., Takeuchi, A., Tamura, K., Kinoshita, M., Ichinose, T., Nitta, H., 2015b. Coarse particulate matter and emergency ambulance dispatches in Fukuoka, Japan: a time-stratified case-crossover study. Environ. Health Prev. Med. 20, 130–136. https://doi.org/10.1007/s12199-014-0439-x

Modesti, P.A., Reboldi, G., Cappuccio, F.P., Agyemang, C., Remuzzi, G., Rapi, S., Perruolo, E., Parati, G., 2016. Panethnic Differences in Blood Pressure in Europe: A Systematic Review and Meta-Analysis. PLoS One 11, e0147601. https://doi.org/10.1371/journal.pone.0147601

Neuberger, M., Moshammer, H., Rabczenko, D., 2013. Acute and subacute effects of urban air pollution on cardiopulmonary emergencies and mortality: Time series studies in Austrian cities. Int. J. Environ. Res. Public Health 10, 4728–4751. https://doi.org/10.3390/ijerph10104728

Nhung, N.T.T., Amini, H., Schindler, C., Kutlar Joss, M., Dien, T.M., Probst-Hensch, N., Perez, L., Künzli, N., 2017. Short-term association between ambient air pollution and pneumonia in children: A systematic review and meta-analysis of time-series and case-crossover studies. Environ. Pollut. 230, 1000–1008. https://doi.org/10.1016/j.envpol.2017.07.063

Peng, R. and Dominici, F., (2008). Statistical Methods for Environmental Epidemiology with R: A case Study in Air Pollution and Health. Batimore, Maryland: Springer, pp.69-71.

Perez, L., Medina-Ramón, M., Künzli, N., Alastuey, A., Pey, J., Pérez, N., Garcia, R., Tobias, A., Querol, X., Sunyer, J., 2009. Size Fractionate Particulate Matter, Vehicle Traffic, and Case-Specific Daily Mortality in Barcelona, Spain. Environ. Sci. Technol. 43, 4707–4714. https://doi.org/10.1021/es8031488

Phung, V.L.H., Ueda, K., Kasaoka, S., Seposo, X., Tasmin, S., Yonemochi, S., Phosri, A., Honda, A., Takano, H., Michikawa, T., Nitta, H., 2018. Acute effects of ambient PM2.5on all-cause and cause-specific emergency ambulance dispatches in Japan. Int. J. Environ. Res. Public Health 15, 1–12. https://doi.org/10.3390/ijerph15020307

Pradeau, C., Rondeau, V., Lévèque, E., Guernion, P.Y., Tentillier, E., Thicoip, M., Brochard, P., 2015. Air pollution and activation of mobile medical team for out-of-hospital cardiac arrest. Am. J. Emerg. Med. 33, 367–372. https://doi.org/10.1016/j.ajem.2014.12.007

Qiao, L., Cai, J., Wang, H., Wang, W., Zhou, M., Lou, S., Chen, R., Dai, H., Chen, C., Kan, H., 2014. PM 2.5 Constituents and Hospital Emergency-Room Visits in Shanghai, China. Environ. Sci. Technol. 48, 10406–10414. https://doi.org/10.1021/es501305k

Raun, L.H., Ensor, K.B., Persse, D., 2014. Using community level strategies to reduce asthma attacks triggered by outdoor air pollution: a case crossover analysis. Environ. Heal. 13. https://doi.org/10.1186/1476-069x-13-58

Raza, A., Bellander, T., Bero-Bedada, G., Dahlquist, M., Hollenberg, J., Jonsson, M., Lind, T., Rosenqvist, M., Svensson, L., Ljungman, P.L.S., 2013. Short-term effects of air pollution on out-of-hospital cardiac arrest in Stockholm. Eur. Heart J. 35, 861–868. https://doi.org/10.1093/eurheartj/eht489

Riley, R.D., Higgins, J.P.T., Deeks, J.J., 2011. Interpretation of random effects meta-analyses. BMJ 342, d549. https://doi.org/10.1136/bmj.d549

Ronksley, P.E., Brien, S.E., Turner, B.J., Mukamal, K.J., Ghali, W.A., 2011. Association of alcohol consumption with selected cardiovascular disease outcomes: A systematic review and meta-analysis. Bmj 342, 479. https://doi.org/10.1136/bmj.d671

Rosenthal, F.S., Carney, J.P., Olinger, M.L., 2008. Out-of-hospital cardiac arrest and airborne fine particulate matter: A case-crossover analysis of emergency medical services data in Indianapolis, Indiana. Environ. Health Perspect. 116, 631–636. https://doi.org/10.1289/ehp.10757

Rosenthal, F.S., Kuisma, M., Lanki, T., Hussein, T., Boyd, J., Halonen, J.I., Pekkanen, J., 2013. Association of ozone and particulate air pollution with out-of-hospital cardiac arrest in Helsinki, Finland: Evidence for two different etiologies. J. Expo. Sci. Environ. Epidemiol. 23, 281–288. https://doi.org/10.1038/jes.2012.121

Sajani, S.Z., Alessandrini, E., Marchesi, S., Lauriola, P., 2014. Are day-to-day variations of airborne particles associated with emergency ambulance dispatches? Int. J. Occup. Environ. Health 20, 71–76. https://doi.org/10.1179/2049396713Y.0000000045

Salimi, F., Henderson, S.B., Morgan, G.G., Jalaludin, B., Johnston, F.H., 2017. Ambient particulate matter, landscape fire smoke, and emergency ambulance dispatches in Sydney, Australia. Environ. Int. 99, 208–212. https://doi.org/10.1016/j.envint.2016.11.018

Shah, A.S. V, Langrish, J.P., Nair, H., Mcallister, D.A., Hunter, A.L., Donaldson, K., Newby, D.E., Mills, N.L., 2013. Global association of air pollution and heart failure: a systematic review and meta-analysis. www.thelancet.com 382, 1039. https://doi.org/10.1016/S0140-6736(13)60898-3

Shang, Y., Sun, Z., Cao, J., Wang, X., Zhong, L., Bi, X., Li, H., Liu, W., Zhu, T., Huang, W., 2013. Systematic review of Chinese studies of short-term exposure to air pollution and daily mortality. Environ. Int. 54, 100–111. https://doi.org/10.1016/j.envint.2013.01.010

Shor, E., Roelfs, D., Vang, Z.M., 2017. The “Hispanic mortality paradox” revisited: Meta-analysis and meta-regression of life-course differentials in Latin American and Caribbean immigrants’ mortality. Soc. Sci. Med. 186, 20–33. https://doi.org/10.1016/j.socscimed.2017.05.049

Silverman, R.A., Ito, K., Freese, J., Kaufman, B.J., De Claro, D., Braun, J., Prezant, D.J., 2010. Association of ambient fine particles with out-of-hospital cardiac arrests in New York city. Am. J. Epidemiol. 172, 917–923. https://doi.org/10.1093/aje/kwq217

Straney, L., Finn, J., Dennekamp, M., Bremner, A., Tonkin, A., Jacobs, I., 2014. Evaluating the impact of air pollution on the incidence of out-of-hospital cardiac arrest in the Perth Metropolitan Region: 2000-2010. J. Epidemiol. Community Health 68, 6–12. https://doi.org/10.1136/jech-2013-202955

Strickland, M.J., Darrow, L.A., Klein, M., Flanders, W.D., Sarnat, J.A., Waller, L.A., Sarnat, S.E., Mulholland, J.A., Tolbert, P.E., 2010. Short-term Associations between Ambient Air Pollutants and Pediatric Asthma Emergency Department Visits. Am. J. Respir. Crit. Care Med. 182, 307–316. https://doi.org/10.1164/rccm.200908-1201OC

Sun, J., Barnes, A., He, D., Wang, M., Wang, J., Sun, J., Barnes, A.J., He, D., Wang, M., Wang, J., 2017. Systematic Review and Meta-Analysis of the Association between Ambient Nitrogen Dioxide and Respiratory Disease in China. Int. J. Environ. Res. Public Health 14, 646. https://doi.org/10.3390/ijerph14060646

Sunyer, J., Spix, C., Quénel, P., Ponce-De-Leó, A., Pönka, A., Barumandzadeh, T., Touloumi, G., Bacharova, L., Wojtyniak, B., Vonk, J., Bisanti, L., Schwartz, J., Katsouyanni, K., 1997. Original articles Urban air pollution and emergency admissions for asthma in four European cities: the APHEA Project The associations between asthma ad-missions and NO 2 in adults and SO 2 in children were independent of black smoke. Methods Conclusions-The evidence of an as-The number of asthma admissions on each. Thorax 52, 760–765. https://doi.org/10.1136/thx.52.9.760

Sutton, A.J., 2000. Empirical assessment of effect of publication bias on meta-analyses. Bmj 320, 1574–1577. https://doi.org/10.1136/bmj.320.7249.1574

Tasmin, S., Ueda, K., Stickley, A., Yasumoto, S., Phung, V.L.H., Oishi, M., Yasukouchi, S., Uehara, Y., Michikawa, T., Nitta, H., 2016. Short-term exposure to ambient particulate matter and emergency ambulance dispatch for acute illness in Japan. Sci. Total Environ. 566–567, 528–535. https://doi.org/10.1016/j.scitotenv.2016.05.054

Teng, T.-H.K., Williams, T.A., Bremner, A., Tohira, H., Franklin, P., Tonkin, A., Jacobs, I., Finn, J., 2014. A systematic review of air pollution and incidence of out-of-hospital cardiac arrest. J. Epidemiol. Community Health 68, 37–43. https://doi.org/10.1136/jech-2013-203116

Ueda, K., Shimizu, A., Nitta, H., Inoue, K., 2012. Long-range transported Asian Dust and emergency ambulance dispatches. Inhal. Toxicol. 24, 858–867. https://doi.org/10.3109/08958378.2012.724729

Valentine, J.C., Pigott, T.D., Rothstein, H.R., 2010. How Many Studies Do You Need? A Primer on Statistical Power for Meta-Analysis. J. Educ. Behav. Stat. 35, 215–247. https://doi.org/10.3102/1076998609346961

Vencloviene, J., Babarskiene, R.M., Dobozinskas, P., Dedele, A., Lopatiene, K., Ragaisyte, N., 2017a. The short-term associations of weather and air pollution with emergency ambulance calls for paroxysmal atrial fibrillation. Environ. Sci. Pollut. Res. 24, 15031–15043. https://doi.org/10.1007/s11356-017-9138-7

Vencloviene, J., Braziene, A., Dedele, A., Lopatiene, K., Dobozinskas, P., 2017b. Associations of short-term exposure to ambient air pollutants with emergency ambulance calls for the exacerbation of essential arterial hypertension. Int. J. Environ. Health Res. 27, 509–524. https://doi.org/10.1080/09603123.2017.1405246

Walters, S., Griffiths, R.K., Ayres, J.G., 1994. Temporal association between hospital admissions for asthma in Birmingham and ambient levels of sulphur dioxide and smoke. Thorax 49, 133–40. https://doi.org/10.1136/THX.49.2.133

Weinmayr, G., Romeo, E., de Sario, M., Weiland, S.K., Forastiere, F., 2010. Short-Term effects of PM10 and NO2 on respiratory health among children with asthma or asthma-like symptoms: A systematic review and Meta-Analysis. Environ. Health Perspect. https://doi.org/10.1289/ehp.0900844

Wells, G., Shea, B., O'Connell, D., Peterson, J., Welch, V., Losos, M., Tugwell, P., 2013. Ottawa Hospital Research Institute [WWW Document]. URL http://www.ohri.ca/programs/clinical_epidemiology/oxford.asp (accessed 9.13.18).

WHO, 2018. Ambient (outdoor) air quality and health [WWW Document]. World Heal. Organ. URL http://www.who.int/en/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health (accessed 5.11.18).

Wichmann, J., Folke, F., Torp-Pedersen, C., Lippert, F., Ketzel, M., Ellermann, T., Loft, S., 2013. Out-of-Hospital Cardiac Arrests and Outdoor Air Pollution Exposure in Copenhagen, Denmark. PLoS One 8. https://doi.org/10.1371/journal.pone.0053684

Woodward, M., 2013. Epidemiology. Chapman and Hall/CRC. https://doi.org/10.1201/b16343

Xia, R., Zhou, G., Zhu, T., Li, X., Wang, G., 2017. Ambient air pollution and out-of-hospital cardiac arrest in beijing, china. Int. J. Environ. Res. Public Health 14. https://doi.org/10.3390/ijerph14040423

Xing, Y.F., Xu, Y.H., Shi, M.H., Lian, Y.X., 2016. The impact of PM2.5 on the human respiratory system. J. Thorac. Dis. https://doi.org/10.3978/j.issn.2072-1439.2016.01.19

Xu, Q., Wang, S., Guo, Y., Wang, C., Huang, F., Li, X., Gao, Q., Wu, L., Tao, L., Guo, J., Wang, W., Guo, X., 2017. Acute exposure to fine particulate matter and cardiovascular hospital emergency room visits in Beijing, China. Environ. Pollut. 220, 317–327. https://doi.org/10.1016/J.ENVPOL.2016.09.065

Yang, B.Y., Qian, Z., Howard, S.W., Vaughn, M.G., Fan, S.J., Liu, K.K., Dong, G.H., 2018. Global association between ambient air pollution and blood pressure: A systematic review and meta-analysis. Environ. Pollut. 235, 576–588. https://doi.org/10.1016/j.envpol.2018.01.001

Yang, C., Chen, A., Chen, R., Qi, Y., Ye, J., Li, S., Li, W., Liang, Z., Liang, Q., Guo, D., Kan, H., Chen, X., 2014. Acute effect of ambient air pollution on heart failure in Guangzhou, China. Int. J. Cardiol. 177, 436–441. https://doi.org/10.1016/j.ijcard.2014.09.003

Youngquist, S.T., Hood, C.H., Hales, N.M., Barton, C.C., Madsen, T.E., Arden Pope, C., 2016. Association between EMS calls and fine particulate air pollution in Utah. Air Qual. Atmos. Heal. 9, 887–897. https://doi.org/10.1007/s11869-016-0392-5

Zhao, R., Chen, S., Wang, W., Huang, J., Wang, K., Liu, L., Wei, S., 2017. The impact of short-term exposure to air pollutants on the onset of out-of-hospital cardiac arrest: A systematic review and meta-analysis. Int. J. Cardiol. 226, 110–117. https://doi.org/10.1016/j.ijcard.2016.10.053

Zheng, X., Ding, H., Jiang, L., Chen, S., Zheng, J., Qiu, M., Zhou, Y., Chen, Q., Guan, W., 2015. Association between Air Pollutants and Asthma Emergency Room Visits and Hospital Admissions in Time Series Studies: A Systematic Review and Meta-Analysis. PLoS One 10, e0138146. https://doi.org/10.1371/journal.pone.0138146

4.11 Supplemental Material

Table 4-9 PRISMA Checklist

Section/topic	#	Checklist item	Reported on page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	76
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	77
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	78
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).	63 (Chapter 3)
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	80
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	81-82
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	81-82
Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.	81-82
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	81-83
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	83-84

Section/topic	#	Checklist item	Reported on page #
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	80-81
Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.	84
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means).	86-87
Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis.	87
Risk of bias across studies	15	Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).	84-85
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.	87
RESULTS			
Study selection	17	Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.	88
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.	91-101
Risk of bias within studies	19	Present data on risk of bias of each study and, if available, any outcome level assessment (see item 12).	91-101
Results of individual studies	20	For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group (b) effect estimates and confidence intervals, ideally with a forest plot.	104-109
Synthesis of results	21	Present results of each meta-analysis done, including confidence intervals and measures of consistency.	104-109
Risk of bias across studies	22	Present results of any assessment of risk of bias across studies (see Item 15).	90-99
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).	110-115

Section/topic	#	Checklist item	Reported on page #
DISCUSSION			
Summary of evidence	24	Summarise the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., healthcare providers, users, and policy makers).	115-121
Limitations	25	Discuss limitations at study and outcome level (e.g., risk of bias), and at review-level (e.g., incomplete retrieval of identified research, reporting bias).	120
Conclusions	26	Provide a general interpretation of the results in the context of other evidence, and implications for future research.	121-122
FUNDING			
Funding	27	Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.	122

CHAPTER 5 : IMPACT OF EXTREME TEMPERATURES ON AMBULANCE DISPATCHES IN LONDON, UK

The work presented in Chapter 5, most of the material was published or under process in following journals:

References:

Sangkharat, K., Mahmood, M.A., Thornes, J.E., Fisher, P.A. and Pope, F.D., 2020. Impact of extreme temperatures on ambulance dispatches in London, UK. Environmental Research, p.109100.

The declaration of author:

Kamolrat Sangkharat: Designed for study design, collected data, analysed data and wrote the manuscript;

Marliyyah Mahmood: Reviewed, edited and revised the manuscript;

John Thrones: Reviewed, edited and revised the manuscript;

Paul Fisher: Reviewed, edited and revised the manuscript;

Francis Pope: Reviewed, edited and revised the manuscript;

5.1 Abstract

Associations between extreme temperatures and health outcomes, such as mortality and morbidity, are often observed. However, relatively little research has investigated the role of extreme temperatures upon ambulance dispatches. A time series analysis using London Ambulance Service (LAS) incident data (2010-2014), consisting of 5,252,375 dispatches was conducted. A generalized linear model (GLM) with a quasi-likelihood Poisson regression was applied to analyse the associations between ambulance dispatches and temperature. The 99th (22.8°C) and 1st (0.0°C) percentiles of temperature were defined as extreme high and low temperature.

Fourteen categories of ambulance dispatches were investigated, grouped into 'respiratory' (asthma, dyspnoea, respiratory chest infection, respiratory arrest and chronic obstructive pulmonary disease), 'cardiovascular' (cardiac arrest, chest pain, cardiac chest pain, cardiac arrhythmia and other cardiac problems) and 'other' non-cardiorespiratory (dizzy, alcohol related, vomiting and 'generally unwell') categories. The effects of long-term trends, seasonality, day of the week, public holidays and air pollution were controlled for in the GLM. The lag effect of temperature was also investigated. The threshold temperatures for each category were identified and a distributed lag non-linear model (DLNM) was reported using relative risk (RR) values at 95% confidence intervals.

Many dispatch categories show significant associations with extreme temperature. Total calls from 999 dispatches and 'generally unwell' dispatch category show significant RRs at both low and high temperatures. Most respiratory categories (asthma, dyspnoea and RCI) have significant RRs at low temperatures represented by estimated RR ranging from 1.392 (95%CI: 1.161-1.699) for asthma to 2.075 (95%CI: 1.673-2.574) for RCI. The RRs for all other non-cardiorespiratory dispatches were often significant for high temperatures ranging from 1.280 (95% CI: 1.128-1.454) for ‘generally unwell’ to 1.985 (95%CI: 1.422-2.773) for alcohol-related. For the cardiovascular group, only chest pain dispatches reported a significant RR at high temperatures. Therefore, ambulance dispatches can be associated with extreme temperatures, dependent on the dispatch category. It is recommended that meteorological factors are factored into ambulance forecast models and warning systems, allowing for improvements in ambulance service efficiency.

Keywords: ambulance; emergency services; health; temperature; extreme events

5.2 Introduction

Previous research has shown significant associations between meteorological variables and health. Typically, this research has focused on mortality and hospital admission data to examine the impact of meteorology on health, especially with respect to respiratory and cardiovascular diseases (Elliot et al., 2016; Hajat et al., 2007; Medina-Ramón et al., 2006; Wichmann, 2004). The World Health Organization (WHO) has highlighted that rising temperatures, due to climate change, can increase mortality and morbidity due to increased heat stress (World Health Organization, 2017). However, rising temperatures could also diminish the effect of cold weather upon health.

Previous research has shown the relationship between temperature and health outcomes exhibits a U-, V- or J-shaped curve. U and V relationships show both hot and cold effects, whereas J relationships only show effects at one temperature extreme. A landmark study by (Gasparrini et al., 2015a) investigated a large mortality dataset from 14 countries. A bigger percentage of temperature-attributable mortality were found in cold conditions (7.29%; 95%

CI: 7.02-7.49) compared to hot conditions (0.42%; 95% CI: 0.39-0.44). Systematic reviews have reported a significant increase in risks of mortality and morbidity at low temperature: 66% of studies reported that low temperatures are associated with rising myocardial infarction (MI) (Bhaskaran et al., 2009). In elderly people, increasing temperature by 1°C above 15°C, increased mortality by 2-5% and decreasing temperature by 1°C, below 15°C, increased mortality by 1% (Yu et al., 2012). Hajat et al. (2007) reported that both low and high temperatures, set at 5^{th} and 95^{th} percentiles, were related to increases in respiratory and cardiovascular diseases with a relative risk (RR) of 1.03 (95% CI: 1.02-1.03) and 1.06 (95% CI: 1.05-1.06) respectively. Stafoggia et al. (2008) highlighted that high temperatures led to a significant increase in heat-related mortality rates and was associated with acute heart failure, stroke and exacerbation of chronic pulmonary disease. These studies analysed data based on hospital admissions and mortality rates.

In many countries, ambulance services are provided for patients requiring response to urgent life-threatening or serious illness or injury. They can also be used for non-urgent cases. Alessandrini et al. (2011) suggested that analysis of ambulance dispatches could be used for observing how environmental conditions affect specific health outcomes. Up to now, only a few studies have reported the associations of temperature and seasonality with emergency ambulance dispatch type (Mahmood et al., 2017; Papadakis et al., 2018; Thornes et al., 2014). There are little published data about the association between the effects of extreme temperature on health outcomes focused on ambulance dispatches.

The London Ambulance Service use the Advanced Medical Priority Dispatch System (AMPDS) and NHS Pathways for their triage system to collect data. The NHS pathways are able to hear and treat more calls while the AMPDS protocols focuses on symptom based from prioritise caller. The AMPDS is more clinician than NHS pathways (Turner et al., 2017). The

AMPDS is used by dispatchers through software, it consists of a series of questions/answers and associated algorithms to decide whether the call is life threatening. The protocol of AMPDS for dispatch process is explained by (Clawson et al., 1998; Deakin and Sherwood, 2006).

Previous research has shown that meteorological factors are associated with the number of ambulance calls and dispatches. Pell et al. (2001) found decreasing response times at 90th percentile of temperature, which was associated with an increase in survival rate. In England, O'Keeffe et al. (2011) reported reducing response times by one minute increased survival rates for cardiac arrest by 24% (95% CI: 4-48). In Italy, Alessandrini et al. (2011) found an increase of one degree in the temperature range 25-30°C was associated with increases in non-traumatic and respiratory categories with RRs equal to 1.45% (95% CI: 0.95-1.95%) and 2.74% (95% CI: 1.34-4.14%), respectively. Bassil et al. (2011) and Cheng et al. (2016) reported an increase in temperature was related to rising in ambulance dispatches. In Japan, Kotani et al. (2018) reported extreme high temperatures were related to ambulance dispatches due to acute illness.

This study analyzes the associations between extreme temperatures (both low and high) and ambulance dispatches using data from the London Ambulance Service (LAS) recorded over a five-year period, between 2010 and 2014. In particular, the study investigates the role of extreme temperatures upon respiratory, cardiovascular, and non-cardiorespiratory dispatches. A better understanding of these associations will allow for improved planning of the emergency services during extreme temperature episodes and will allow for early warning forecasting systems to be established (Todkill et al., 2017).

5.3 Methods

5.3.1 Ambulance dispatches data

Emergency ambulance dispatches (ambulances requested via dialling 999) data were provided by the London Ambulance Service (LAS) from January 1st 2010 to November 30th 2014. LAS provides emergency services to approximately eight million people and in 2016/2017 there were more than 1.8 million dispatches (London Ambulance Service, 2017). Once a 999 call is received, call handlers take details about the condition of the patient. If an emergency response is required, an ambulance is dispatched to the patient's location. These 999 dispatches are divided into two categories: Red calls and Green calls. Red calls are life-threatening events that require rapid responses and Green calls are for illnesses and events not requiring immediate attention. The standard performance targets of response time for Red calls is set at 75% of ambulances to reach the patient within eight minutes (NHS, 2017). The LAS breakdown the dispatch calls into 103 distinct categories (Table 5-1).

Table 5-1 Illness code and illness type for London Ambulance Service data

Code/illness	Code/illness
Abdominal pains	Rape/sexual assault
Allergic reaction/rash	Renal problems
Amputation	Respiratory/Chest infection
Anaphylactic shock	Retention
Asthma	Seizure (non ep.)
Bleeding PR	Shock - hypovolaemic
Bleeding PV	Sickle cell crisis
Catheter problems	Smoke inhalation
Hypotension	Solvent related
Burns	Alcohol related
Cardiac arrest	Spinal injury
Choking	Sprain/strain
Collapse - reason unknown	Stab/shot/weapon wound
Confusion/distressed/upset	Unable to cope
Haemoptysis	Unconscious
Dyspnoea	Urological

Code/illness	Code/illness
Diabetic	Vomiting
Flu	Haematemesis
Diarrhoea	Compression
Drowning	Concussion
Drug overdose	Eye injury
Electrocution	Haematuria
Epileptic Fit	Head injury (minor)
Epistaxis	Hyperglycaemia
Eye problem	Hypoglycaemia
Dizzy/near faint/loss of coordination	Laceration/incision (superficial)
Fracture/possible fracture	Laceration/incision - major
Gastrointestinal	Melaena
Generally unwell	Obstetric - birth imminent
Gynaecological	Cardiac chest pain (ACS)
Hanging	Respiratory arrest
Head injury (major)	COPD
Hyperthermia	Cardiac arrhythmias
Hyperventilation/Panic attack	Cardiac Problems - Other
Hypothermia	Confirmed MI by 12-Lead ECG
Minor cuts & bruising	Palliative care
Minor injuries (other)	Pyrexia of unknown origin
Multiple injuries	Cancer
Neurological problems-other	No injury or illness
Psychiatric problems - diagnosed	No patient on arrival
Psychiatric problems-other	Patient already taken by another
Obstetric - BBA	Standby
Obstetric - Miscarriage	Cancelled - no further action required
Obstetric-normal labour	Cancelled - to another vehicle
Obstetric - Premature labour	Hypertension
Obstetric emergency - other	Heart failure
Other medical conditions	CO Poisoning/intoxication
Pain - Back	T/LOC
Pain - Chest	End of life care (Cancer)
Pain - Other	End of life care (organ failure)
Poisioning Purple + (obvious deceased)	Stroke Fast Positive

Previous studies have reported the association between health impacts and temperature focusing on mortality data especially for the association with cardiovascular, respiratory and heat-stoke-related conditions (Fu et al., 2018; Kotani et al., 2018; Scovronick et al., 2018). This study investigates 14 dispatch categories which were likely related to excess risks from extreme hot and cold temperatures (Alessandrini et al., 2011; Basu and Samet, 2002; Mahmood et al., 2017). The categories are subset into three classes: respiratory, cardiovascular, and non-cardiorespiratory categories. Dispatch categories related to respiratory conditions include asthma, dyspnoea, respiratory chest infection (RCI), respiratory arrest and chronic obstructive pulmonary disease (COPD). Dispatch categories related to cardiovascular conditions include chest pain, cardiac chest pain, cardiac arrhythmia and 'other cardiac problems'. The final non-cardiorespiratory category consists of dizzy, alcohol-related, vomiting and 'generally unwell'. The 14 specific dispatches categories investigated in this study represent 25.1% of the total 999 dispatches, see Table 5-2.

5.3.2 Meteorological and air pollution data

The British Atmospheric Data Centre (BADC) provides a repository of UK meteorological data (BADC, http://www.badc.nerc.ac.uk). Hourly data of temperature (°C), relative humidity (%) and wind speed (knots) were obtained for the St James Park (SJP) meteorological station, which is situated in central London. The longitude and latitude coordinates of SJP are 54.97554 and -1.62162, respectively. Previous studies on the associations between health and meteorology used meteorological data from Heathrow airport station, which is to the west of the city (Hajat et al., 2007; Leonardi et al., 2006). Mahmood et al. (2017) used meteorological data from SJP station. Comparison of the meteorological variables from the two stations (SJP and Heathrow) showed very high correlation. For this study, SJP data was favoured because of the location of SJP within the centre of the geographical remit of the LAS.

In this study, extreme low and high daily temperatures are defined as those daily mean temperatures that fall below the 1st percentile and above the 99th percentile of the total daily temperature distribution, respectively. This definition is similar to that used in previous research (Fu et al., 2018; Gasparrini and Leone, 2014; Scovronick et al., 2018). Using this percentile based definition, for the period studied, the extreme low temperature threshold is less than or equal to 0.0°C, and the high extreme threshold is greater than or equal to 22.8°C.

Air pollutants have been observed to affect ambulance despatch data, see review by Sangkharat et al. (2019), hence the effect of air pollution on ambulane dispatch data needs to be controlled for. Daily air pollution data for London was aquired by averaging the daily mean data from seven urban background measurement sites located in London: London Bloomsbury, London Haringey Priory Park South, London Hillingdon, London N. Kensington, London Teddington Bushy Park, London Harrow Stanmore and London Westminster. All sites were part of the Automatic Urban and Rural Network (AURN: https://uk-air.defra.gov.uk/) in London. Average daily pollutant levels were obtained from each monitoring station for particulate matter of diameter less than or equal to 10 µm (PM_{10}), particulate matter of diameter less than or equal to 2.5 µm ($PM_{2.5}$), Ozone (O_3), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), black carbon (BC) and carbon monoxide (CO).

5.3.3 Statistical analysis

Firstly, a descriptive analysis was conducted upon the ambulance dispatch, meteorological and pollutant data sets. Then, time series analyses were conducted to investigate the effects of exposure to extreme temperature (low and high) on ambulance dispatches.

A generalized linear model (GLM) approach with a quasi-likelihood Poisson distribution for dispersion data was conducted to investigate the association between ambulance dispatches and extreme temperature conditions (both low and high). The Poisson model was fitted with overdispersion. To control for the long term trend and seasonal cycles, a natural cubic B-spline with seven degrees of freedom per year was used (Chen et al., 2015; Guo et al., 2014). The model included the following confounding factors: day of week (DOW), public holidays (Holiday), relative humidity (RH) and ambulance dispatches caused by influenza ('flu'), as measured by the LAS dispatch data. A sensitivity analysis of the model to air pollutants was undertaken by individually adding air pollutant variables as confounders (Alessandrini et al., 2011), see Table 5-6.

Influenza is likely not an appropriate confounding factor for some ambulance despatch categories, e.g. alcohol-related. To test this, the model is run with and without the use of influenza as a confounding factor, the results are shown in Table5-7. The inclusion or exclusion of influenza as a confounding factor did not make any differences to the significance of results. All main results include influenza as a confounding factor.

To study the effect of lag periods, between extreme temperature and ambulance dispatch data, a distributed lag non-linear model (DLNM) was used. This model is widely used to investigate the association between health outcomes and temperature (Gasparrini et al., 2015b). The lag response was performed by using a cross-basis function which presented association for temperature at different days after specific exposure. A total of 21 days were investigated to describe delay effect associations (Gasparrini et al., 2015a; Vicedo-Cabrera et al., 2016). A quadratic B-spline with two equal knots in exposure response function and three knots in log response were analysed (Gasparrini and Leone, 2014).

This study defines a new metric: the Minimum Ambulance Dispatch Temperature (T_{MADT}) at minimum dispatches percentile (MDP), which is similar to Minimum Mortality

Temperature (MMT) defined by previous studies (Fu et al., 2018; Gasparrini et al., 2015a). T_{MADT} represents the minimum of the exposure-response or the temperature at the lowest risk obtained from specific dispatch model. The RR for each category was compared to the reference T_{MADT} temperature and reported with both 95% confidence intervals (CI) and 99% CI, see Table 5-5. All statistical analyses were carried out with the R software version 3.3.1 using DLNM package for distributing lag exposure (Gasparrini, 2011).

5.4 Results

5.4.1 Descriptive statistics

Within the study period, there were 1,975 days and 5,252,375 ambulance dispatches. Mean (±1SD) daily 999 dispatches and Red dispatches were 2,926 ± 155.0 and 1,137.0 ± 172.8 calls, respectively. The daily mean for work performance (meeting the 8 minute target) of the Red dispatch was 74%, which is just below the target performance (75%), specified by the LAS. The work performance reached the target in all years except for 2014.

In the respiratory grouping of ambulance call-outs, the maximum mean daily number of dispatches was for dyspnoea (114.4 ± 21.0), and the minimum was for respiratory arrest (2.6 ± 1.4). In the cardiovascular grouping, the maximum mean daily number of dispatches was for chest pain (132.1 ± 23.7), and the minimum was for 'other cardiac problems' (20.2 ± 5.0). In the non-cardiorespiratory grouping, the maximum mean daily number of dispatches was for 'generally unwell' (93.7 ± 19.9), and the minimum was for vomiting (59.2 ± 14.4). See Table 5-2 for full details.

The descriptive statistics for the meteorological and air pollution parameters are summarized in Table 5-3. The average daily temperature and relative humidity were 11.8 ±

5.5°C and 75.2 ± 10.5%, respectively, with both parameters showing clear seasonality. All the mean average air quality levels measured are below the EU limit values except for NO_2, which is above the specified annual limit of 40 µg/m^3.

Table 5-2 Summary statistics of daily average of ambulance dispatches between 2010 and 2014

Ambulance categories	Mean ± SD	Percentiles				
		Min	P25	P50	P75	Max
Ambulance dispatches (calls)						
999 dispatches (calls)	2926.1±155.0	1447.0	2825.0	2926.0	3027.0	3774.0
Red dispatches (calls)	1137.3±172.8	165.0	989.0	1150.0	1269.0	1806.0
Work performance (%)	74.0±0.07	22.0	70.0	76.0	79.0	90.0
Respiratory categories (calls)						
Asthma	23.8±6.4	1.0	19.0	23.0	28.0	66.0
Dyspnoea	114.4±21.0	18.0	101.0	114.0	127.0	193.0
RCI	60.2±22.2	7.0	43.0	56.0	74.0	150.0
Respiratory arrest	2.6±1.4	1.0	2.0	2.0	3.0	9.0
COPD	16.5±6.4	1.0	12.0	16.0	21.0	51.0
Cardiovascular categories (calls)						
Cardiac arrest	13.0±4.0	1.0	10.0	13.0	16.0	30.0
Chest pain	132.1±23.7	12.0	115.0	133.0	149.0	207.0
CCP	34.3±7.7	3.0	29.0	34.0	39.0	60.0
Cardiac arrhythmia	21.7±6.5	3.0	17.0	22.0	26.0	42.0
Other cardiac problems	20.2±5.0	3.0	17.0	20.0	23.0	41.0
Other-related categories (calls)						
Dizzy	62.9±11.5	13.0	55.0	62.0	70.0	114.0
Alcohol related	81.7±31.3	2.0	59.0	75.0	99.0	283.0
Vomiting	59.2±14.4	7.0	49.0	59.0	69.0	120.0
Generally unwell	93.7±19.9	15.0	79.0	92.0	106.0	179.0

Abbreviations: SD: standard deviation, P_x $_x$th: percentile, Min: minimum, Max: maximum, RCI: respiratory chest infection, COPD: chronic obstructive pulmonary disease, CCP: Cardiac chest pain.

Table 5-3 Summary statistics of daily meteorological and air pollution data pollutants between 2010 and 2014

Environmental variables	Mean ± SD	Percentiles				
		Min	P25	P50	P75	Max
Meteorological data						
Temperature (°C)	11.8±5.5	-2.2	7.8	12.0	16.1	25.4
RH (%)	75.2±10.5	22.8	67.7	76.0	83.3	99.2
Wind speed (knots)	3.7±1.5	1.0	3.0	4.0	5.0	9.00
Pollutant data						
$PM_{2.5}$ (μg/m^3)	14.6±8.8	4.5	9.07	11.8	16.9	69.4
PM_{10} (μg/m^3)	20.3±10.2	6.3	14.2	17.3	22.7	85.8
O_3 (μg/m^3)	33.8±16.1	1.6	21.8	33.7	45.0	90.6
NO_2 (μg/m^3)	45.4±9.4	23.4	39.1	44.7	50.9	96.8
SO_2 (μg/m^3)	2.2±1.6	0.0	1.4	1.9	2.8	29.5
BC (μg/m^3)	4.9±2.4	0.6	2.9	4.7	6.5	14.6
CO (mg/m^3)	0.2±0.0	0.1	0.2	0.2	0.3	1.3

Abbreviations: RH: relative humidity, PM_{10}: particulate matter of diameter less than or equal to 10 micrometres (microns), $PM_{2.5}$: particulate matter of diameter less than or equal to 2.5 micrometres (microns), O_3: Ozone, NO_2: nitrogen dioxide, SO_2: sulphur dioxide, BC: black carbon and CO: carbon monoxide.

5.4.2 Time series

The time series of different ambulance dispatches are shown in Figure 5-1 and Figure 5-2. To aid clarity, the monthly averaged daily data are presented in the figures. Figure 5-1 also shows ambulance dispatches, the monthly averaged daily temperatures and $PM_{2.5}$ concentrations.

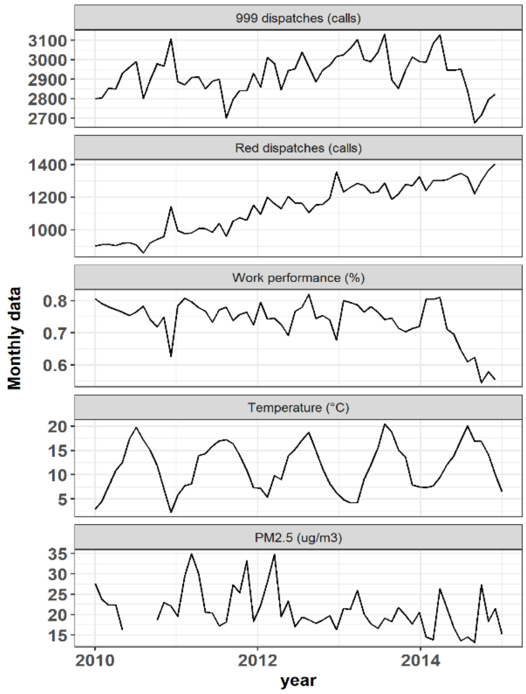


Figure 5-1 Monthly average ambulance dispatches for LAS data between 2010 and 2014 consisting of 999 dispatches, Red dispatches, Work performance (%), Temperature (°C) and PM2.5 (µg/m^3).

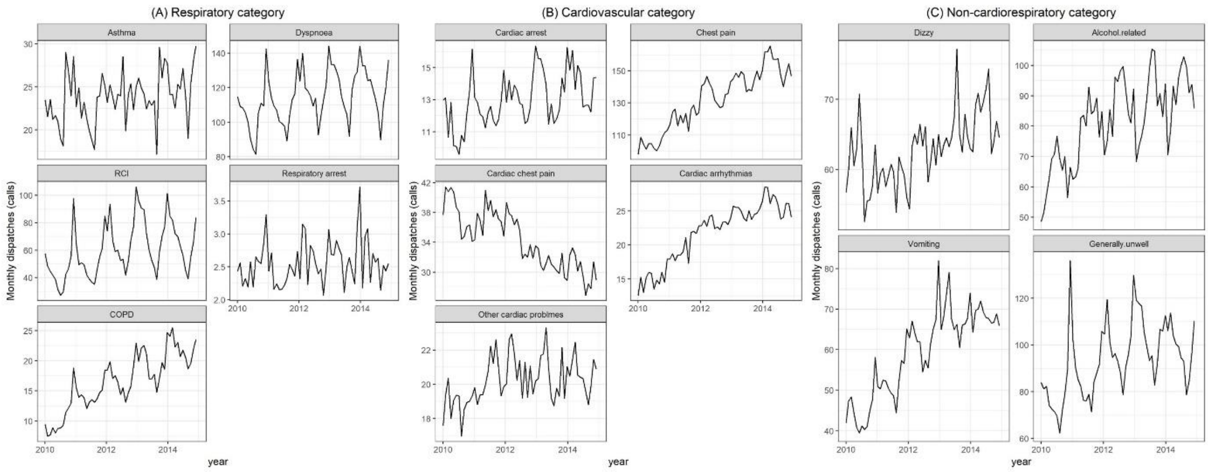


Figure 5-2 Monthly average ambulance dispatches each category for LAS data between 2010 and 2014 (A) Respiratory categories, (B) Cardiovascular categories and (C) Non-cardiorespiratory categories.

Seasonal trends are clearly observed in many of the dispatch data categories, including within the respiratory class see Figure 5-2 (A): including dyspnoea, RCI, and COPD; the cardiovascular class see Figure 5-2 (B): including cardiac arrest, and chest pain; and the non-cardiorespiratory class (Figure 5-2(C.): including vomiting, 'generally unwell' and alcohol-related. Most categories of dispatches were generally higher in winter and lower in summer, except calls for alcohol-related and dizzy which were generally higher in summer and lower in winter. Most categories exhibit an increasing long-term trend (e.g. chest pain), whereas only a few categories (e.g. cardiac chest pain) show decreasing trends.

5.4.3 The impact of extreme low and high temperature

The exposure-response curves between temperature and dispatches, and the T_{MADT} temperatures are shown in Figure 5-3 and Figure 5-4 for the different dispatch categories. The T_{MADT} for 999 and Red dispatches were found to be 18.0°C (86.4th percentile) and 3.0°C (6.4th percentile), respectively. The Red calls show more of a J type curve with only a hot effect, whereas 999 shows more of a U type curve. This suggests that the more serious calls (red) tend to have a bigger effect at extreme hot temperatures rather than low extremes.

Both extreme low and high temperatures were associated with an increase in risks (RR>1) for 999 dispatches, whereas Red incidents were only associated with increased risks at high temperatures.

Some dispatch categories had increased risks with both low and high temperatures compared to $T_{MADT.}$ For example, respiratory chest infection, cardiac arrest, 'generally unwell', vomit and dizzy dispatches presented their T_{MADT} values found at 20.5°C, 20.5°C, 18°C, 17.5°C and 2.5°C, respectively. Some other dispatch categories only had increased risks associated with only low or high temperatures, showing J-curve type dependence. The T_{MADT} for COPD, chest pain, cardiac arrhythmia and alcohol-related dispatches were all less than the 1st temperature percentile indicating increased risks only at higher temperatures. Conversely, the

T_{MADT} for dyspnoea, respiratory arrest, cardiac chest pain and 'other cardiac problem' were above the 99th percentile indicating increased risks only at lower temperatures.

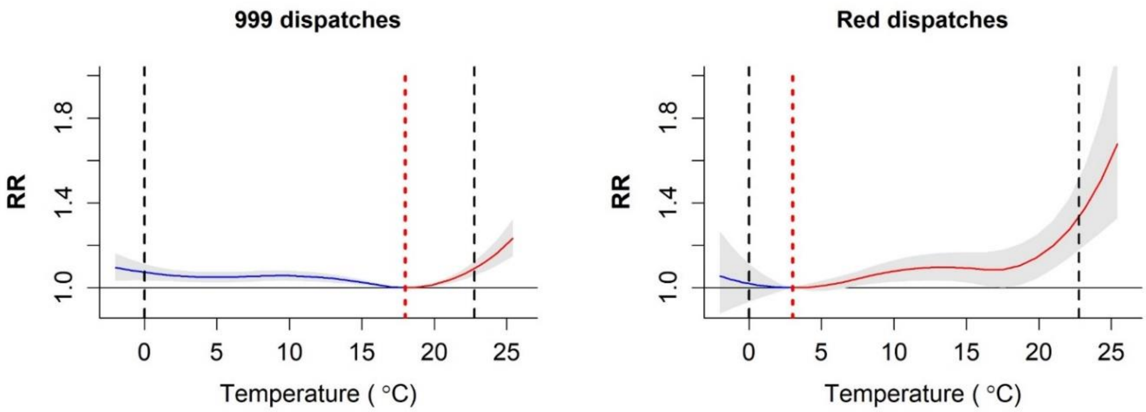


Figure 5-3 Cumulative association between daily mean temperature and London ambulance dispatches over lag 0-21 days with 95% CI for 999 dispatches (left) and red dispatches (right).

Solid curves in blue and red color are represented pooled estimated relative risks with 95% CIs as show in grey shade. Red dotted in a vertical line shows the lowest risk at the minimum ambulance dispatches temperature (T_{MADT}). Black vertical lines present the T_{MADT} at the 1st (0.0°C) and 99th (22.8°C) percentile of London temperature. CI, confidence interval; RR, relative risk.

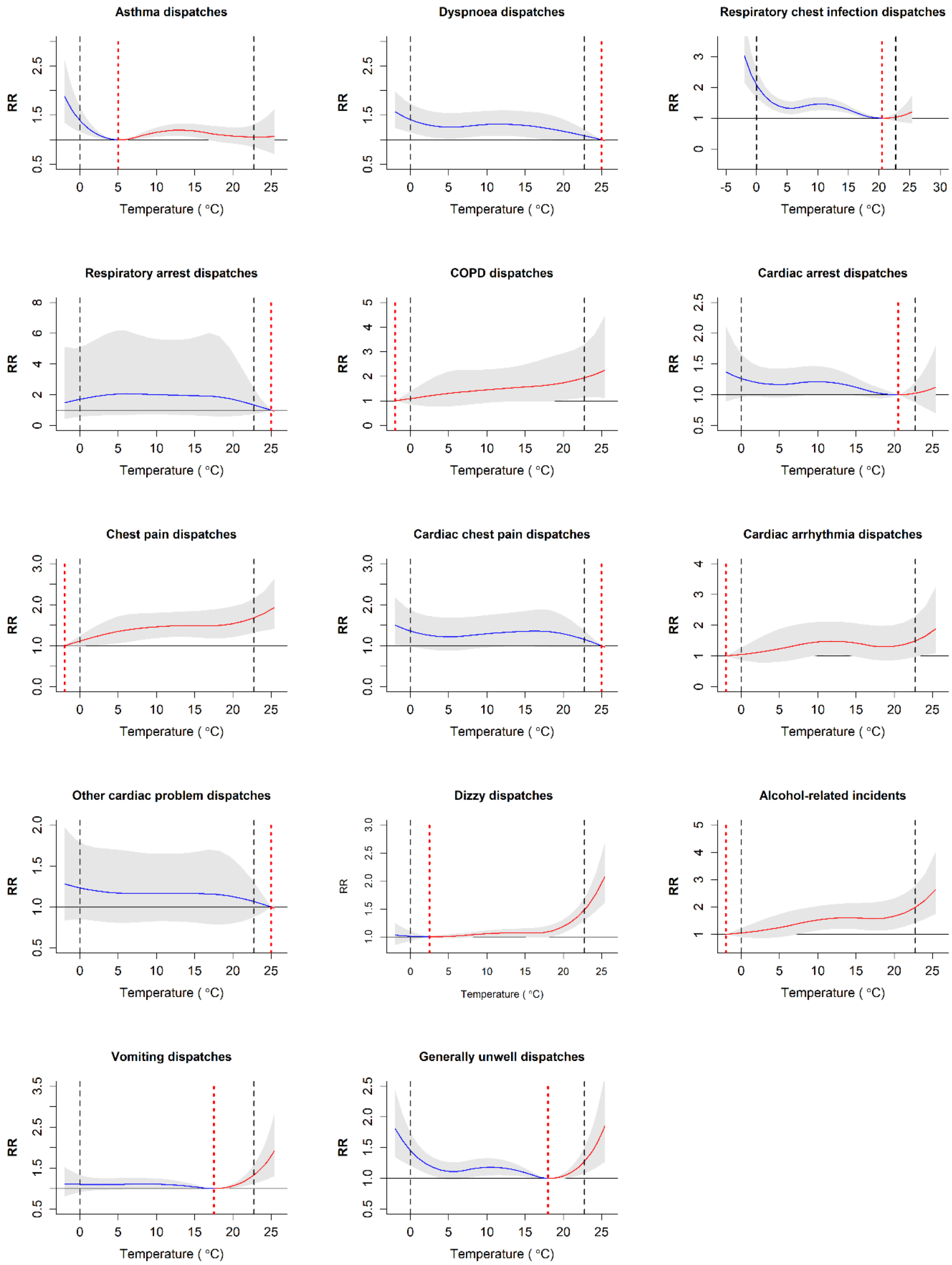


Figure 5-4 Cumulative association between daily mean temperature and London ambulance dispatches over lag 0-21 days with 95%CI for 14 categories.

Solid curves in blue and red color are represented pooled estimated relative risks with 95 % CIs as show in grey shade. Red dotted vertical line shows the lowest risk at the minimum ambulance dispatch temperature (T_{MADT}). Black vertical lines present the T_{AIT} at the 1st (0°C) and 99th (22.8°C) percentile of London temperature. CI, confidence interval; RR, relative risk.

Table 5-4 reports estimated RR for associations caused by low and high temperature between daily average temperature and ambulance dispatches in London between 2010 and 2014 during extreme low and high temperatures with 95% CI for lag 0, lag 1, lag 2, lag 0-2, lag 0-14 and lag over 21 days. All categories showing significant RR at the 95% level are also significant at the 99% level except for COPD at high temperatures, which is only significant at the 95% level, see Table 5-5. Henceforth in this paper, all analysis is discussed at the 95% CI level.

In the respiratory class of dispatches show an excess risk associated with low temperature in three out of five categories: asthma RR = 1.392 (95% CI: 1.161-1.669), dyspnoea RR = 1.410 (95% CI: 1.149-1.730), and RCI RR = 2.075 (95% CI: 1.673-2.574). Only COPD shows an increased risk for high temperature over T_{MADT}, RR = 1.944 (95% CI: 1.143-3.306).

In the cardiovascular class of dispatches only chest pain shows a significant for high temperature effect, RR = 1.684 (95% CI: 1.320-2.150). No significant estimated RR for low temperature are seen in this class of dispatch data.

In the non-cardiorespiratory class of dispatches show a high temperature was responsible for all four categories: dizzy RR = 1.482 (95% CI: 1.295-1.697), alcohol-related RR = 1.985 (95% CI: 1.422-2.773), vomiting RR = 1.337 (95% CI: 1.124-1.590), and ‘generally unwell’ RR = 1.280 (95% CI: 1.128-1.454). ‘Generally unwell’ also shows a significant estimated RR for low temperature with RR = 1.450 (95% CI: 1.261-1.668).

Table 5-4 Results by dispatch categories: the lowest risk at minimum ambulance dispatch temperature (T_{MADT}), estimated relative risk (RR) of ambulance dispatches at 95% confidence intervals with daily average temperature in London between 2010 and 2014 at low and high temperature compared with T_{MADT} as the reference

Ambulance dispatches	T_{MADT} (°C)/ MDP (percentiles)	Lag 0		Lag 1		Lag 2		Lag 0-2		Lag0-14		Lag0-21	
		Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
999	18.0 (86.4)	0.929 (0.911-0.948)	**1.045 (1.030-1.061)***	0.995 (0.985-1.005)	**1.017 (1.009-1.024)***	**1.017 (1.006-1.029)***	1.004 (0.996-1.021)	0.941 (0.923-0.960)	**1.067 (1.050-1.084)***	**1.049 (1.019-1.081)**	**1.071 (1.043-1.100)***	**1.073 (1.035-1.111)***	**1.091 (1.057-1.125)***
Red	3.0 (6.4)	0.973 (0.933-1.016)	**1.267 (1.182-1.359)***	0.999 (0.977-1.021)	**1.058 (1.023-1.094)***	1.008 (0.983-1.033)	0.990 (0.951-1.029)	0.980- 0.937-1.025)	**1.326 (1.236-1.424)***	1.045 (0.973-1.123)	**1.269 (1.140-1.413)***	1.019 (-0.934 1.113)	**1.333 (-1.179 1.508)***
Respiratory categories													
Asthma	5.0 (12.2)	1.060 (0.967-1.162)	0.928 (0.828-1.040)	0.966 (0.922-1.012)	1.048 (0.992-1.108)	0.963 (0.913-1.016)	1.066 (0.999-1.136)	0.985 (0.896-1.084)	1.036 (0.921-1.167)	**1.268 (1.094-1.470)***	1.039 (0.863-1.250)	**1.392 (-1.161 1.669)***	1.057 (-0.850 1.314)
Dyspnoea	25.0 (99.8)	0.838 (0.754-0.932)	0.954 (0.911-0.998)	0.949 (0.901-1.000)	0.987 (0.964-1.010)	1.012 (0.953-1.076)	1.004 (0.978-1.030)	0.805 (0.722-0.899)	0.945 (0.898-0.994)	**1.270 (1.069-1.508)***	1.041 (0.951-1.140)	**1.410 (1.149-1.730)***	1.083 (0.971-1.207)
RCI	20.5 (95.5)	1.043 (0.923-1.180)	0.992 (0.935-1.053)	1.004 (0.945-1.066)	1.022 (0.992-1.053)	1.010 (0.941-1.084)	1.019 (0.986-1.053)	1.058 (0.938-1.193)	1.033 (0.968-1.103)	**1.841 (1.539-2.203)***	0.998 (0.891-1.117)	**2.075 (1.673-2.574)***	1.036 (0.909-1.181)
Respiratory arrest	25.0 (99.8)	0.815 (0.475-1.400)	0.884 (0.701-1.116)	1.059 (0.800-1.401)	1.050 (0.926-1.190)	1.092 (0.792-1.505)	1.071 (0.933-1.230)	0.942 (0.535-1.660)	0.994 (0.763-1.297)	1.182 (0.469-2.980)	1.104 (0.677-1.801)	1.713 (0.576-5.094)	1.336 (0.742-2.404)
COPD	-2.0 (0.0)	1.027 (0.919-1.148)	1.286 (0.962-1.720)	1.020 (0.963-1.079)	1.151 (0.997-1.330)	1.017 (0.954-1.085)	1.080 (0.913-1.279)	1.065 (0.944-1.202)	**1.601 (1.197-2.141)***	1.003 (0.824-1.220)	1.391 (0.900-2.151)	1.098 (0.864-1.396)	**1.944 (1.143-3.306)***
Cardiovascular categories													
Cardiac arrest	20.5 (95.5)	0.994 (0.851-1.160)	1.015 (0.943-1.092)	1.018 (0.943-1.098)	1.023 (0.986-1.061)	1.027 (0.939-1.124)	1.019 (0.978-1.061)	1.039 (0.892-1.211)	1.058 (0.976-1.147)	1.119 (0.890-1.407)	1.027 (0.891-1.184)	1.265 (0.961-1.667)	1.026 (0.871-1.210)
Chest pain	-2.0 (0.0)	1.032 (0.980-1.087)	**1.208 (1.056-1.383)***	1.006 (0.979-1.033)	1.063 (0.994-1.137)	0.999 (0.969-1.029)	1.013 (0.936-1.095)	1.037 (0.980-1.097)	**1.301 (1.137-1.489)***	1.048 (0.956-1.148)	**1.309 (1.070-1.600)***	1.116 (0.999-1.248)	**1.684 (1.320-2.150)***

Ambulance dispatches	T_{MADT} (°C)/ MDP (percentiles)	Lag 0		Lag 1		Lag 2		Lag 0-2		Lag0-14		Lag0-21	
		Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
Cardiac chest pain	25.0 (99.8)	0.839 (0.707-0.996)	1.020 (0.949-1.098)	1.052 (0.967-1.144)	1.025 (0.988-1.063)	1.101 (0.999-1.214)	1.020 (0.989-1.063)	0.972 (0.814-1.161)	1.067 (0.983-1.158)	**1.435 (1.089-1.889)***	**1.225 (1.061-1.415)***	1.358 (0.984-1.872)	1.153 (0.972-1.367)
Cardiac arrhythmia	-2.0 (0.0)	1.013 (0.924-1.110)	1.180 (0.931-1.496)	1.036 (0.989-1.086)	**1.153 (1.025-1.297)***	1.027 (0.974-1.083)	1.087 (0.948-1.247)	1.078 (0.976-1.191)	**1.479 (1.165-1.876)***	0.984 (0.839-1.154)	1.257 (0.884-1.787)	1.051 (0.865-1.276)	1.489 (0.972-2.282)
Other cardiac problem	25.0 (99.8)	0.795 (0.654-0.967)	0.961 (0.884-1.044)	0.986 (0.895-1.086)	1.010 (0.969-1.054)	1.041 (0.930-1.164)	1.015 (0.969-1.064)	0.815 (0.666-0.999)	0.985 (0.898-1.081)	1.078 (0.786-1.479)	1.026 (0.875-1.211)	1.233 (0.851-1.787)	1.066 (0.876-1.299)
Non-cardiorespiratory categories													
Dizzy	2.5 (5.5)	0.963 (0.923-1.004)	**1.706 (1.581-1.840)***	1.009 (0.988-1.031)	1.005 (0.968-1.043)	1.019 (0.994-1.044)	0.874 (0.837-0.913)	0.990 (0.947-1.035)	**1.497 (1.387-1.617)**	1.035 (0.965-1.111)	**1.406 (1.251-1.579)**	1.011 (0.927-1.101)	**1.482 (1.295-1.697)***
Alcohol-related	-2.0 (0.0)	1.016 (0.945-1.092)	**1.750 (1.455-2.105)***	1.027 (0.989-1.065)	**1.230 (1.122-1.348)***	1.020 (0.978-1.064)	1.045 (0.938-1.163)	1.064 (0.984-1.150)	**2.249 (1.870-2.705)***	0.982 (0.866-1.114)	**1.729 (1.313-2.275)***	1.052 (0.902-1.226)	**1.985 (1.422-2.773)***
Vomiting	17.5 (84.1)	0.835 (0.750-0.930)	**1.106 (1.020-1.200)***	1.009 (0.957-1.064)	**1.044 (1.003-1.087)**	**1.065 (1.001-1.133)**	1.013 (0.968-1.060)	0.898 (0.808-0.998)	**1.171 (1.072-1.279)***	1.110 (0.949-1.300)	**1.276 (1.101-1.480)***	1.106 (0.915-1.336)	**1.337 (1.124-1.590)***
Generally unwell	18.0 (86.4)	0.897 (0.830-0.970)	**1.084 (1.023-1.150)**	0.996 (0.959-1.035)	**1.046 (1.016-1.077)**	1.035 (0.990-1.083)	1.023 (0.990-1.057)	0.926 (0.857-0.999)	**1.161 (1.089-1.237)**	**1.337 (1.190-1.502)**	**1.173 (1.052-1.307)**	**1.450 (1.261-1.668)***	**1.280 (1.128-1.454)***

* Statistically significant at 95% CI. Abbreviations: RCI, Respiratory chest infection; CI, confidence interval; RR, relative risk; T_{MADT}, temperature at minimum dispatch temperature; MDP, minimum dispatches percentiles.

Table 5-5 Results by dispatch categories: the lowest risk at minimum ambulance dispatch temperature (T_{MADT}), estimated relative risk (RR) of ambulance dispatches at 95% and 99% confidence intervals with daily average temperature in London between 2010 and 2014 at low and high temperature compared with T_{MADT} as the reference

Ambulance dispatches	**T_{MADT} (°C) MDP (percentiles)**	**RR (95% CI)**		**RR (99% CI)**	
		Low temperature (at 0.0°C)	**High temperature (at 22.8°C)**	**Low temperature (at 0.0°C)**	**High temperature (at 22.8°C)**
999	18.0 (86.4)	**1.073 (1.035-1.111)***	**1.091 (1.057-1.125)***	**1.073 (1.024-1.124)***	**1.091 (1.047-1.136)***
Red	3.0 (6.4)	1.019 (0.934-1.113)	**1.333 (1.179-1.508)**	1.019 (0.908-1.143)	**1.333 (1.134-1.568)***
Respiratory categories					
Asthma	5.0 (12.2)	**1.392 (1.161-1.669)***	1.057 (0.850-1.314)	**1.391 (1.096-1.767)***	1.057 (0.794-1.407)
Dyspnoea	25.0 (99.8)	**1.410 (1.149-1.730) ***	1.083 (0.971-1.207)	**1.410 (1.077-1.845) ***	1.083 (0.939-1.249)
RCI	20.5 (95.5)	**2.075 (1.673-2.574)***	1.036 (0.909-1.181)	**2.075 (1.564-2.754)***	1.036 (0.872-1.230)
Respiratory arrest	25.0 (99.8)	1.713 (0.576-5.094)	1.336 (0.742-2.404)	1.713 (0.409-7.173)	1.336 (0.617-2.891)
COPD	-2.0 (0.0)	1.098 (0.864-1.396)	**1.944 (1.143-3.306)***	1.098 (0.801-1.505)	1.944 (0.967-3.907)
Cardiovascular Categories					
Cardiac arrest	20.5 (95.5)	1.265 (0.961-1.667)	1.026 (0.871-1.210)	1.265 (0.881-1.817)	1.026 (0.826-1.274)
Chest pain	-2.0 (0.0)	1.116 (0.999-1.248)	**1.684 (1.320-2.150)***	1.116 (0.965-1.292)	**1.684 (1.222-2.312)***
Cardiac chest pain	25.0 (99.8)	1.358 (0.984-1.872)	1.153 (0.972-1.367)	1.358 (0.890-2.071)	1.153 (0.922-1.443)
Cardiac arrhythmia	-2.0 (0.0)	1.051 (0.865-1.276)	1.489 (0.972-2.282)	1.051 (0.814-1.356)	1.489 (0.850-2.609)
Other cardiac problem	25.0 (99.8)	1.233 (0.851-1.787)	1.066 (0.876-1.299)	1.233 (0.758-2.007)	1.067 (0.824-1.382)
Non-cardiorespiratory categories					
Dizzy	2.5 (5.5)	1.011 (0.927-1.101)	**1.482 (1.295-1.697)***	1.011 (0.903-1.131)	**1.482 (1.241-1.770)***
Alcohol-related	-2.0 (0.0)	1.052 (0.902-1.226)	**1.985 (1.422-2.773)***	1.052 (0.860-1.287)	**1.986 (1.280-3.079)***
Vomiting	17.5 (84.1)	1.106 (0.915-1.336)	**1.337 (1.124-1.590)***	1.106 (0.862-1.418)	**1.337 (1.064-1.679)***
Generally unwell	18.0 (86.4)	**1.450 (1.261-1.668)***	**1.280 (1.128-1.454)***	**1.450 (1.206-1.743)***	**1.280 (1.084-1.513)***

* Statistically significant at 95% CI and 99% CI. Abbreviations: RCI, Respiratory chest infection; CI, confidence interval; RR, relative risk; T_{MADT}, temperature at minimum dispatch temperature; MDP, minimum dispatches percentiles.

5.4.4 Impact of lagged effects

Figure 5-5 provides the cumulative RR of exposure over 21 days to both low and high temperatures for 999 and Red dispatches. The effect of lag time under low temperature conditions is distinct to that under high temperature conditions for both 999 and Red dispatches. For 999 dispatches at low temperature, a significantly increased RR is initially observed after two days (lag 2) and persists until day 16. The greatest RR of low temperature was found at lag 2 (RR = 1.017, 95%CI: 1.006-1.029). At high temperatures, a significant RR is only detected at lag 0 and lag 1. The highest RR of high temperature for 999 dispatches was 1.045 (95% CI: 1.030-1.061) at lag 0. For Red dispatches, risks at low temperature were not significant over 21 days. RR at low temperature were increased after current day and could be observed up to lag 2, then slightly went down on following days. However, the significant RR of lag 0-21 days, lag 0 and lag 1 were reported at high temperature. The highest RR was found at lag 0 (RR = 1.267, 95% CI: 1.182-1.359). Figure 5-6 provides the RR values over 21 lag days for the exposure to low temperature and high temperature for the 14 specific dispatch categories investigated.

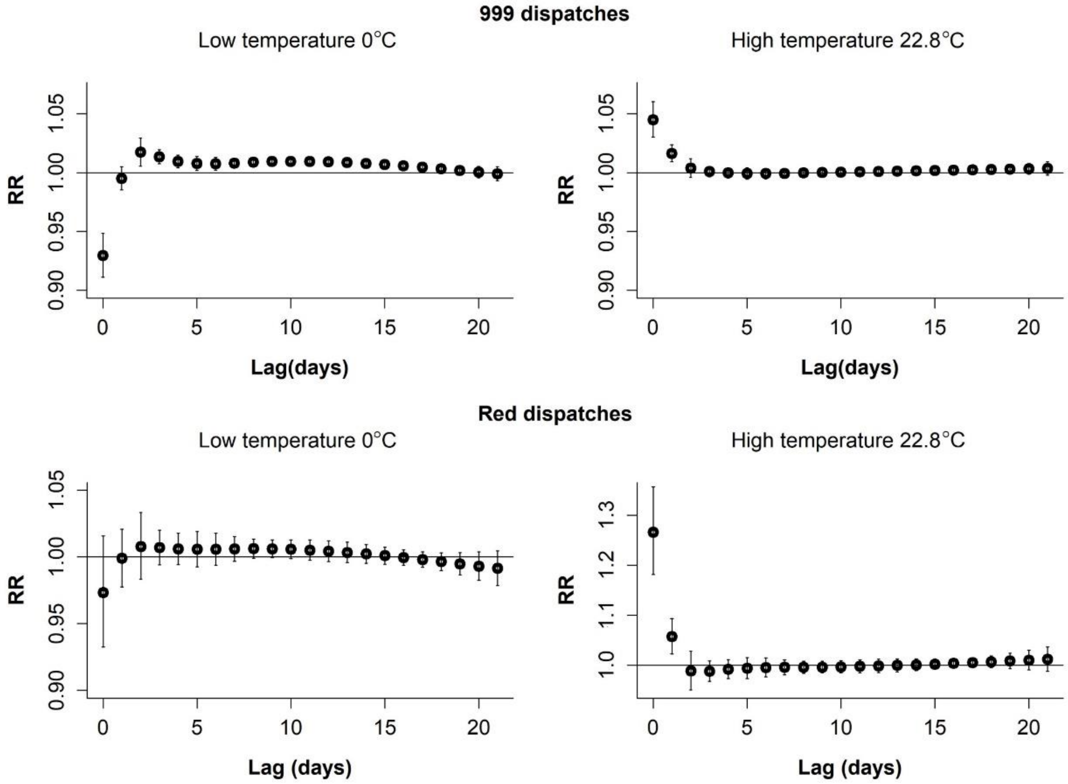
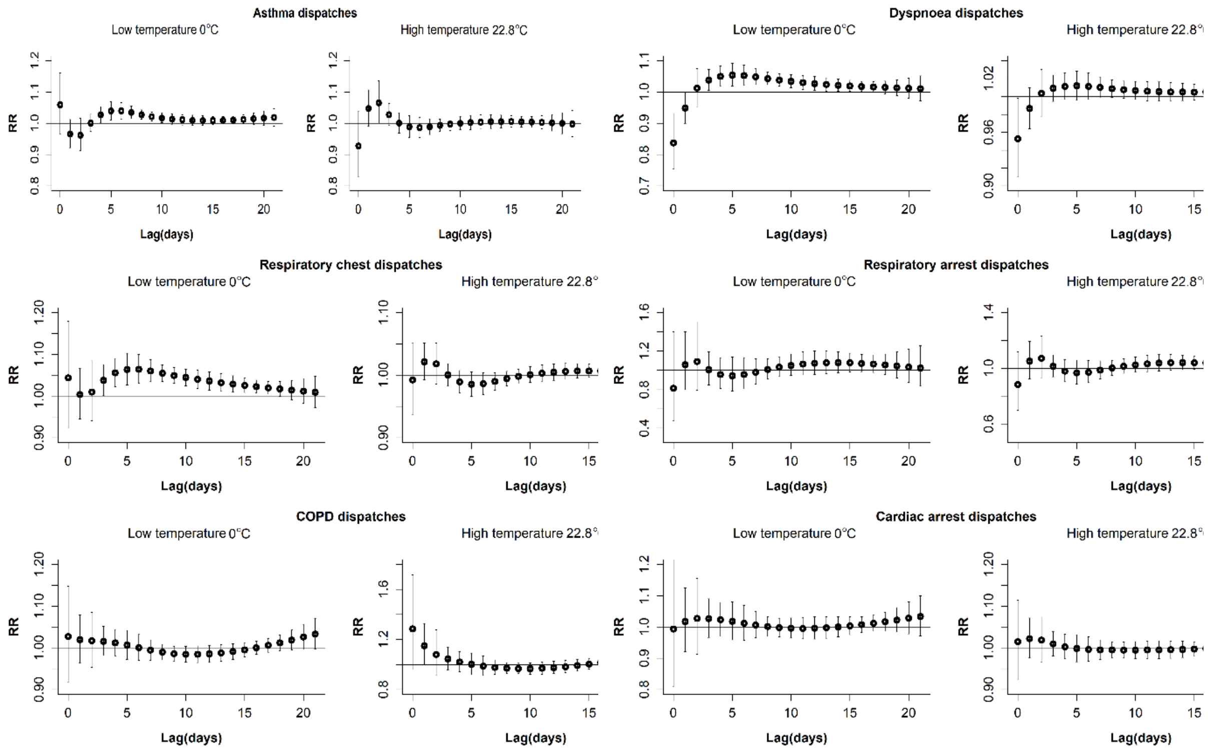


Figure 5-5 Lag effects for low temperature at 1st percentile and high temperature at 99th percentile of compared with the temperature at minimum ambulance dispatch temperature (T_{MADT}) over 21 lag days for 999 and Red dispatches.



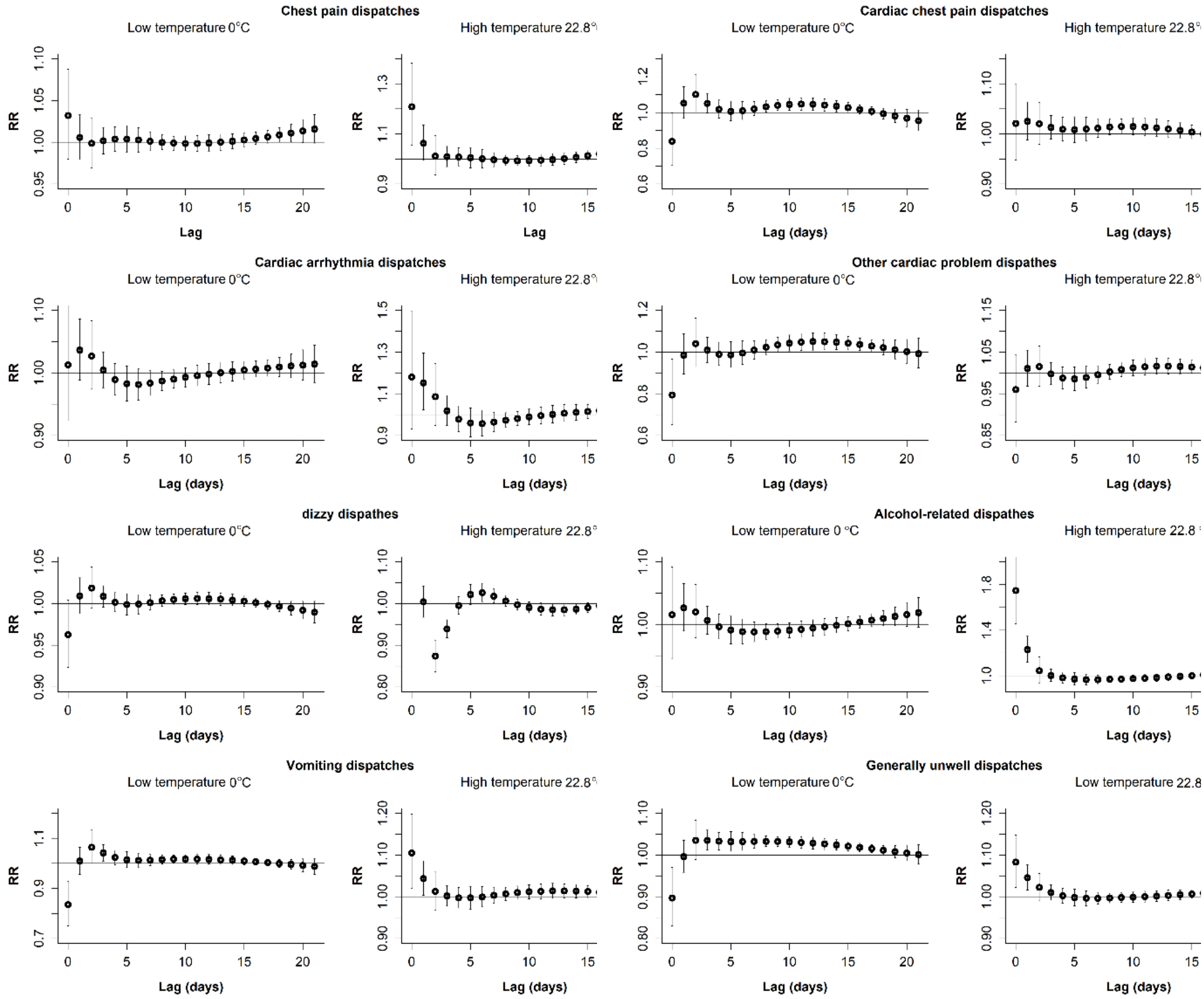


Figure 5-6 Lag effects for low temperature at 5th percentile and high temperature at 95th percentile of dispatches compared with the temperature at minimum ambulance dispatches temperature (T_{MADT}) over 21 lag days for 14 dispatches.

To examine if air pollution is a confounding factor in the relationship between ambulance dispatches and temperature, a sensitivity analysis was conducted. Individual air pollutants were added to the GLM. The inclusion of the individual pollutants to the model resulted in negligible changes to the estimated RR associations between extreme temperature and ambulance dispatches (see Table 5-6).

Table 5-6 Results by dispatch categories: the lowest risk at minimum ambulance dispatch temperature (T_{MADT}) and MDP, estimated relative risk (RR) of ambulance dispatches at 95% confidence intervals with adjusted pollutants (PM_{10} and O_3)

Ambulance dispatches	Adjusted pollutants					
	PM_{10}			O_3		
	T_{MADT} (°C) MDP (percentiles)	**Low temperature (at 0.0°C)**	**High temperature (at 22.8°C)**	**T_{MADT} (°C) MDP (percentiles)**	**Low temperature (at 0.0°C)**	**High temperature (at 22.8°C)**
999	18.0 (86.4)	1.077 (0.995-1.040)	**1.036 (1.000-1.074)***	18.0 (86.4)	**1.070 (1.033-1.109)***	**1.090 (1.057-1.124)***
Red	3.0 (6.5)	1.019 (0.933-1.113)	**1.332 (1.177-1.509)***	2.5 (5.5)	1.012 (0.937-1.095)	**1.331 (1.177-1.505)***
Respiratory categories						
Asthma	5.5 (14.2)	**1.376 (1.144-1.655)***	1.029 (0.827-1.280)	5 (12.2)	**1.357 (1.131-1.627)***	1.049 (0.844-1.303)
Dyspnoea	25.0 (99.8)	**1.410 (1.142-1.720)***	1.083 (0.972-1.208)	25.0 (99.8)	**1.409 (1.148-1.730)***	1.084 (0.972-1.208)
RCI	20.5 (95.5)	**2.053 (1.655-2.549)***	1.036 (0.909-1.181)	20.5 (95.5)	**2.079 (1.676-2.580)***	1.036 (0.909-1.181)
Respiratory arrest	25.0 (99.8)	1.723 (0.579-5.127)	1.335 (0.742-2.402)	25.0 (99.8)	1.713 (0.576-5.096)	1.335 (0.742-2.403)
COPD	-2.0 (0.0)	1.096 (0.861-1.395)	**1.944 (1.143-3.307)***	-2.0 (0.0)	1.076 (0.845-1.369)	1.879 (1.103-3.200)*
Cardiovascular Categories						
Cardiac arrest	20.5 (95.5)	1.252 (0.950-1.650)	1.027 (0.871-1.210)	20.5 (95.5)	1.283 (0.974-1.691)	1.029 (0.873-1.213)
Chest pain	-2.0 (0.0)	1.113 (0.996-1.245)	**1.685 (1.320-2.151)***	-2.0 (0.0)	1.117 (0.999-1.249)	**1.685 (1.319-2.152)***
Cardiac chest pain	25.0 (99.8)	1.358 (0.984-1.872)	1.153 (0.972-1.367)	25.0 (99.8)	1.358 (0.984-1.872)	1.153 (0.972-1.367)
Cardiac arrhythmia	-2.0 (0.0)	1.043 (0.858-1.267)	1.492 (0.974-2.286)	-2.0 (0.0)	1.052 (0.866-1.279)	1.493 (0.973-2.291)
Other cardiac problem	25.0 (99.8)	1.233 (0.851-1.787)	1.067 (0.876-1.299)	25.0 (99.8)	1.234 (0.852-1.788)	1.066 (0.875-1.297)
Non-cardiorespiratory categories						
Dizzy	3.0 (6.4)	1.015 (0.921-1.119)	**1.497 (1.306-1.717)***	1.5 (3.2)	1.003 (0.947-1.062)	**1.480 (1.290-1.700)***
Alcohol-related	-2.0 (0.0)	1.073 (0.920-1.251)	**1.982 (1.421-2.766)***	-2.0 (0.0)	1.084 (0.930-1.264)	**2.093 (1.500-2.922)***
Vomiting	17.5 (84.1)	1.101 (0.910-1.331)	**1.338 (1.125-1.592)***	17.5 (84.1)	1.102 (0.911-1.332)	**1.336 (1.123-1.589)***

Ambulance dispatches	Adjusted pollutants					
	PM_{10}			O_3		
	T_{MADT} (°C) MDP (percentiles)	**Low temperature (at 0.0°C)**	**High temperature (at 22.8°C)**	**T_{MADT} (°C) MDP (percentiles)**	**Low temperature (at 0.0°C)**	**High temperature (at 22.8°C)**
Generally unwell	18.0 (86.4)	**1.435 (1.248-1.651)***	**1.284 (1.131-1.457)***	18.0 (86.4)	**1.452 (1.262-1.671)***	**1.281 (1.128-1.454)***

*Statistically significant at 95% CI. Abbreviations: RCI, Respiratory chest infection; CI, confidence interval; RR, relative risk; T_{MADT}, temperature at minimum dispatch temperature; MDP, minimum dispatches percentiles.

Table 5-7 Results by dispatch categories: the lowest risk at minimum ambulance dispatch temperature (T_{MADT}) and MDP, estimated relative risk (RR) of ambulance dispatches at 95% confidence intervals with adjusted/non-adjusted by influenza variables

Ambulance dispatches	Adjusted pollutants					
	With influenza			**Without influenza**		
	TMADT (°C) MDP (percentiles)	Low temperature (at 0.0°C)	High temperature (at 22.8°C)	TMADT (°C) MDP (percentiles)	Low temperature (at 0.0°C)	High temperature (at 22.8°C)
999	18.0 (86.4)	**1.073 (1.035-1.111)***	**1.091 (1.057-1.125)***	18.0 (86.4)	**1.116 (1.080- 1.154)***	**1.096 (1.066-1.127)***
Red	3.0 (6.5)	1.019 (0.934-1.113)	**1.333 (1.179-1.508)***	4 (8.9)	1.051 (0.956- 1.154)	**1.338 (1.193- 1.501)***
Respiratory categories						
Asthma	5.5 (14.2)	**1.392 (1.161-1.669)***	1.057 (0.850-1.314)	25 (99.8)	**1.510 (1.103- 2.067)**	1.044 (0.880- 1.238)
Dyspnoea	25.0 (99.8)	**1.410 (1.149-1.730) ***	1.083 (0.971-1.207)	23 (99.1)	**1.323 (1.174- 1.490)**	1.000 (0.992-1.009)
RCI	20.5 (95.5)	**2.075 (1.673-2.574)***	1.036 (0.909-1.181)	20.5 (95.5)	**2.276 (1.885- 2.750)**	1.037 (0.927- 1.161)
Respiratory arrest	25.0 (99.8)	1.713 (0.576-5.094)	1.336 (0.742-2.404)	25.0 (99.8)	1.601 (0.676- 3.791)	1.175 (0.727- 1.899
COPD	-2.0 (0.0)	1.098 (0.864-1.396)	**1.944 (1.143-3.306)***	2.5 (0.6)	1.023 (0.858-1.221)	**1.514 (1.137- 2.016)***
Cardiovascular Categories						
Cardiac arrest	20.5 (95.5)	1.265 (0.961-1.667)	1.026 (0.871-1.210)	19.5 (92.9)	1.300 (1.031-1.640)	1.049 (0.882-1.246)
Chest pain	-2.0 (0.0)	1.116 (0.999-1.248)	**1.684 (1.320-2.150)***	-2.0 (0.0)	1.111 (1.001- 1.232)	**1.710 (1.377-2.124)**
Cardiac chest pain	25.0 (99.8)	1.358 (0.984-1.872)	1.153 (0.972-1.367)	25.0 (99.8)	1.297 (0.992- 1.696)	1.145 (0.990- 1.326)
Cardiac arrhythmia	-2.0 (0.0)	1.051 (0.865-1.276)	1.489 (0.972-2.282)	-2.0 (0.0)	1.049 (0.879- 1.252)	**1.592 (1.100- 2.305)***

Ambulance dispatches	Adjusted pollutants					
	With influenza			Without influenza		
	TMADT (°C) MDP (percentiles)	Low temperature (at 0.0°C)	High temperature (at 22.8°C)	TMADT (°C) MDP (percentiles)	Low temperature (at 0.0°C)	High temperature (at 22.8°C)
Other cardiac problem	25.0 (99.8)	1.233 (0.851-1.787)	1.066 (0.876-1.299)	25.0 (99.8)	1.199 (0.884- 1.628)	1.086 (0.919-1.284)
Non-cardiorespiratory categories						
Dizzy	3.0 (6.4)	1.011 (0.927-1.101)	**1.482 (1.295-1.697)***	4 (8.9)	1.026 (0.929-1.134)	**1.455 (1.289- 1.641)***
Alcohol-related	-2.0 (0.0)	1.052 (0.902-1.226)	**1.985 (1.422-2.773)***	-2.0 (0.0)	1.053 (0.916-1.204)	**1.968 (1.482-2.613)***
Vomiting	17.5 (84.1)	1.106 (0.915-1.336)	**1.337 (1.124-1.590)***	-2.0 (0.0)	1.056 (0.923- 1.208)	**1.355 (1.022- 1.797)***
Generally unwell	18.0 (86.4)	**1.450 (1.261-1.668)***	**1.280 (1.128-1.454)***	18.0 (86.4)	**1.790 (1.576- 2.032)***	**1.277 (1.148- 1.420)***

* Statistically significant at 95% CI. Abbreviations: RCI, Respiratory chest infection; CI, confidence interval; RR, relative risk; T_{MADT}, temperature at minimum dispatch temperature; MDP, minimum dispatches percentiles.

5.5 Discussion

The results show that extreme temperatures are associated with certain ambulance dispatch categories caused by low and high temperatures in each category. Both the total number of 999 and Red category dispatches are associated with extreme temperatures (either low or high). Of the 14 specific dispatch categories investigated, four show a significant association with extreme low temperature and six show an increased risk with extreme high temperatures.

Extreme low temperatures were related to increased risks of 999 dispatches, RCI, asthma, dyspnoea, and ‘generally unwell’. RCI, asthma and dyspnoea are all in the respiratory class of dispatches, ‘generally unwell’ is a category with wide ranging symptoms. This result is largely consistent with previous studies. Cold exposure affects the respiratory system because pulmonary mechanisms are weakened, which leads to decreases in immune function and resilience to pollutants (Giesbrecht, 1995). Extreme low temperatures can also increase blood pressure and reduce blood vessel function, which can lead to increases in cardiovascular diseases and heart attack (Lavigne et al., 2014). Cold effects can also be caused by greater mixing of the population, leading to greater communication of diseases (Suzanne, 2014). However, extreme low temperature was not associated with the cardiovascular class of dispatches for this study.

High extreme temperatures significantly increased dispatches of 999 and Red category dispatches, they also were associated with several of the non-cardiorespiratory dispatch categories: dizzy, alcohol-related, vomiting and ‘generally unwell’, which is consistent with the study by Thornes et al. (2014). High extreme temperatures also showed a positive association with COPD and chest pain dispatches. Extreme high temperatures are associated with adverse health due to changes in blood flow from vital organ to the skin surface decreasing temperature in body, this places increased stress on the cardiorespiratory systems. Furthermore, increased blood viscosity, elevated cholesterol levels associated with higher temperatures, and higher sweating threshold may also trigger heat-related effects mortality (Åstrand et al., 2003). It is important to note that the impact of extreme temperatures does not only affect patients with a definitive heat related illness, for example heat stroke. The vast majority of patients who are affected by extreme temperatures are affected because of exacerbation of other chronic conditions.

Previous work has found increases in hospital visits for respiratory conditions to be associated with hot temperatures (Lavigne et al., 2014) and increases in 1°C were associated with rising in the respiratory admission dispatches in age ≥ 75 years at 4.5% (95% CI: 1.9-7.3%) (Michelozzi et al., 2009). These findings broadly support the COPD result from this study. The increases in alcohol-related dispatches is consistent with the work of Mahmood et al. (2017) in London and Petralli et al. (2012) in Italy. A possible explanation for this might be a high level of alcohol consumption in public places during hot weather with corresponding dehydration. Contrary to this study Leonardi et al. (2006) found that there was no association between temperature and health effects caused by vomiting and difficult breathing symptoms.

The only categories associated with both extreme low and high temperatures were the 999 and ‘generally unwell’ dispatches, these categories are both generic and contain multiple illnesses under their banners.

Distinctly different lag patterns were observed between the associations of extreme low and high temperature with health impacts, as shown in Figure 5. This is consistent with previous studies which showed that exposure to high temperatures typical exhibit a shortage lag period whereas low temperatures typically reported longer lags that can be up 3-4 weeks (Gasparrini et al., 2015a; Onozuka and Hagihara, 2015, Zhan et al., 2018).

Delayed effects (lag) is important to understand. Some dispatch categories showed the greatest relative risk on the day concurrent with the extreme high temperature (lag 0) with a subsequent decline in the following two to three days, for example 999 dispatch and red dispatch categories. Conversely, exposure to extreme low temperature for these categories showed a slight increase in relative risk for two to three days following the extreme event. Hence, these lags can be useful for forward planning within the health service. For example, public warnings could be made to vulnerable groups following extreme weather about illnesses known to be associated with lags. It is noted, previous publications have reported evidence of harvesting effects, especially with respect to heat-related outcomes in frail persons (Baccini et al., 2013; Bhaskaran et al., 2013; Guo et al., 2011; Onozuka and Hagihara, 2015; Zhan et al., 2018). Bhaskaran et al. (2013) mentioned the cumulative lag over study period should take account to the harvesting effect was observed. No harvesting effects were observed in this study with respect to extreme low temperature exposure.

This study has several possible limitations, which could be explored in future work. The meteorological and air pollution data from monitoring stations provide only an approximation of personnel exposure to meteorology and air pollutants. The study did not analyse individual vulnerability factors, such as age, gender, race, occupation, geographical situation, underlying health condition, and socioeconomic status, which previous studies suggest affect responses to extreme temperatures (e.g. Basu, 2009; Shah et al., 2012; Berko et al. 2014; Zhao et al. 2017).

The major strength of this study is to provide new evidential support on the impact of extreme temperatures upon health. Ambulance data can provide temporal and spatial information about where and when ill health occurs that hospital and GP data do not. In the future, ambulance data should be fed into syndromic and early warning systems to reduce morbidity and mortality associated with extreme temperature events. The data from this study can also be used to provide better forecasts for ambulatory requirements dependent on season and short range meteorological forecasts.

Our findings suggest that ambulance dispatch data should be successful incorporated into health surveillance systems. They could be used as an early warning system about the likely effects of extreme temperature events. Furthermore, public health messaging should be used after extreme events, especially for categories that experience lags in peak risk factors. These actions should help improve overall survival rates within health systems

5.6 Conclusions

This study provides strong evidence for the associations between extreme temperatures and higher health risks. Demands on ambulance services increase during low temperatures for 999, asthma, dyspnoea, RCI and ‘generally unwell’ dispatches. Extreme high temperatures increase 999, Red, COPD, chest pain, dizzy, alcohol-related vomiting and ‘generally unwell’ dispatches. Climate change action plans need to consider the changing likelihoods of extreme temperates and the resulting impact on ambulatory service provision. This study can also inform the development of early warning syndromic surveillance systems. In summary, the data and analysis from this work can help improve emergency service provision and reduce response times, which can increase patient survival rates and treatment costs.

5.7 Conflict of interest

The authors declare that they have no conflict of interest.

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5.10 Ethical approval

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5.11 References

Alessandrini, E., Zauli Sajani, S., Scotto, F., Miglio, R., Marchesi, S., Lauriola, P., 2011. Emergency ambulance dispatches and apparent temperature: A time series analysis in Emilia-Romagna, Italy. Environ. Res. 111, 1192–1200. https://doi.org/10.1016/j.envres.2011.07.005

Åstrand, P.-O., Rodahl, K.R., Dahl, H.A., Stromme, S.B., 2003. Textbook of work physiology : physiological bases of exercise, 4th edn., United States, Human Kinetics,of America.

Baccini, M., Kosatsky, T., Biggeri, A., 2013. Impact of Summer Heat on Urban Population Mortality in Europe during the 1990s: An Evaluation of Years of Life Lost Adjusted for Harvesting. PLoS One 8. https://doi.org/10.1371/journal.pone.0069638

Bassil, K.L., Cole, D.C., Moineddin, R., Lou, W., Craig, A.M., Schwartz, B., Rea, E., 2011. The relationship between temperature and ambulance response calls for heat-related illness in Toronto, Ontario, 2005. J. Epidemiol. Community Health 65, 829–831. https://doi.org/10.1136/jech.2009.101485

Basu, R., 2009. High ambient temperature and mortality: A review of epidemiologic studies from 2001 to 2008. Environ. Heal. A Glob. Access Sci. Source 8. https://doi.org/10.1186/1476-069X-8-40

Basu, R., Samet, J.M., 2002. Relation between elevated ambient temperature and mortality: a review of the epidemiologic evidence. Epidemiol. Rev. 24, 190–202. https://doi.org/10.1093/epirev/mxf007

Berko, J., Ingram, D.D., Saha, S., Parker, J.D., 2014. Deaths attributed to heat, cold, and other weather events in the United States, 2006-2010. Natl. Health Stat. Report. 1–15.

Bhaskaran, K., Gasparrini, A., Hajat, S., Smeeth, L., Armstrong, B., 2013. Time series regression studies in environmental epidemiology. Int. J. Epidemiol. 42, 1187–1195. https://doi.org/10.1093/ije/dyt092

Bhaskaran, K., Hajat, S., Fmedsci, A.H., Herrett, E., Frcp, P.W., Smeeth, L., 2009. THE EFFECTS OF AMBIENT TEMPERATURE ON THE INCIDENCE OF MYOCARDIAL INFARCTION – A SYSTEMATIC REVIEW 3.

Chen, Y., Lai, Y., Ke, J., Chen, Y., Xu, Y., Ma, Y., Yuan, J., Liang, T., Mai, P., Lin, C., 2015. Impact of subtropical climate on frequency of ambulance use for trauma patients in a coastal area of China. Chinese J. Traumatol. 18, 141–146.

Cheng, J., Xu, Z., Zhao, D., Xie, M., Yang, H., Wen, L., Li, K., Su, H., 2016. Impacts of temperature change on ambulance dispatches and seasonal effect modification. Int. J. Biometeorol. 60, 1863–1871. https://doi.org/10.1007/s00484-016-1173-4

Clawson, J.J., Cady, G.A., Martin, R.L., Sinclair, R., 1998. Effect of a comprehensive quality management process on compliance with protocol in an emergency medical dispatch center. Ann. Emerg. Med. https://doi.org/10.1016/S0196-0644(98)70036-8

Deakin, C.D., Sherwood, D.M., 2006. PREHOSPITAL CARE Does telephone triage of emergency (999) calls using advanced medical priority dispatch (AMPDS) with Department of Health (DH) call prioritisation effectively identify patients with an acute coronary syndrome? An audit of 42 657 emergency calls to Hampshire Ambulance Service NHS Trust. Emerg Med J 23, 232–235. https://doi.org/10.1136/emj.2004.022962

Elliot, A.J., Smith, S., Dobney, A., Thornes, J., Smith, G.E., Vardoulakis, S., 2016. Monitoring the effect of air pollution episodes on health care consultations and ambulance call-outs in England during March/April 2014: A retrospective observational analysis. Environ. Pollut. 214, 903–911. https://doi.org/10.1016/j.envpol.2016.04.026

Fu, S.H., Gasparrini, A., Rodriguez, P.S., Jha, P., 2018. Mortality attributable to hot and cold ambient temperatures in India: a nationally representative case-crossover study. PLOS Med. 15, e1002619. https://doi.org/10.1371/journal.pmed.1002619

Gasparrini, A., 2011. Distributed Lag Linear and Non-Linear Models in R: The Package dlnm. J. Stat. Softw. 43, 1–20. https://doi.org/http://dx.doi.org/10.18637/jss.v043.i08

Gasparrini, A., Guo, Y.-L.L.Y., Hashizume, M., Lavigne, E., Zanobetti, A., Schwartz, J., Tobias, A., Tong, S., Rocklöv, J., Forsberg, B., Leone, M., De Sario, M., Bell, M.L., Guo, Y.-L.L.Y., Wu, C.-F., Kan, H., Yi, S.-M., de Sousa Zanotti Stagliorio Coelho, M., Saldiva, P.H.N., Honda, Y., Kim, H., Armstrong, B., De, M., Zanotti, S., Coelho, S., Hilario, P., Saldiva, N., Honda, Y., Kim, H., Armstrong, B., 2015a. Mortality risk attributable to high and low ambient temperature: a multicountry observational study. Lancet 386, 369–375. https://doi.org/10.1016/S0140-6736(14)62114-0

Gasparrini, A., Guo, Y., Hashizume, M., Kinney, P.L., Petkova, E.P., Lavigne, E., 2015b. Temporal Variation in Heat – Mortality Associations : A Multicountry Study. Environ. Health Perspect. 1200, 1200–1207.

Gasparrini, A., Leone, M., 2014. Attributable risk from distributed lag models. BMC Med. Res. Methodol. 14, 55. https://doi.org/10.1186/1471-2288-14-55

Giesbrecht, G.G., 1995. The respiratory system in a cold environment. Aviat. Space. Environ. Med. 66, 890–902.

Guo, Y., Barnett, A.G., Pan, X., Yu, W., Tong, S., 2011. The impact of temperature on mortality in Tianjin, china: A case-crossover design with a distributed lag nonlinear model. Environ. Health Perspect. 119, 1719–1725. https://doi.org/10.1289/ehp.1103598

Guo, Y., Gasparrini, A., Armstrong, B., Li, S., Tobias, A., Lavigne, E., Sousa, M. De, Stagliorio, Z., 2014. Europe PMC Funders Group Global variation in the effects of ambient temperature on mortality : a systematic evaluation. Epidemiology 25, 781–789. https://doi.org/10.1097/EDE.0000000000000165.Global

Hajat, S., Kovats, R.S., Lachowycz, K., 2007. Heat-related and cold-related deaths in England and Wales: who is at risk? Occup. Environ. Med. 64, 93–100.

Kotani, K., Ueda, K., Seposo, X., Yasukochi, S., Matsumoto, H., Ono, M., Honda, A., Takano, H., 2018. Effects of high ambient temperature on ambulance dispatches in different age groups in Fukuoka, Japan. Glob. Health Action 11, 1437882. https://doi.org/10.1080/16549716.2018.1437882

Lavigne, E., Gasparrini, A., Wang, X., Chen, H., Yagouti, A., Fleury, M.D., Cakmak, S., 2014. Extreme ambient temperatures and cardiorespiratory emergency room visits: Assessing risk by comorbid health conditions in a time series study. Environ. Heal. A Glob. Access Sci. Source 13, 1–8. https://doi.org/10.1186/1476-069X-13-5

Leonardi, G.S., Hajat, S., Kovats, R.S., Smith, G.E., Cooper, D., Gerard, E., 2006. Syndromic surveillance use to detect the early effects of heat-waves: an analysis of NHS direct data in England. Sozial-und Präventivmedizin 51, 194–201.

London Ambulance Service, 2017. Annual Report 2016-17 [WWW Document]. URL https://www.londonambulance.nhs.uk/document-search/annual-report-2016-17/ (accessed 2.18.18).

Mahmood, M.A., Thornes, J.E., Pope, F.D., Fisher, P.A., Vardoulakis, S., 2017. Impact of Air Temperature on London Ambulance Call-Out Incidents and Response Times. Climate 5, 61.

Medina-Ramón, M., Zanobetti, A., Cavanagh, D.P., Schwartz, J., 2006. Extreme temperatures and mortality: assessing effect modification by personal characteristics and specific cause of death in a multi-city case-only analysis. Environ. Health Perspect. 1331–1336.

Michelozzi, P., Accetta, G., De Sario, M., D'Ippoliti, D., Marino, C., Baccini, M., Biggeri, A., Anderson, H.R., Katsouyanni, K., Ballester, F., Bisanti, L., Cadum, E., Forsberg, B., Forastiere, F., Goodman, P.G., Hojs, A., Kirchmayer, U., Medina, S., Paldy, A., Schindler, C., Sunyer, J., Perucci, C.A., 2009. High temperature and hospitalizations for cardiovascular and respiratory causes in 12 european cities. Am. J. Respir. Crit. Care Med. 179, 383–389. https://doi.org/10.1164/rccm.200802-217OC

NHS, 2017. Ambulance Response Programme Review NHS England Gateway Publication Reference: 08296 Ambulance Response Programme Review. National Health Service England.

O'Keeffe, C., Nicholl, J., Turner, J., Goodacre, S., 2011. Role of ambulance response times in the survival of patients with out-of-hospital cardiac arrest. Emerg. Med. J. 28, 703–706.

Onozuka, D., Hagihara, A., 2015. All-Cause and cause-specific risk of emergency transport attributable to temperature: A nationwide study. Med. (United States) 94. https://doi.org/10.1097/MD.0000000000002259

Papadakis, G., Chalabi, Z., Thornes, J., Papadakis, G., Chalabi, Z., Thornes, J.E., 2018. Ambulance Service Resource Planning for Extreme Temperatures: Analysis of Ambulance 999 Calls during Episodes of Extreme Temperature in London, UK. Atmosphere (Basel). 9, 182. https://doi.org/10.3390/atmos9050182

Pell, J.P., Sirel, J.M., Marsden, A.K., Ford, I., Cobbe, S.M., 2001. Effect of reducing ambulance response times on deaths from out of hospital cardiac arrest: cohort study. Bmj 322, 1385–1388.

Petralli, M., Morabito, M., Cecchi, L., Crisci, A., Orlandini, S., 2012. Urban morbidity in summer: Ambulance dispatch data, periodicity and weather. Cent. Eur. J. Med. 7, 775–782. https://doi.org/10.2478/s11536-012-0056-2

Sangkharat, K., Fisher, P., Neil Thomas, G., Thornes, J., D Pope, F., 2019. The impact of air pollutants on ambulance dispatches: A systematic review and meta-analysis of acute effects. Environ. Res.

Scovronick, N., Sera, F., Acquaotta, F., Garzena, D., Fratianni, S., Wright, C.Y., Gasparrini, A., 2018. The association between ambient temperature and mortality in South Africa: A time-series analysis. Environ. Res. 161, 229–235. https://doi.org/10.1016/J.ENVRES.2017.11.001

Shah, A.S. V, Langrish, J.P., Nair, H., Mcallister, D.A., Hunter, A.L., Donaldson, K., Newby, D.E., Mills, N.L., 2012. Global association of air pollution and heart failure : a systematic review and meta-analysis. Lancet 382, 1039–1048. https://doi.org/10.1016/S0140-6736(13)60898-3

Stafoggia, M., Forastiere, F., Agostini, D., Caranci, N., De'Donato, F., Demaria, M., Michelozzi, P., Miglio, R., Rognoni, M., Russo, A., 2008. Factors affecting in-hospital heat-related mortality: a multi-city case-crossover analysis. J. Epidemiol. Community Heal. 62, 209–215.

Suzanne, 2014. How does cold weather affect your health? [WWW Document]. URL https://www.health.harvard.edu/staying-healthy/how-does-cold-weather-affect-your-health (accessed 3.9.18).

Thornes, J.E., Fisher, P.A., Rayment-Bishop, T., Smith, C., 2014. Ambulance call-outs and response times in Birmingham and the impact of extreme weather and climate change. Emerg. Med. J. 31, 220–228. https://doi.org/10.1136/emermed-2012-201817

Todkill, D., Loveridge, P., Elliot, A.J., Morbey, R.A., Edeghere, O., Rayment-Bishop, T., Rayment-Bishop, C., Thornes, J.E., Smith, G., 2017. Utility of Ambulance Data for Real-Time Syndromic Surveillance: A Pilot in the West Midlands Region, United Kingdom. Prehosp. Disaster Med. 32, 1–6. https://doi.org/10.1017/S1049023X17006690

Turner, J., Jacques, R., Crum, A., Coster, J., Stone, T., Nicholl, J., 2017. Ambulance Response Programme Evaluation of Phase 1 and Phase 2 Final Report.

Turner, L.R., Barnett, A.G., Connell, D., Tonga, S., 2012. Review Article: Ambient Temperature and Cardiorespiratory Morbidity: A Systematic. Source Epidemiol. 23, 594–606. https://doi.org/10.1097/EDE.0b013e3182572795

Vicedo-Cabrera, A.M., Forsberg, B., Tobias, A., Zanobetti, A., Schwartz, J., Armstrong, B., Gasparrini, A., 2016. Associations of Inter- and Intraday Temperature Change with Mortality. Am. J. Epidemiol. 183, 286–293. https://doi.org/10.1093/aje/kwv205

Wichmann, H.E., 2004. What can we learn today from the Central European smog episode of 1985 (and earlier episodes)? Int. J. Hyg. Environ. Health 207, 505–520. https://doi.org/10.1078/1438-4639-00322

World Health Organization, 2017. Climate change and health [WWW Document]. URL http://www.who.int/mediacentre/factsheets/fs266/en/

Yu, W., Mengersen, K., Wang, X., 2012. Daily average temperature and mortality among the elderly : a meta-analysis and systematic review of epidemiological evidence 569–581. https://doi.org/10.1007/s00484-011-0497-3

Zhan, Z.-Y., Yu, Y.-M., Qian, J., Song, Y.-F., Chen, P.-Y., Ouid, C.-Q., 2018. Effects of ambient temperature on ambulance emergency call-outs in the subtropical city of Shenzhen, China. https://doi.org/10.1371/journal.pone.0207187

Zhao, Q., Zhang, Y.M., Zhang, W.Y., Li, S.S., Chen, G.B., Wu, Y.B., Qiu, C., Ying, K.J., Tang, H.P., Huang, J.A., Williams, G., Huxley, R., Guo, Y.M., 2017. Ambient temperature and emergency department visits: Time-series analysis in 12 Chinese cities. Environ. Pollut. 224, 310–316. https://doi.org/10.1016/j.envpol.2017.02.010

CHAPTER 6 : ASSOCIATION BETWEEN TEMPERATURE AND PRECIPITATION WITH ROAD ACCIDENTS IN NORTHERN AND SOUTHERN THAILAND

6.1 Introduction

The World Health Organization (WHO, 2018) has highlighted that the number of deaths worldwide due to road accidents increases every year. Worldwide in 2016, 1.35 million persons died as a result of a road accident. Children and young people, defined as those who are aged between 5 and 29 years, are the group most at risk with the highest records of road accidents. The WHO suggested that countries should set a plan to reduce the number of road accidents, with a corresponding Sustainable Development Goal (SDG) target which aims to reduce the number of global deaths and injuries from road traffic accidents by 50% by 2020 and provide a sustainable and safe transport system by 2030. The WHO reported that the number of accidents and death from road accidents in low income countries did not decrease during 2013 to 2016 while 48 middle and high income countries had a decline.

Previous studies have reported significant positive associations between rainfall and road accidents (Bergel-Hayat et al., 2013; Brodsky and Hakkert, 1988; Hermans et al., 2006). Heavy rain is a danger because of the reduced road skid resistance associated with a wet road (Bernardin et al., 2014). However, some publications claim that rainfall can also be a protective factor because a decrease in road accidents during heavy rain was observed. A possible explanation for these observations could be a reduction of traffic during a heavy rain (Bergel-Hayat et al., 2013; Yannis and Karlaftis, 2010) or driving slowly to reduce risk (Brodsky and Hakkert, 1988). Another study investigated whether delay effects were prevalent, with a decrease in estimated risks effect found on the day following the rain event (Brijs et al., 2008).

This chapter investigates the use of ambulance data in Thailand to investigate the relationships between rainfall and road accidents. Thailand is a middle-income country located in South East Asia. Records indicate that ambulance dispatches due to road accidents represent the highest volume of ambulance dispatches countrywide and in every province. Ambulance dispatches due to road accidents have increased each year and by 32.8% between 2012 to 2018 as shown in Figure 6-1.

Figure 6-1 Yearly number of reported road accidents in Thailand from 2012 to 2018 (ITEMS, 2018).

Prior to this study, no studies in Thailand have investigated the impact of rainfall on ambulance dispatches due to road accidents. Hence, this study investigates the effect of rainfall factors on road accidents resulting in an ambulance dispatch. Furthermore, the chapter compares the difference between the provinces located in the North and the South of Thailand. This grouping of provinces is chosen because of the distinct meteorological regimes observed in both regions. A time series analysis with a Poisson regression model in a distributed lag nonlinear model was conducted to evaluate estimated risks, reported as a relative risk with 95% confidential intervals. The model was controlled for confounding factors such as a long-term trend, seasonality, day of week, holiday days, temperature and relative humidity. A meta-analysis is used to pool the estimated risk at region level (Northern and Southern). The results identify the effects of rainfall upon road accidents and ambulance responses. The new understanding gained from this study can be translated to policymakers to help them improve road safety and risk management.

6.2 Method

6.2.1 Data

Thai ambulance dispatch data, via the Thai emergency number 1699, which is similar to the 999 number used in the UK, was acquired from the National Institute for Emergency Medicine (NIEM). The data records the number of ambulance dispatches resulting from road traffic accidents that led to a patient being taken to the hospital. The ambulance data was available for 76 provinces, which represents all provinces other than the Bangkok metropolitan administration, which has their data collated by The Erawan Medical Center Bangkok. The data for the provinces, includes the nine provinces that form the Northern provinces and the 14 that form the Southern provinces in Thailand. In the first section, the association between temperature and ambulance dispatches was examined using Poisson regression with time series analysis for each province. In the second section, the role of precipitation was investigated with respect to the relationship with total ambulance call and road accident dispatch data. The pooled estimated effect was reported using a random-effect to give region estimates.

6.2.2 Statistics

Three statistical analyses were conducted in this study. Firstly, the association between temperature and total dispatches was analysed using time series analysis design with negative binomial regression model due to the over-dispersion of total dispatch data (Guo et al., 2012; Onozuka et al., 2018). A distributed lag non-linear model (DLNM) was used to study non-linear and delay effects (Guo et al., 2012). Confounding factors were controlled, such as day of week as a category variable, holiday, seasonality and a long-term trend. Relative humidity and temperature were adjusted in the model through the use of natural cubic splines and the degree of freedom (df) at 7 for calendar effects and three df for temperature and relative humidity following Xu et al's approach (2017). The model presents relative risks (RR) of total dispatches at an extreme temperature; the cold effect is defined for the daily temperatures that were less than the 5th percentile of temperatures distribution for each city while the extreme high temperature effect was defined when daily temperatures were more than the 95th percentile of province temperatures. Both extreme high and low temperature effects were investigated because previous cognate studies highlight that both the U-shape or J-shape patterns can be observed for these associations. The specific city relative risk was investigated for up to 21 lag days (Guo et al., 2018) as shown in a basic model compared to the threshold temperature, which reported the lowest risk. A distributed lag non-linear model (DLNM) package was conducted in R to estimate the impact of temperature on ambulance dispatches. Results were reported in RR with 95% confidence intervals (CIs) at cumulative lag of 0-2 days, lag of 0-14 days and lag of 0-21 days and compared to a reference temperature (°C) referring to the lowest risk. The model was specified as equation (1) :

$$\text{Log}\,[E(Y)] = \alpha + cb\,(\text{Temp, lag} = 21) + ns\,(\text{Time, df} = 7*7) + \beta\,\text{DOW} + \gamma\text{Holiday} + \delta\text{RH} + \varepsilon\text{Rain} \quad \textbf{(1)}$$

Where E(Y) is the category of daily ambulance dispatches, cb is a cross basis for two dimensions between temperature and lag times. The natural cubic spline (ns) is a smoother for time with a df of 7 which gave a lowest Akike Information Criterion (AIC) for removing the effect of a long-term trend and seasonality. Day of week (DOW), holiday days and relative humidity (RH) were allowed in the model to adjust for confounding factors. β, γ, δ and ε is a vector of coefficients for DOW, Holiday, RH and Rain respectively.

Secondly, the effects of precipitation on road accidents was investigated and stratified by groups of different rain intensities, as measured by the hourly rate of precipitation. The association was described as having a linear trend between rain and accident (Bergel-Hayat et al., 2013). The model was adjusted for confounding factors such as temperature, relative humidity, day of week and public holiday. Results were reported in RR with 95% CIs for an increase in different rain groups compared with dry days and a delay effect for one day by using DLNM package in R. The core model was shown as equation (2).

$$\text{Log}\,[E(Y)] = \alpha + cb\,(\text{Rain\_group}, \text{lag} = 1) + ns\,(\text{Time}, df = 7*7) + \beta\,\text{DOW} + \gamma\text{Holiday} + \delta\text{RH} + \varepsilon\text{Temp} \quad \textbf{(2)}$$

Rain groups or x are categorical variables (range: 0-6, 0 for no rain (x=0), 1 for rain groups 0<x<1 mm, 2 for rain group 1≤x<2 mm, 3 for rain group 2≤x<5 mm, 4 for rain group 5≤x<10 mm, 5 for rain group 10≤x<20 mm and 6 for rain group more than 20 mm (x≥20) per day). Akaike's Information Criterion (AIC) was used to consider the number of degree of freedom to be used in the analysis (Guo et al., 2018), the lowest AIC was chosen. Day of week and holiday variables also were adjusted into the core model. The rainfall effect was estimated by RR of each rain group compared with no rain day (rain groups =0).

Thirdly, a meta-analysis to pool the risk effects was conducted to report the association of an increase in rain per day across the region by rain groups. Meta-analysis with random effect was used to analyse the association between rainfall and ambulance dispatches in the Northern and the Southern. The heterogeneity was evaluated by Cochran Q test and I^2 number.

6.3 Results

6.3.1 The association between temperature and total dispatches

6.3.1.1 Descriptive Data

Ambulance data for 23 provinces in the Northern and the South regions of Thailand, from January 2012 to December 2018, were obtained. In total 2557 days of data were obtained.

In the Northern region of Thailand, there are nine provinces: Chaing Rai, Chaing Mai, Nan, Payao, Phrea, Mae Hong Son, Lampang, Lamphun and Uttaradit as shown in Figure 6-2 The Southern region has 14 provinces which are Chumphon, Nakhon Si Thammarat, Narathiwat, Pattani, Phatthalung, Songkhla, Surat Thani, Yala, Krabi, Phang Nga, Phuket, Ranong, Satun and Trang. In Thailand, the rainy season starts from middle of May until October while the rain remains until December in the Gulf Coast of the southern Pennisula (Cavanagh, 2008). The Southern region is a peninsula and has an average rainfall higher than the Northern region of Thailand. Ambulance dispatch data were obtained from the National Institute for Emergency Medicine (NIEM) with 25 categories following Table 6-1., which were all aggregated for all Thai provinces except Bangkok. This study extracted data for only total dispatches and road accident dispatch data. Once a 1699 call is received, the phone operator staff interviews the patient to take their details and then dispatches a paramedic to the scene of the accident. The road accident dispatch data has the greatest number of dispatches of any category in all years of data collection. Figure 6-3 shows the bar chart of ambulance dispatches by categories in 2018.

Meteorological data (temperature, relative humidity and precipitation) were obtained from monitoring stations in each province and provided by the Thai Meteorological Department (www.tmd.go.th) as daily averages. If there are two monitoring stations in a province, we chose the station located in urban areas rather than rural areas.

Figure 6-2 The six regions of Thailand and their provinces (Camel Travel, 2017)

Table 6-1 Summary of total yearly ambulance dispatches in Thailand (76 provinces) between 2012 and 2018

Symptoms	Year						
	2012	2013	2014	2015	2016	2017	2018
01:Abdominal/Back/Groin Pain	107977	112713	116460	122314	128980	124471	133649
02:Anaphylaxis/Allergic Reaction	3580	3441	4261	5012	5206	5801	6624
03:Infectious Disease	10938	10084	11413	11285	11200	11832	13258

Symptoms	Year						
	2012	2013	2014	2015	2016	2017	2018
04:Bleeding (Non-traumatic)	8099	7709	8885	9294	10149	10839	12043
05:Breathing Difficulty	43289	46311	51808	57900	62675	68202	71591
06:Cardiac arrest	80	86	95	138	138	144	202
07:Chest Pain/Discomfort/Heart Problems	12098	13530	14824	18100	19755	22028	24596
08:Choking	639	650	701	832	909	1052	1069
09:Diabetic	13301	13963	13576	13928	13740	12577	12221
10: Environmental/Toxic Exposure	350	276	404	475	402	420	572
11: Medical Knowledge (Medical Facility Only)							
12:Head/Neck	25899	26922	26663	29546	30409	32103	32984
13:Mental/Emotional/Psychological	6282	6311	7161	8089	8662	9564	10782
14:Overdose/Poisoning	3281	3065	2919	3277	3366	3510	3549
15:Pregnancy/Childbirth/Gyn.	22074	20422	20405	20009	19734	19304	18588
16:Seizures	11159	12366	14072	16411	18291	19589	20975
17:Sick (Unknown)/Other	141619	160510	171875	195052	212489	218947	230997
18:Stroke (CVA)	1949	2112	2569	3455	4261	5233	6228
19:Unconscious/Unresponsive/Syncope	12548	13836	15875	19059	20819	22936	25735
20:Pediatric Emergencies	45803	51184	47227	46454	50758	39202	43057
21:Assault/Trauma	22481	19534	20340	20520	18294	17848	17791
22:Burns - Thermal/Electrical/Chemical	2016	2059	2026	2155	2188	2230	2374
23:Drowning/Near Drowning/Diving or Water-related Injury	1845	663	638	631	750	845	788
24:Falls/Accidents/Pain	58930	61753	66569	72682	77622	83436	88875
25:Road accidents	195685	196779	201329	220517	240220	254261	259903
Not identify	5390	5443	3621	4104	4473	3543	1520
Total	**757312**	**791722**	**825716**	**901239**	**965490**	**989917**	**1039971**

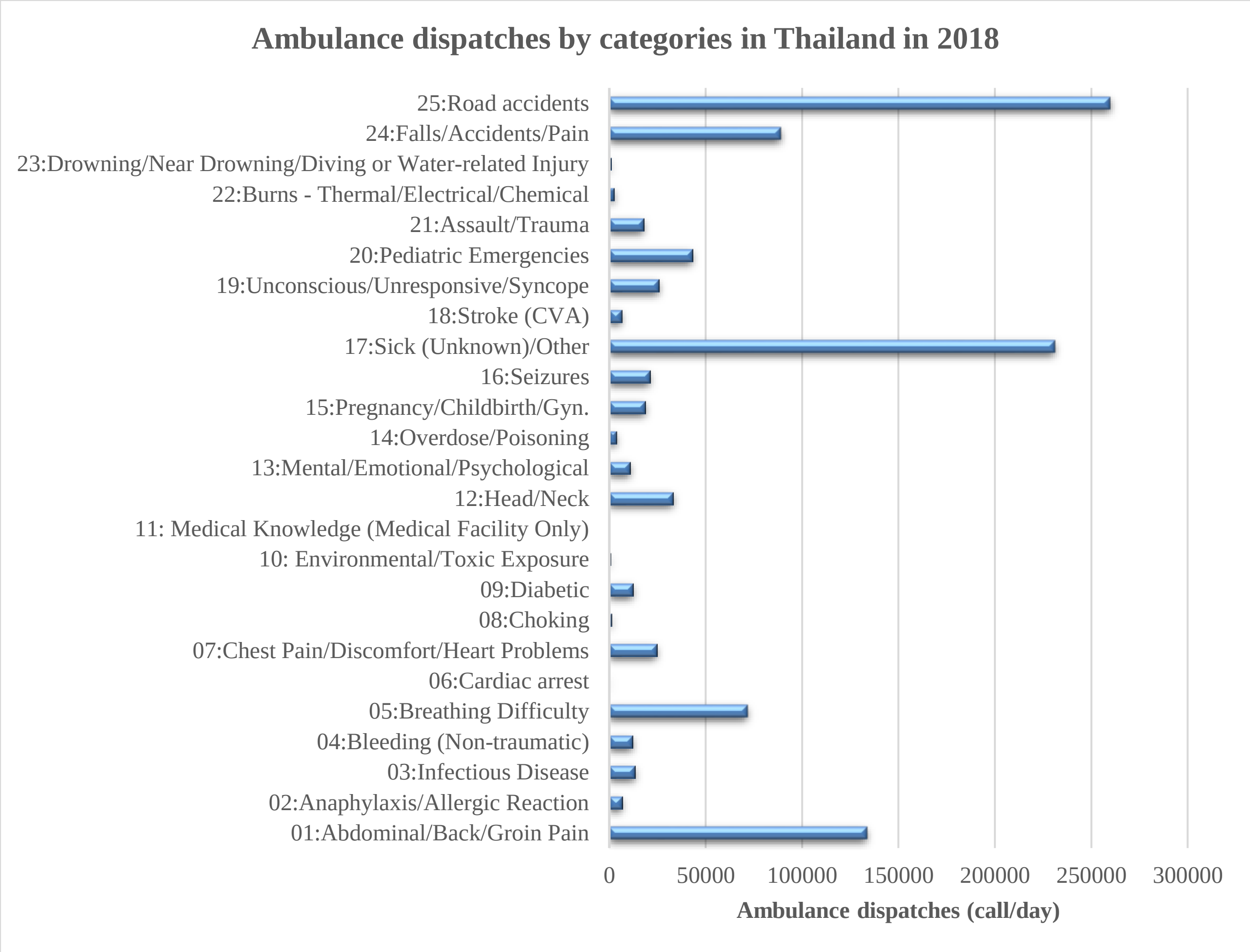


Figure 6-3 Bar chart of Thai ambulance dispatches by categories in 2018

6.3.1.2 Summary of statistics for meteorology (temperature, relative humidity and rainfall)

Daily meteorological variables are summarized in Table 6-2, Table 6-3 and Table 6-4. The daily averages observed during the study period study, show that the Northern provinces have lower average temperatures and relative humidity compared to the Southern provinces. The mean (±1SD) of temperature in the Northern provinces ranged from 25.3±3.1°C to 28.1±2.5°C (Northern provinces) and from 27.0±1.2°C to 28.8±2.7°C (Southern provinces) (Table 6-2). The mean relative humidity in the Northern provinces ranged from 70.1±10.6 % to 77.9±9.5 %, while the mean in the Southern ranged from 77.8±5.7 to 83.8 ±5.7 (Table 6-3).

Mean precipitation is higher in the Southern provinces ranging from 4.3±12.5 to 11.9±24.7 mm/day compared to the Northern provinces 3.0±8.4 to 5.1±12.7 mm/day (Table 6-4).

The frequency of road accidents were compared between the different provinces. Most provinces show a consistent pattern, with a higher number of accidents found during the months of October to December. Investigation of day of the week effects, reveals a smaller number of road accidents at the weekend compared to weekdays as shown in Supplementary Figure 6-13

Table 6-2 Summary daily statistics for temperature in Thailand during 2012-2018 over Northern and Southern provinces. All values in °C.

Province	Mean ± SD	Percentiles				
		Min	P25	P50	P75	Max
Temperature (°C)						
Northern provinces						
Chiang Rai	25.3±3.1	8.9	23.4	26.0	27.4	33.6
Chiang Mai	27.0±2.7	11.5	25.6	27.4	28.7	35.1
Nan	26.7±2.9	9.6	25.3	27.3	28.6	33.8
Payao	25.7±3.1	9	24.0	26.3	27.8	34.9
Phrae	27.0±2.8	10.9	25.7	27.4	28.6	36.2
Mae Hong Son	26.3±3.3	15.3	24.3	26.7	28.2	35.6
Lampang	26.9±2.9	10.5	25.6	27.3	28.7	35.3
Lamphun	26.8±2.9	10.9	25.3	27.2	28.6	35.6
Uttaradit	28.1±2.5	12.1	26.8	28.3	29.5	36.6
Southern provinces						
Krabi	27.0±1.2	23.4	26.2	27.0	27.8	31.2
Chumphon	27.4±1.4	21.2	26.5	27.5	28.3	31.9
Trang	27.6±1.3	23.5	26.8	27.6	28.4	31.8
Nakhon Si Thammarat	27.5±1.3	23.5	26.6	27.5	28.4	31.3
Narathiwat	27.5±1.2	22.6	26.8	27.6	28.4	31.1
Pattani	27.6±1.2	23.4	26.8	27.7	28.5	31.8
Phang Nga	27.7±1.2	23.4	27.0	27.9	28.6	31.5
Phatthalung	27.8±1.2	23.4	27.0	27.8	28.5	31.4

Province	Mean ± SD	Percentiles				
		Min	P25	P50	P75	Max
Phuket	28.7±1.2	24.4	28.0	28.8	29.6	32.2
Ranong	27.4±1.3	23.7	26.5	27.4	28.2	32.0
Satun	27.9±1.1	24.1	27.1	28.0	28.7	32.0
Songkhla	28.8±1.2	23.1	27.4	28.2	29.0	32.5
Surat Thani	27.3±1.3	22.6	26.4	27.2	28.1	32.9
Yala	27.3±1.3	23.1	26.5	27.3	28.1	32.0

Abbreviations: SD: standard deviation, $P_{x\ x}$th: percentile, Min: minimum, Max: maximum

Table 6-3 Summary daily statistics for relative humidity in Thailand during 2012-2018 over Northern and Southern provinces. All values in %.

Province	Mean ± SD		Percentiles			
		Min	P25	P50	P75	Max
Relative humidity (%)						
Northern provinces						
Chiang Rai	76.5±8.3	45.0	72.0	78.0	82.0	95.0
Chiang Mai	70.1±10.6	39.0	63.0	72.0	78.0	96.0
Nan	76.7±8.5	51.0	72.0	78.0	82.0	98.0
Payao	77.9±9.5	40.0	73.0	80.0	84.0	98.0
Phrae	76.0±9.3	43.0	70.0	78.0	83.0	97.0
Mae Hong Son	75.8±11.1	40.0	69.0	80.0	84.0	95.0
Lampang	74.1±10.3	41.0	68.0	76.0	81.0	96.0
Lamphun	73.1±11.2	40.0	66.0	75.0	81.0	98.0
Uttaradit	71.6±9.7	39.0	65.0	72.0	79.0	95.0
Southern provinces						
Krabi	83.34±7.3	58.0	79.0	84.0	88.0	99.0
Chumphon	81.44±5.9	60.0	78.0	81.0	85.0	98.0
Trang	81.1±7.5	58.0	77.0	82.0	87.0	98.0
Nakhon Si Thammarat	82.82±5.8	59.0	79.0	83.0	86.0	100.0
Narathiwat	81.4±4.6	67.0	79.0	81.0	84.0	97.0
Pattani	81.0±5.3	59.0	77.0	81.0	84.0	98.0

Province	Mean ± SD		Percentiles			
		Min	P25	P50	P75	Max
Phang Nga	83.6±6.6	50.0	80.0	84.0	83.6	88.0
Phatthalung	82.1±5.7	63.0	78.3	82.0	86.0	98.0
Phuket	81.0±6.9	56.0	72.0	77.0	81.0	97.0
Ranong	79.9±7.8	56.0	75.0	81.0	86.0	95.0
Satun	79.2±7.2	55.0	75.0	80.0	84.0	96.0
Songkhla	77.8±5.7	62.0	74.0	77.0	81.0	96.0
Surat Thani	83.8±5.7	65.0	80.0	84.0	88.0	99.0
Yala	81.0±6.1	54.0	77.0	81.0	85.0	99.0

Abbreviations: SD: standard deviation, P_x xth: percentile, Min: minimum, Max: maximum

Table 6-4 Summary daily statistics for precipitation in Thailand during 2012-2018 over Northern and Southern provinces. All values in mm/day.

Province	**Mean ± SD**		**Percentiles**			
		Min	**P25**	**P50**	**P75**	**Max**
Rainfall (mm/day)						
Northern provinces						
Chiang Rai	5.1±12.7	0.0	0.0	2.0	2.9	147.1
Chiang Mai	3.0±8.4	0.0	0.0	0.0	0.9	124.8
Nan	3.2±8.5	0.0	0.0	0.0	0.8	136.0
Payao	3.2±9.7	0.0	0.0	0.0	0.8	145.6
Phrae	3.2±9.3	0.0	0.0	0.0	0.9	115.5
Mae Hong Son	3.3±8.4	0.0	0.0	0.0	3.3	74.8
Lampang	3.2±9.3	0.0	0.0	0.0	1.2	115.9
Lamphun	3.1±9.3	0.0	0.0	0.2	5.0	92.2
Uttaradit	3.6±11.1	0.0	0.0	0.4	5.6	128.6
Southern provinces						
Krabi	6.5±16.1	0.0	0.0	0.0	4.8	159.0
Chumphon	5.5±14.9	0.0	0.0	0.0	3.6	250.3
Trang	6.7±14.5	0.0	0.0	0.0	6.5	149.0
Nakhon Si Thammarat	7.7±24.6	0.0	0.0	0.0	4.5	405.0

Province	Mean ± SD		Percentiles			
		Min	P25	P50	P75	Max
Narathiwat	8.2±22.6	0.0	0.0	0.0	5.1	441.6
Pattani	5.3±14.8	0.0	0.0	0.0	3.1	219
Phang Nga	11.9±24.7	0.0	0.0	0.6	12.8	288.8
Phatthalung	6.4±18.3	0.0	0.0	0.0	4.0	302.4
Phuket	7.1±15.5	0.0	0.0	0.0	7.0	177.0
Ranong	12.9±25.5	0.0	0.0	0.5	14.0	208.0
Satun	6.6±14.7	0.0	0.0	0.0	6.4	192.6
Songkhla	6.6±19.2	0.0	0.0	0.0	4.2	290.5
Surat Thani	4.3±12.5	0.0	0.0	0.0	3.0	274.1
Yala	6.4±16.7	0.0	0.0	0.0	4.4	197.3

Abbreviations: SD: standard deviation, P_{x} xth: percentile, Min: minimum, Max: maximum

6.3.1.3 The low and high effects of temperature on total ambulance dispatches

A cumulative exposure-response association between extreme temperature and ambulance dispatches was investigated with RR (95%CI) and compared to the reference temperature which is a temperature at minimum ambulance dispatch temperature (T_{MADT}, °C), see Chapter 5 for discussion on T_{MADT}. A plot of cumulative association between daily mean temperature and total ambulance dispatches over 21 days. We chose the selected-province from the top 3 of ambulance dispatches caused by road accidents ranking in the Northern and Southern regions for observed temperature and total ambulance responses Table 6.5. For the Northern provinces, the minimum ambulance dispatches temperature (T_{MADT}) which provides the temperature for the lowest risk were reported at 99.9th percentile of the temperature distribution in Chiang Mai and Chiang Rai is 3.5 and 35.0°C, respectively. while T_{MADT} for Nan was found at the lowest at 10°C with 0th percentile . The pattern association did not show a U-shape relationship, so only estimated RRs for low temperature compared to T_{MADT} were reported for Chiang Mai and Chiang Rai while the estimated RR only for high temperature was reported (Figure 6-4). The results showed a significant association between daily mean temperature and total dispatches of pooled adjust RR at lag 0-21 for the temperature at 5th and 95th percentile of the temperature distribution in Chiang Rai and Chaing Mai (Table 6-5).

For the Southern provinces, the results indicate a T_{MADT} at 23.6 °C, 23.2 °C and 32.8 °C for Nakhon Si Thammarat, Songkhla and Surat Thani, respectively (Table 6-6.). The results also did not indicate a U-shape pattern of association, so the results only report extreme hot events (see Figure 6-5.). The RR of temperature to total dispatches only showed a significant association for extreme hot temperature in Nakhon Si Thammarat of 1.11 (95%CI: 1.00-1.23). The other results did not show a significant association.

Table 6-5 Results by province in the Northern for total ambulance dispatches: the lowest risk at minimum ambulance dispatch temperature (T_{MADT}), estimated relative risk (RR) of ambulance dispatches at 95% confidence intervals with daily average temperature between 2012 and 2018 at low and high temperature compared with T_{MADT} as the reference

Province	T_{MADT} (°C) MDP (percentiles)	RR (95% CI)					
		Lag 0-2		Lag 0-14		Lag 0-21	
		Low temperature (at 5th percentile)	High temperature (at 95th percentile)	Low temperature (at 5th percentile)	High temperature (at 95th percentile)	Low temperature (at 5th percentile)	High temperature (at 95th percentile)
Chiang Rai	33.5 (99.9%) 19.7,29.2	0.90 (0.80-1.01)		**1.40 (1.14-1.71)**		**1.72 (1.34-2.20)**	
Chiang Mai	35 (99.9%) 22,31	0.87 (0.80-0.96)		1.15 (0.97-1.36)		**1.29 (1.05-1.59**	
Nan	10 (0.0%) 21.5,30.8		1.33 (0.96-1.84)		1.04 (0.51-2.13)		1.06 (0.41-2.88)

Bold = Statistically significant at 95% CI. Abbreviations: T_{MADT}, temperature at minimum dispatch temperature; MDP, minimum dispatches percentiles.

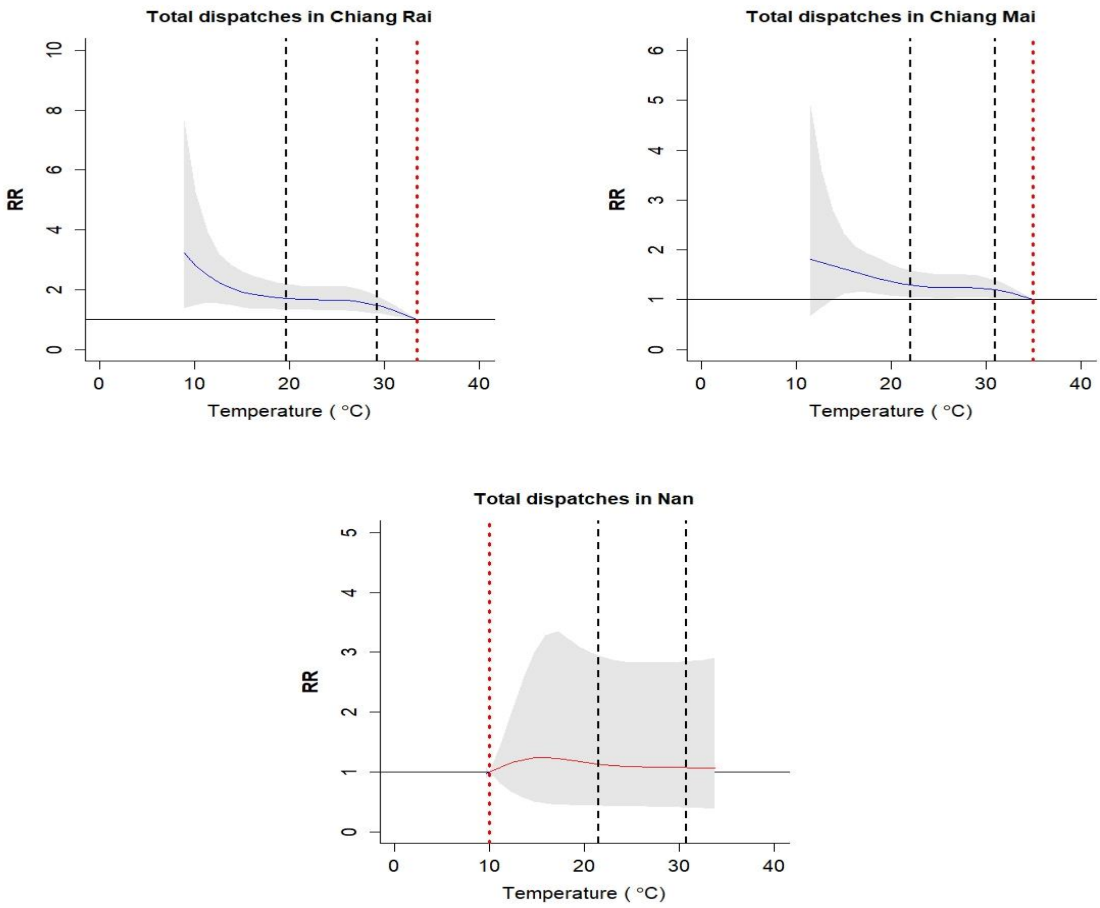


Figure 6-4 Cumulative association between daily mean temperature and Total dispatches over lag 0-21 days with 95% CI in the Northern.

Solid curves in blue and red color represent the pooled estimated relative risks with 95% CIs as show in grey shade. Red dotted in a vertical line shows the lowest risk at the minimum ambulance dispatches temperature (T_{MADT}). Black vertical lines present the T_{MADT} at the 5st and 95th percentile of temperature in each province. CI, confidence interval; RR, relative risk.

Table 6-6 Results by province in the Southern for total ambulance dispatches: the lowest risk at minimum ambulance dispatch temperature (T_{MADT}), estimated relative risk (RR) of ambulance dispatches at 95% confidence intervals with daily average temperature between 2012 and 2018 at low and high temperature compared with T_{MADT} as the reference

Province	T_{MADT} (°C) MDP (percentiles)	RR (95% CI)					
		Lag 0-2		Lag 0-14		Lag 0-21	
		Low temperature (at 5th percentile)	High temperature (at 95th percentile)	Low temperature (at 5th percentile)	High temperature (at 95th percentile)	Low temperature (at 5th percentile)	High temperature (at 95th percentile)
Nakhon Si Thammarat	23.6 (0.0%) 25.3,29.6		**1.11 (1.01-1.23)**		1.19 (0.96-1.48)		1.16 (0.87-1.53)

Province	T_{MADT} (°C) MDP (percentiles)	RR (95% CI)					
		Lag 0-2		Lag 0-14		Lag 0-21	
		Low temperature (at 5th percentile)	High temperature (at 95th percentile)	Low temperature (at 5th percentile)	High temperature (at 95th percentile)	Low temperature (at 5th percentile)	High temperature (at 95th percentile)
Songkhla	23.2 (0.0%) 26.3, 30.0		1.03 (0.81-1.29)		1.01 (0.60-1.69)		1.51 (0.77-2.94)
Surat Thani	32.8 (99.9%) 25.2, 29.3	1.10 (0.87-1.38)		0.99 (0.65-1.53)		1.32 (0.72-2.11)	

Bold = Statistically significant at 95% CI. Abbreviations: T_{MADT}, temperature at minimum dispatch temperature; MDP, minimum dispatches percentiles.

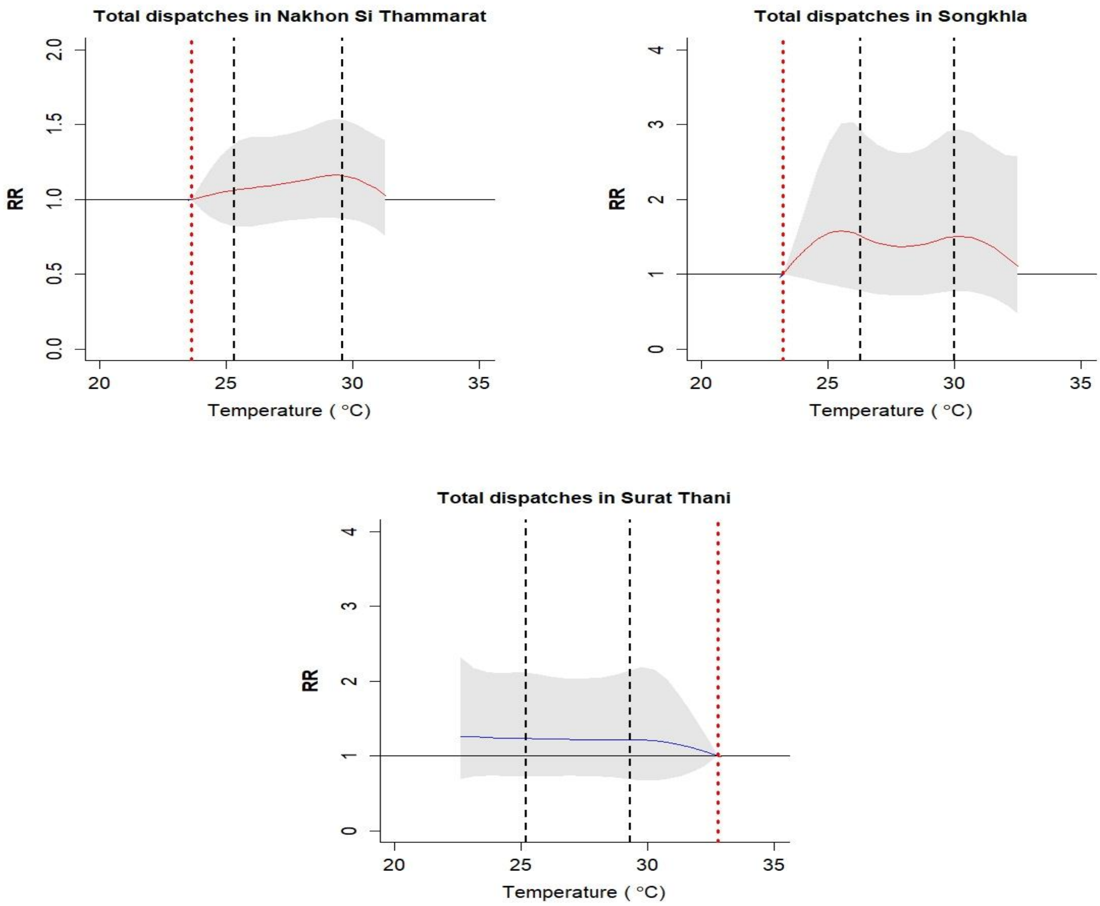


Figure 6-5 Cumulative association between daily mean temperature and Total dispatches over lag 0-21 days with 95% CI in the Southern.

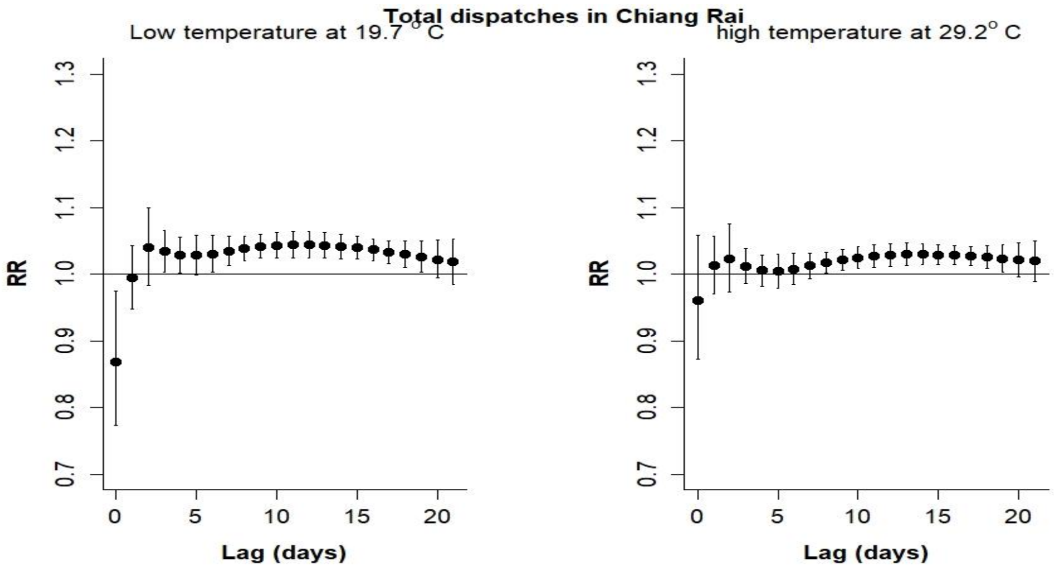
Solid curves in blue and red colour represent the pooled estimated relative risks with 95% CIs as shown in grey shade. Red dotted in a vertical line shows the lowest risk at the minimum ambulance dispatches temperature (T_{MADT}). Black vertical lines present the T_{MADT} at the 5st and 95th percentile of temperature in each province.CI, confidence interval; RR, relative risk.

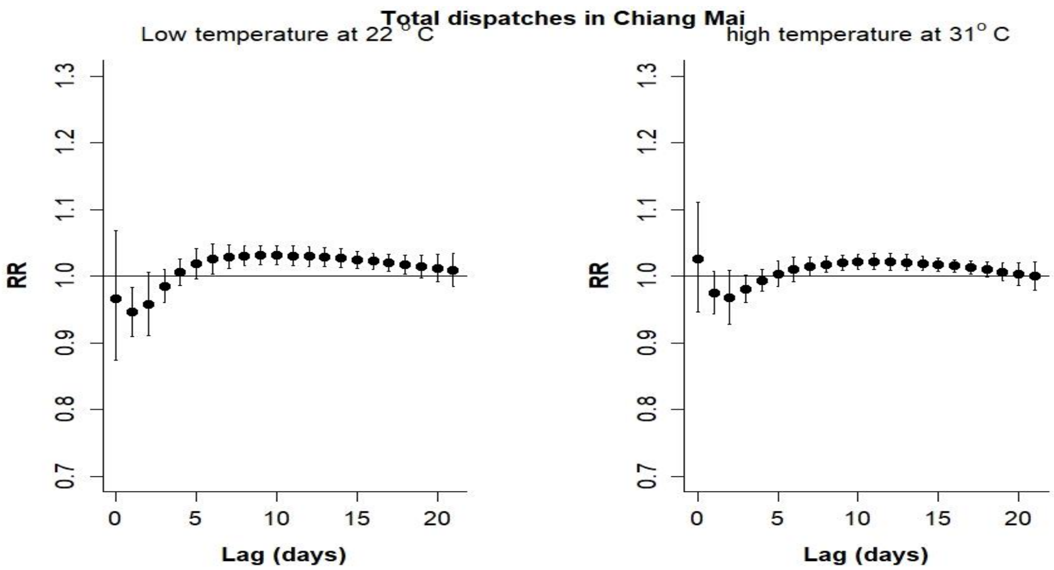
From Figure 6-4 and 6-5., it is evident that the pattern of association between temperature and total dispatches was not clear. The curve is a J type or reversed-J type with only cold or hot effect. The cold effect was found in Chiang Rai and Chaing Mai in the Northern province and Surat Thani in Southern province. Conversely, Nan, Nakhon Si Thammarat and Songkhla observed an effect at high temperature. The estimated effect of ambulance dispatches in Chiang Rai was significantly associated only with low temperature both over 14 days (lag 0-14) and 21 days (lag 0-21) but it was not observed for lag over 2 days. In Chiang Mai, a significant association with cold effect at lag 0-21 days (RR, 1.29; 95% CI: 1.05-1.59) was observed, but Nan results were not significantly associated with both low and high temperature (Table 6-5.)

The estimated effect for the combined Southern provinces showed a significant association with high temperature only for Nakhon Si Thammarat province (RR = 1.11, 95% CI: 1.01-1.23) at lag 0-2 days. However, the results differed from other provinces in the Southern province, which does not show a significant association for both cold and hot effects (Table 6-6).

6.3.1.4 The lag pattern

The effect of lagged days is reported in Figure 6-6 and Figure 6-7. The patterns for both extreme cold and hot temperature effects were the same. Chiang Mai results found the biggest effect at lag 7, whilst Nan and Chiang Rai have different patterns. Nan's results had the biggest RR at lag 0 and decreased for the following day at lag 3. It then raised until lag 7 declined until lag 11 and increased again until lag 21. However, the lowest RR in Chiang Rai were reported at lag 0, rising until lag 3 and then declining until lag 6 and rising again at lag 12 and then decreasing. All three province in the Southern showed the same pattern of delayed effects on extreme cold or hot temperature. The highest effect was found at lag 0. It decreased until lag 3 or lag 4 and then increased again.





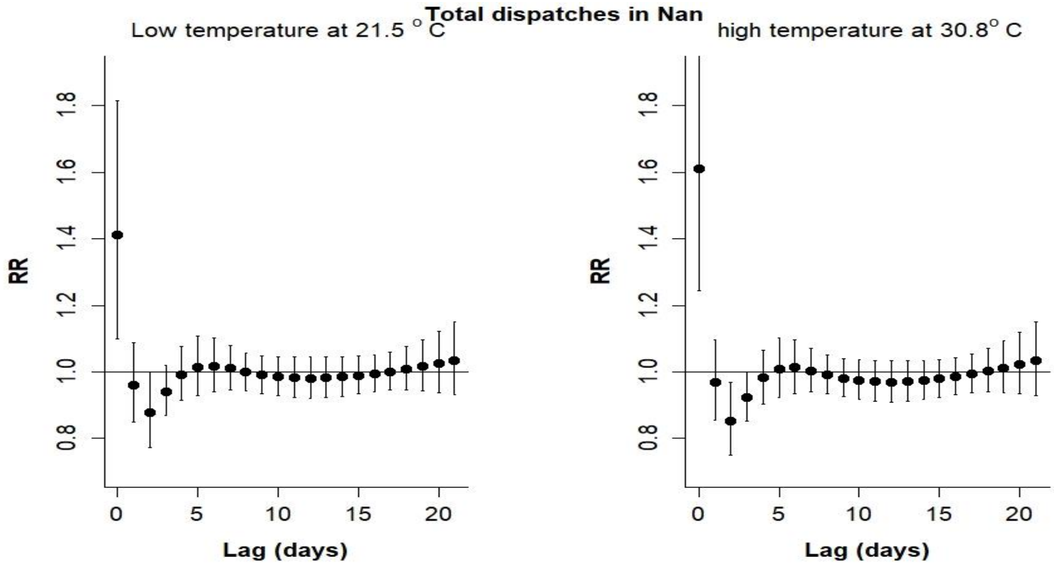
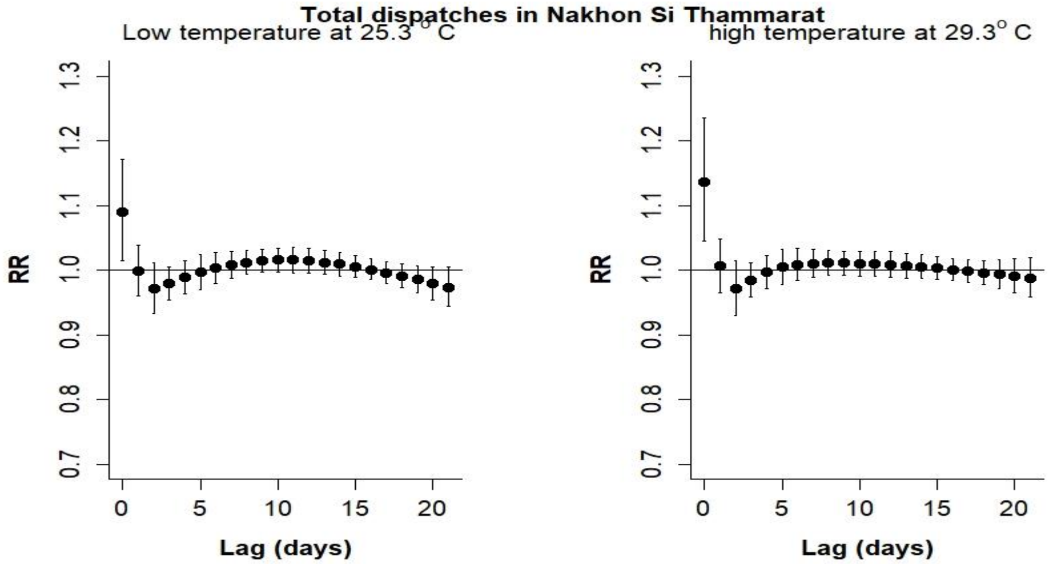


Figure 6-6 Lag effects for low temperature at the 5th percentile and high temperature at the 95th percentile compared with the temperature at minimum ambulance dispatch temperature (T_{MADT}) over 21 lag days in the Northern of Thailand.



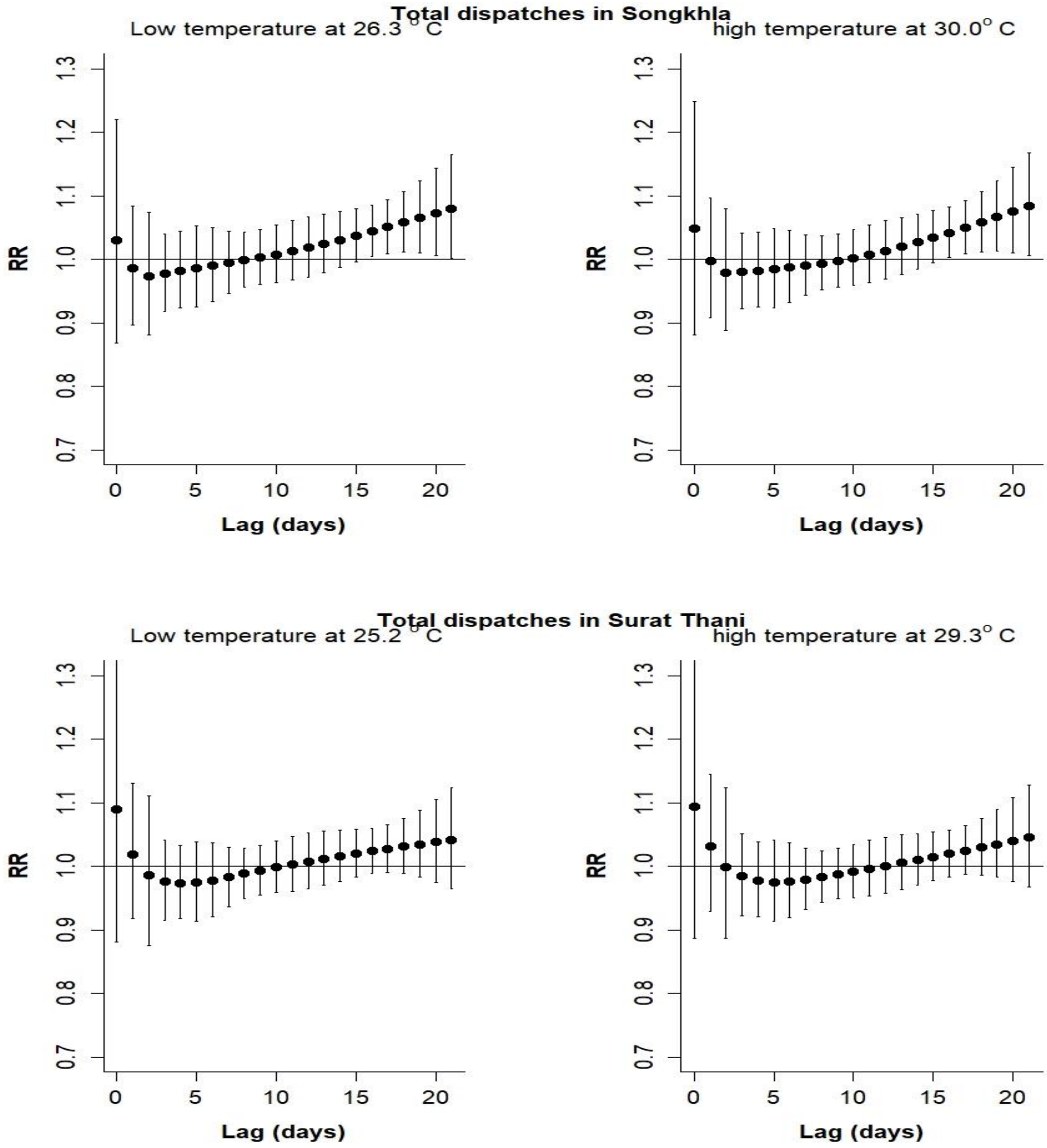


Figure 6-7 Lag effects for low temperature at 5th percentile and high temperature at 95th percentile of compared with the temperature at minimum ambulance dispatch temperature (T_{MADT}) over 21 lag days in the Southern of Thailand.

6.3.2 The association between rainfall and ambulance dispatches caused by road accidents

The summary statistics highlight that rain volume in the Southern provinces is higher than in the Northern provinces. Previous studies have reported that road accidents can be associated with rainfall (Bergel-Hayat et al., 2013; Keay and Simmonds, 2006), suggesting that driving during rainfall can increase the risk of accident. The role of rain upon road accidents can also be associated with other factors such as the type of road e.g. motorway or urban road (Bergel-Hayat et al., 2013). Previously, the pattern of association between meteorological variables and road accident was investigated for short-term effects using linear regression (Keay and Simmonds, 2006). Hence, this section investigates the possible relationship between rain upon ambulance dispatches via increases in road accidents. This may help in understanding the effect of the amount of rain on road accident compared to the Northern and the Southern in Thailand. The rainfall database was broken up into six groups: dry days with no rain is the reference group (rain = 0), more than zero but less than 1 mm/day ($0<\text{rain}<1$), from 1 but less than 2 mm/day ($1\leq\text{rain}<2$), from 2 but less than 5 mm/day ($2\leq\text{rain}<5$), from 5 but less than 10 mm/day ($5\leq\text{rain}<10$), from 10 but less than 20 mm/day ($10\leq\text{rain}<20$) and more than 20 mm ($\geq$20 mm). The results are presented as estimated risks for road accidents at different rain groups. The knowledge gained can be used to develop safety related policy and improve the ambulance service during the Thai rainy season.

6.3.2.1 Statistic

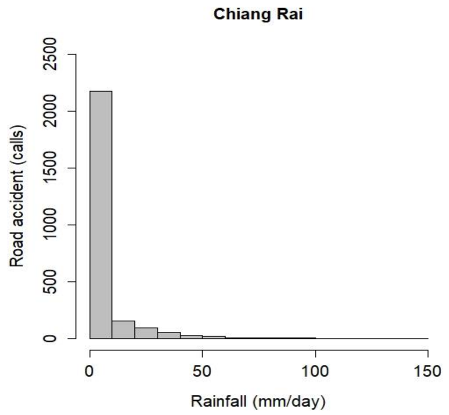
In order to investigate the association between rainfall and road accidents, Generalized Linear Models (GLM) with binomial negative function were used. The effect of day of week (DOW), holiday effects (H) and a long term trend with natural cubic spline were incorporated into the model. The lag up to one day was added to check whether the delay effects is due to meteorology parameters. Lags longer than one day were assumed to be of negligible significance. The effect of rain can be calculated by an exponential of the coefficient which is an estimate to explain the relationship between exposure variable (a rainfall variable) and response (road accidents) stratified by rain groups.

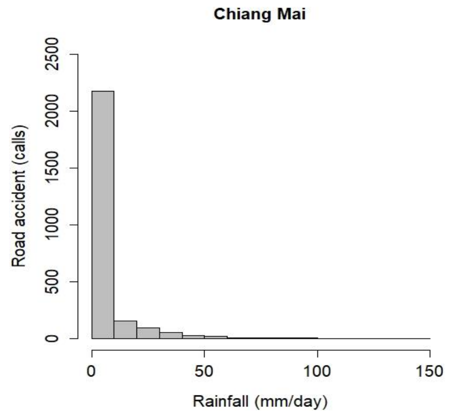
6.3.2.2 Results

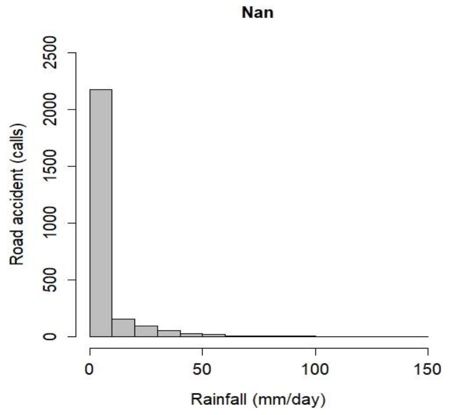
Rain data in the Northern and Southern provinces were obtained to investigate the association between rainfall and road accidents. The characteristics of rainfall data is shown in Table 6-4. The “no rain, dry days” make up the majority of days in both the Northern and the Southern provinces. The percentage of dry days range from 61.36 to 69.85% in the Northern provinces and from 44.62 to 60.70% in the Southern provinces, respectively. Histograms of frequency of different rain events are shown in Figure 6.8. The amount of road accidents associated with ambulance dispatches varied by the quantity of rain. For dry days, the daily average number of road accidents ranged from 3.54 calls in Mae Hong Son to 39.44 calls in Chiang Mai in the Northern provinces. In the Southern provinces, the number ranged from 4.60 calls in Pattani to 24.30 calls in Songkhla. For the 0-1 mm/day group, the average was from 2.93 to 35.21 in the Northern, while there was 3.39 to 23.69 in the Southern provinces. For $1 \leq rain < 2$ mm group, average road accidents were reported for 3.18 to 36.10 in the Northern and 3.66 to 23.06 in the Southern (see Table 6-7.).

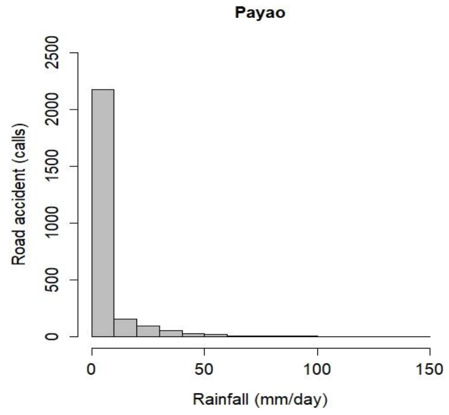
The number of daily road accidents associated with ambulance dispatches and rainfall data between 2012 and 2018 were plotted to investigate any association (Figure 6-9). Both parameters show a clear seasonality as shown in smoothed trends of the rainfall (black line) and road accidents (red line). The number of road accidents showed a slightly increasing long term trend during the study period in most provinces. Interestingly, the correlation between rainfall and ambulance dispatches were negative in all provinces, with an inversed pattern between rainfalls and road accidents, as shown in Figure 6-9 and which contrasts with earlier findings (Bergel-Hayat et al., 2013). The Spearman correlation was used to report the association between rainfall and road accidents. A negative correlation between rainfall and ambulance dispatches was observed in every province and ranged from $r = -0.154$ to $r = -0.0007$ as shown in Table 6-8.

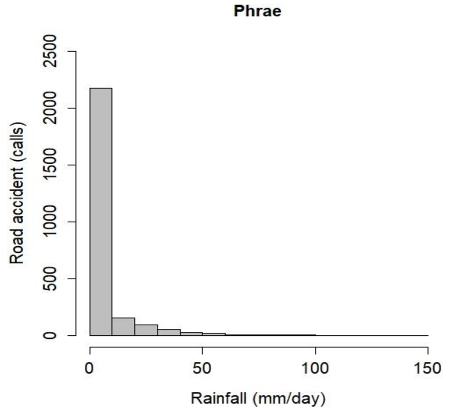
Northern provinces

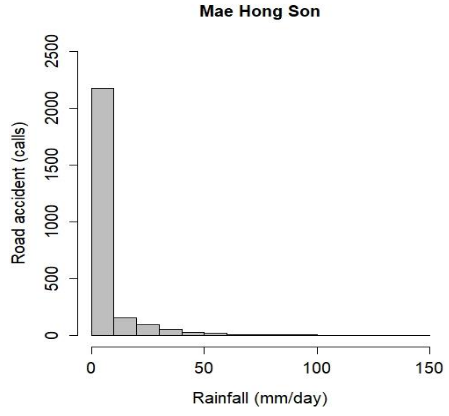


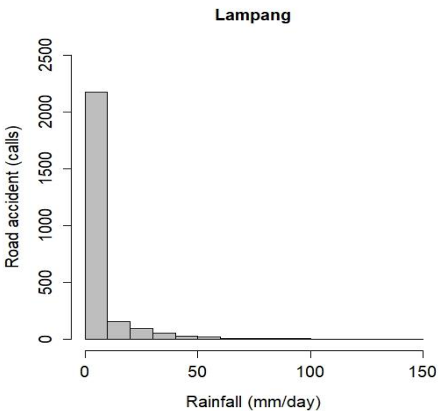


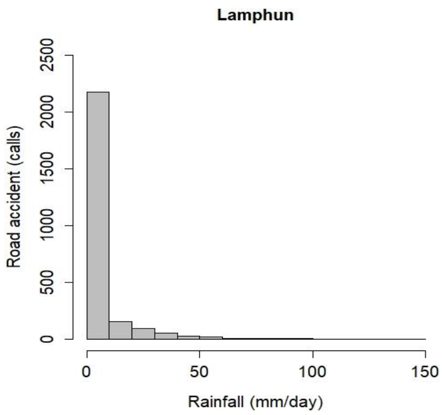


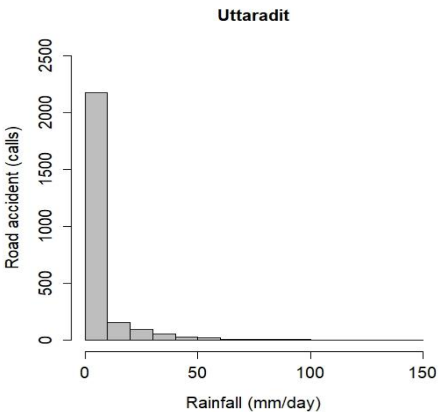




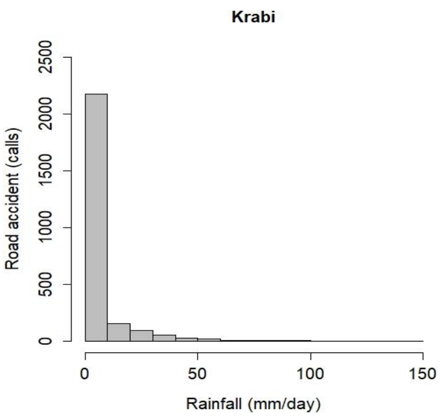


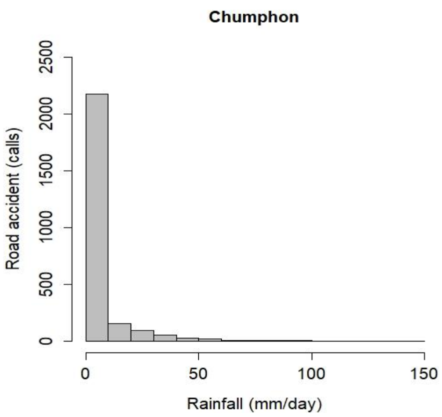


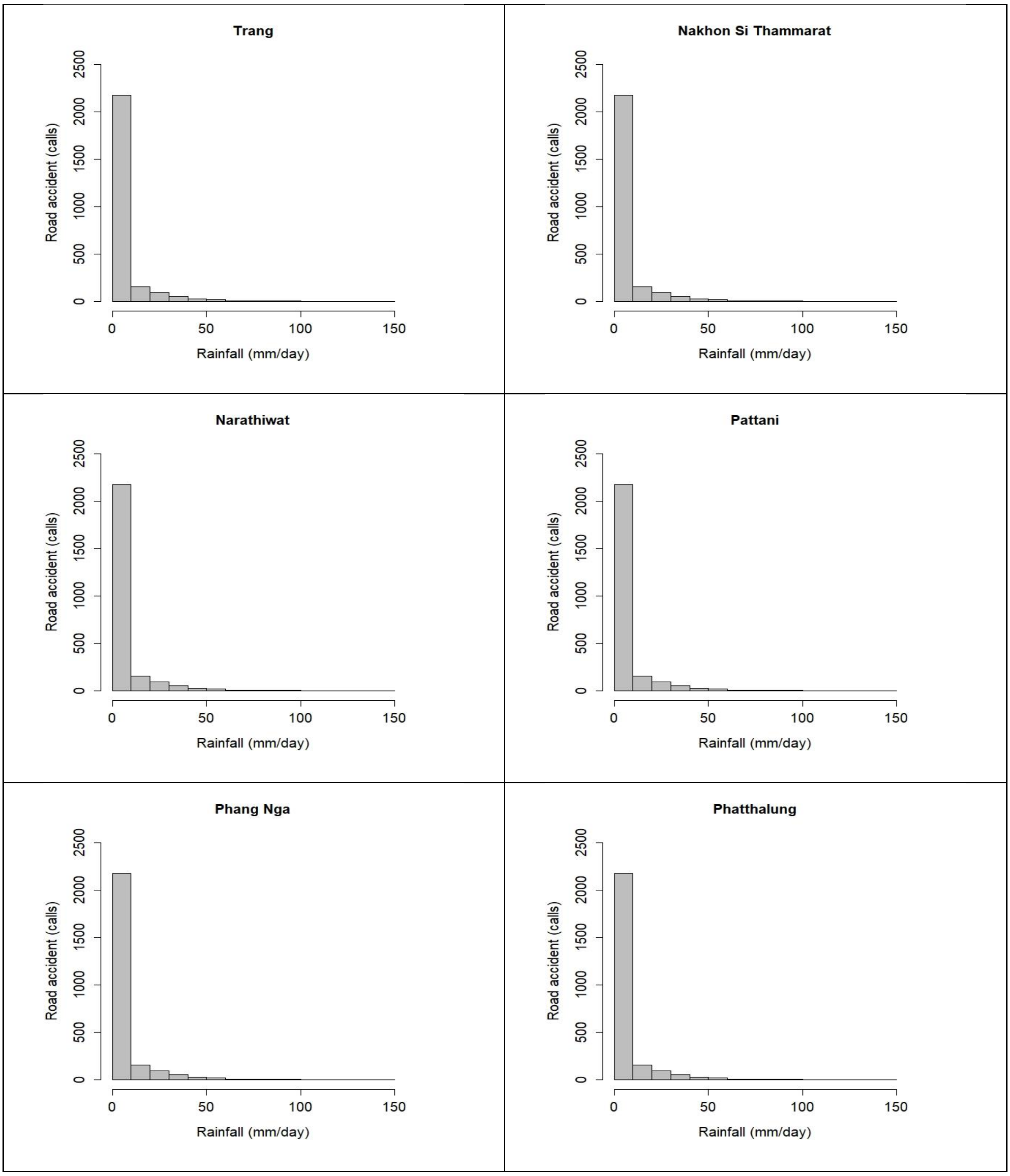




Southern provinces






Trang
Nakhon Si Thammarat
Narathiwat
Pattani
Phang Nga
Phatthalung
Road accident (calls)
Rainfall (mm/day)
0
500
1000
1500
2000
2500
0
50
100
150

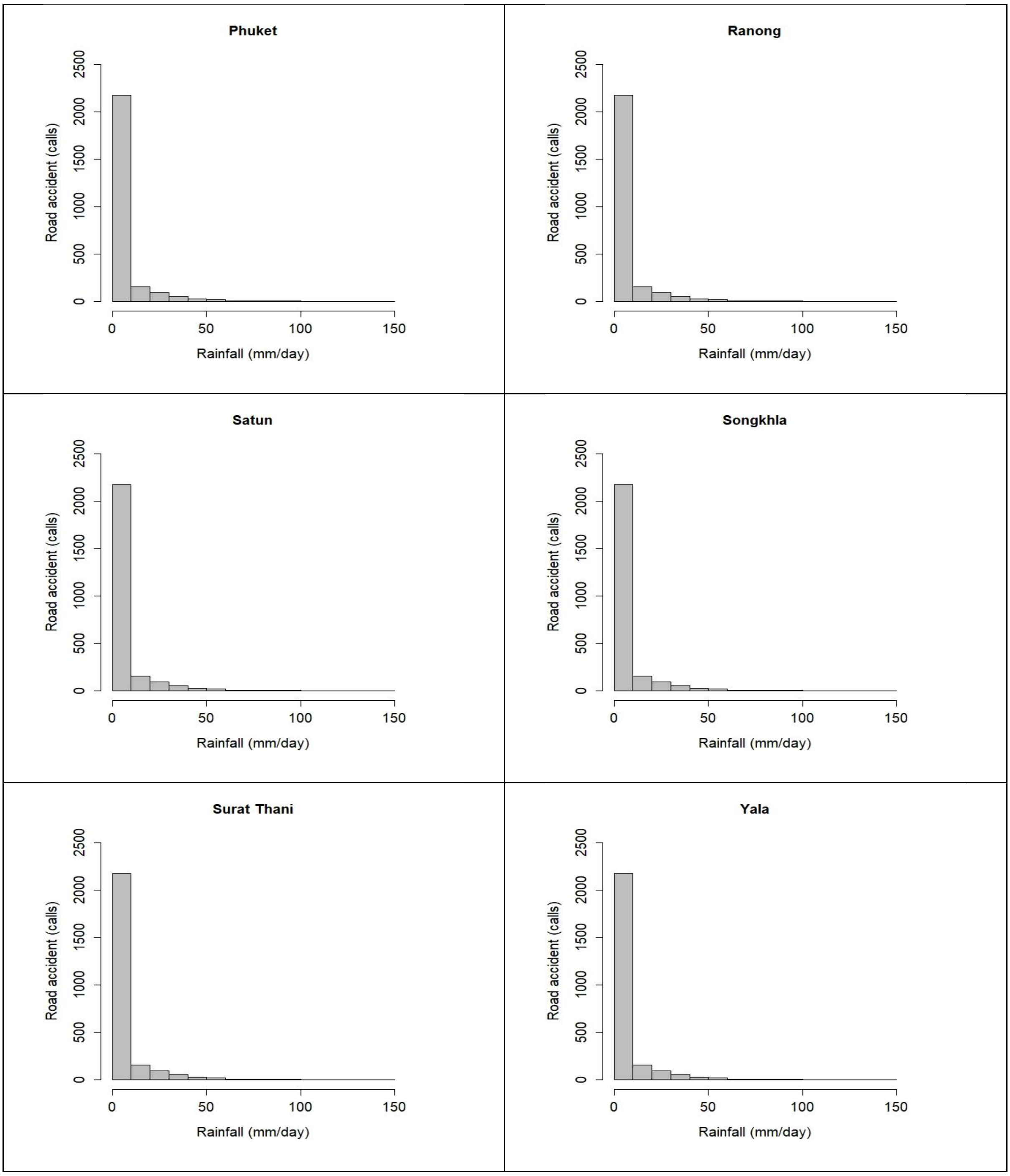


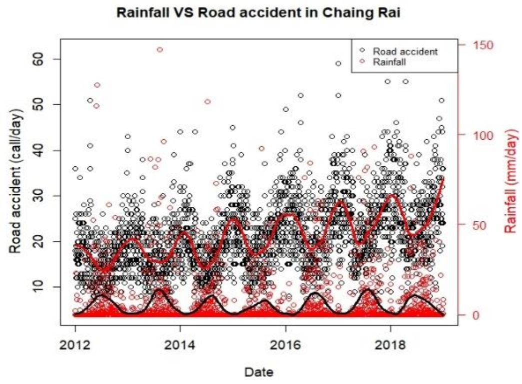
Figure 6-8 Histograms of daily road accidents (y-axis) against rainfall (mm/day) (x-axis) in each province in the Northern and Southern province groupings.

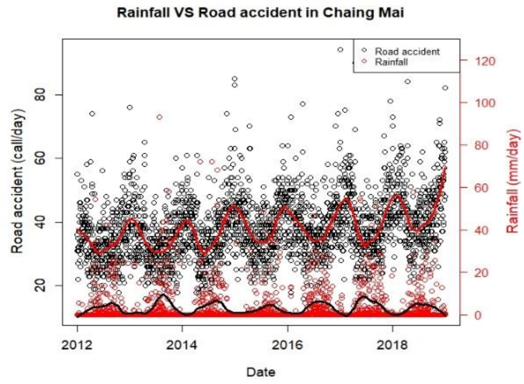
Table 6-7 Summary for road accident dispatches from 2012 to 2018 stratified by rainfall groups

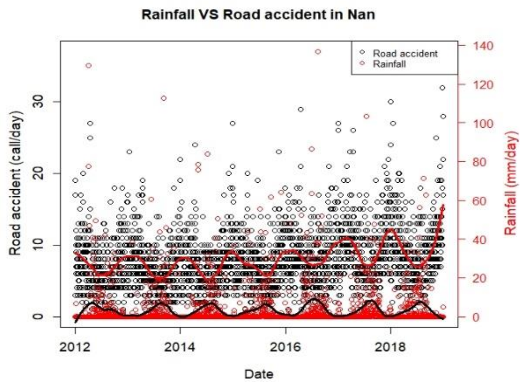
Province	Dry day		0<X<1		1≤X<2		2≤X<5		5≤X<10		10≤X<20		≥20	
	N	x̄ ± SD	N	x̄ ± SD	N	x̄ ± SD	N	x̄ ± SD	N	x̄ ± SD	N	x̄ ± SD	N	x̄ ± SD
Northern provinces														
Chiang Rai	1569	22.5±7.7	167	19.0±6.2	100	18.2±6.5	183	19.1±7.3	155	18.6±6.9	161	18.8±6.9	222	19.4±7.1
Chiang Mai	1694	39.4±9.9	229	35.2±8.9	101	36.2±8.9	147	36.4±10.4	134	36.3±10.2	125	34.8±9.1	127	32.6±7.4
Nan	1739	8.4±4.1	199	7.0±3.7	104	7.2±3.6	147	7.5±4.8	124	7.1±3.5	116	6.8±3.4	128	6.9±3.3
Payao	1760	8.0±4.0	169	7.0±3.1	80	6.8±3.7	165	7.1±3.8	148	7.2±3.7	110	7.4±3.6	125	7.0±3.7
Phrae	1695	5.0±2.8	229	4.6±2.7	87	4.8±2.4	150	4.2±2.4	138	4.5±2.7	126	4.7±2.8	132	4.5±2.8
Mae Hong Son	1594	3.5±2.4	200	2.9±2.1	119	3.2±2.3	175	2.8±2.1	208	3.0±2.4	141	2.8±2.1	118	2.8±1.9
Lampang	1723	16.0±8.0	174	15.7±9.4	97	14.3±6.1	169	14.9±7.6	145	14.8±8.5	126	15.4±5.7 4	123	14.6±6.6
Lamphun	1808	10.7±4.4	183	9.7±4.3	81	9.6±4.6	128	10.0±4.2	116	9.2±3.9	115	10.34±4. 8	126	10.1±4.1
Uttaradit	1786	8.5±3.6	154	7.6±3.3	101	8.2±3.5	144	7.7±3.5	123	7.7±3.5	94	7.9±2.9	155	7.7±3.2
Southern provinces														
Krabi	1482	11.9±6.1	141	12.4±6.5	117	11.5±7.3	182	11.7±6.3	174	11.1±5.4	182	11.3±5.8	279	11.7±5.6
Chumphon	1427	10.1±4.4	244	9.8±4.5	121	10.2±4.0	196	9.8±3.9	175	9.8±4.0	165	10.2±4.2	229	9.4±5.0
Trang	1288	16.6±7.7	206	16.2±7.1	138	16.9±9.1	221	15.5±7.9	214	16.8±12.6	212	15.3±7.8	278	14.8±7.3
Nakhon Si Thammarat	1390	19.8±6.6	217	20.3±6.9	127	20.5±6.3	202	19.2±6.2	186	18.7±6.1	175	20.2±7.0	259	18.5±6.8
Narathiwat	1456	6.2±3.0	174	6.2±3.3	101	6.6±3.9	180	5.7±3.1	173	6.2±3.3	170	6.2±3.3	303	6.1±3.3
Pattani	1552	4.6±2.9	168	4.3±2.9	105	4.5±3.0	194	4.8±2.8	155	4.7±3.0	180	4.5±3.0	203	4.8±3.1
Phang Nga	1160	6.5±3.5	165	6.3±3.8	114	7.1±4.1	206	6.6±3.2	185	6.4±3.5	239	5.8±3.6	488	5.6±3.0
Phatthalung	1424	7.7±3.4	231	7.6±4.2	108	7.4±3.9	206	7.8±3.6	174	7.4±3.7	175	7.9±4.0	239	6.7±3.3

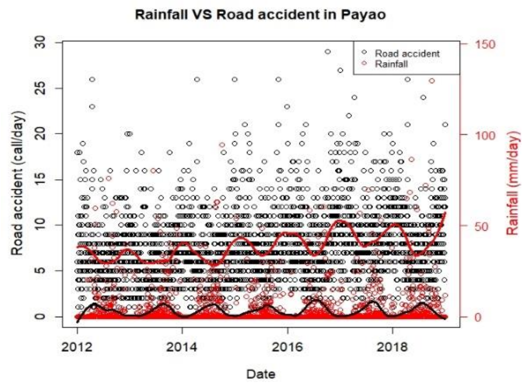
Province	Dry day		0<X<1		1≤X<2		2≤X<5		5≤X<10		10≤X<20		≥20	
	N	$\bar{x} \pm SD$	N	$\bar{x} \pm SD$	N	$\bar{x} \pm SD$	N	$\bar{x} \pm SD$	N	$\bar{x} \pm SD$	N	$\bar{x} \pm SD$	N	$\bar{x} \pm SD$
Phuket	1298	10.4±7.0	205	9.9±6.8	115	9.8±6.7	204	10.0±8.3	211	9.6±6.8	221	10.7±7.0	303	9.1±6.8
Ranong	1141	3.6±2.4	202	3.4±2.3	91	3.7±2.3	184	3.4±2.5	194	3.2±2.4	213	2.9±2.1	532	2.9±1.9
Satun	1308	6.1±3.5	206	5.7±3.4	122	5.3±2.7	223	5.5±3.3	204	5.3±2.8	212	5.5±3.4	282	5.6±3.1
Songkhla	1439	24.0±9.4	190	24.2±9.4	118	24.6±9.5	200	24.2±9.6	196	23.2±9.4	175	23.8±9.5	239	23.4±9.8
Surat Thani	1459	24.3±7.1	234	23.7±7.0	131	23.1±6.4	229	23.7±7.1	188	23.0±7.2	165	24.1±7.7	151	22.7±6.9
Yala	1397	7.5±3.3	213	7.2±3.4	111	7.5±3.7	216	7.1±3.3	170	7.6±3.6	192	7.0±3.5	239	6.8±3.2

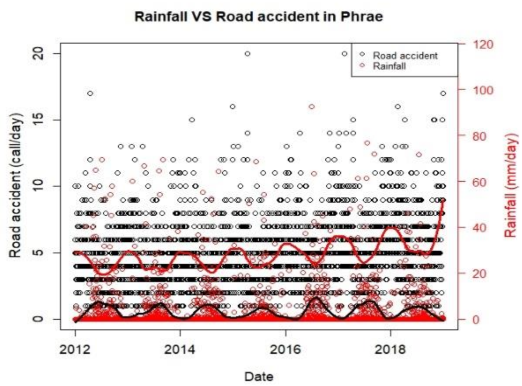
Northern provinces

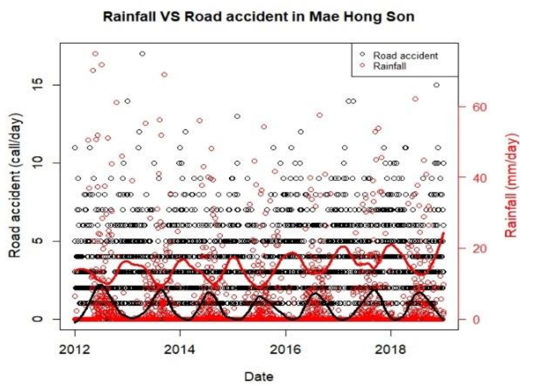


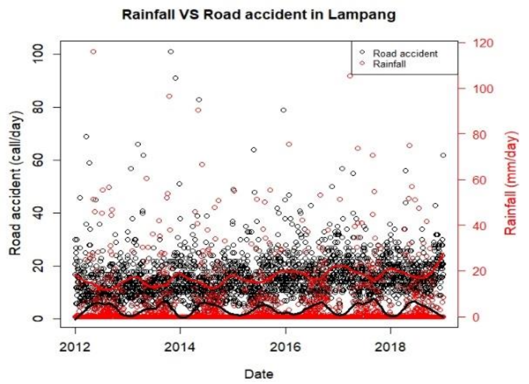


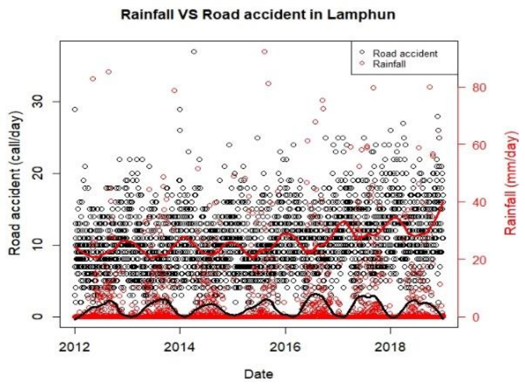


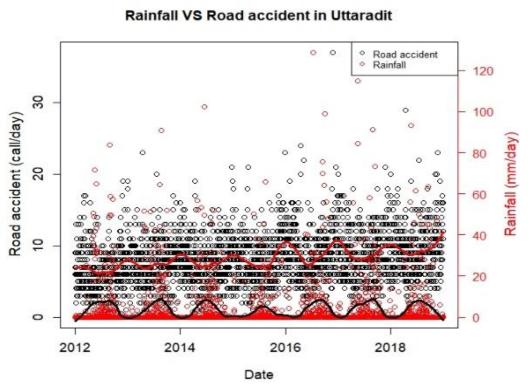




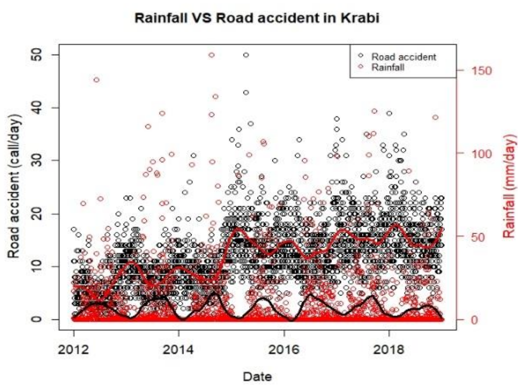


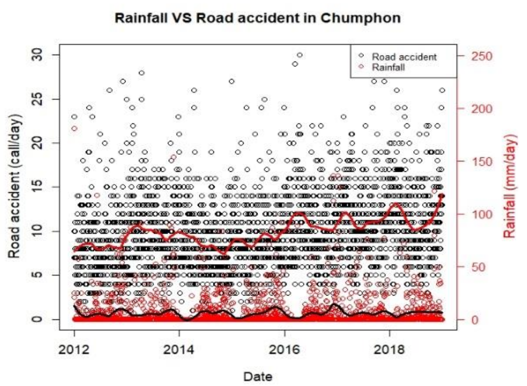


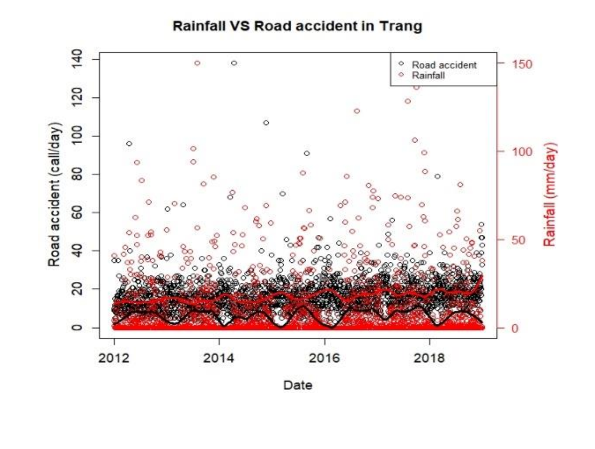


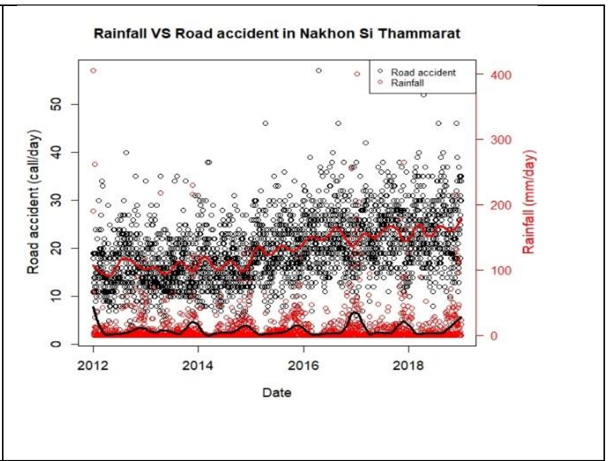


Southern provinces






Rainfall VS Road accident in Trang
Road accident
Rainfall
Road accident (call/day)
Rainfall (mm/day)
Date
0 20 40 60 80 100 120 140
0 50 100 150
2012 2014 2016 2018


Rainfall VS Road accident in Nakhon Si Thammarat
Road accident
Rainfall
Road accident (call/day)
Rainfall (mm/day)
Date
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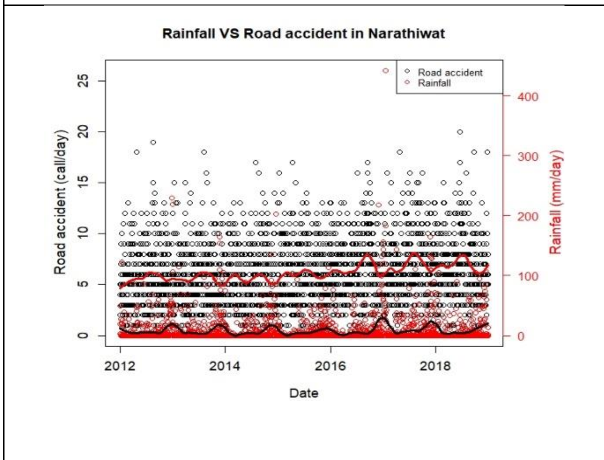
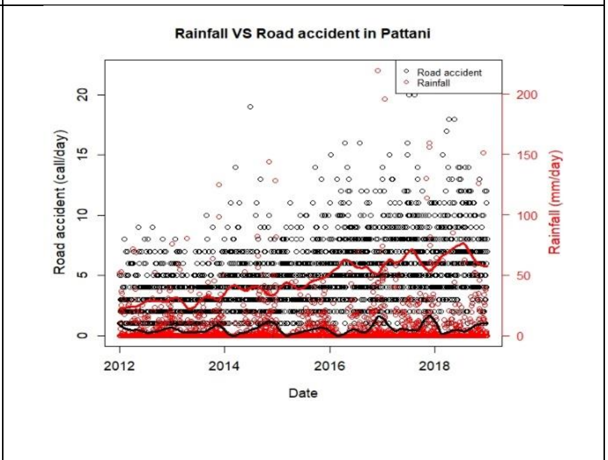
0 100 200 300 400
2012 2014 2016 2018


Rainfall VS Road accident in Narathiwat
Road accident
Rainfall
Road accident (call/day)
Rainfall (mm/day)
Date
0 5 10 15 20 25
0 100 200 300 400
2012 2014 2016 2018


Rainfall VS Road accident in Pattani
Road accident
Rainfall
Road accident (call/day)
Rainfall (mm/day)
Date
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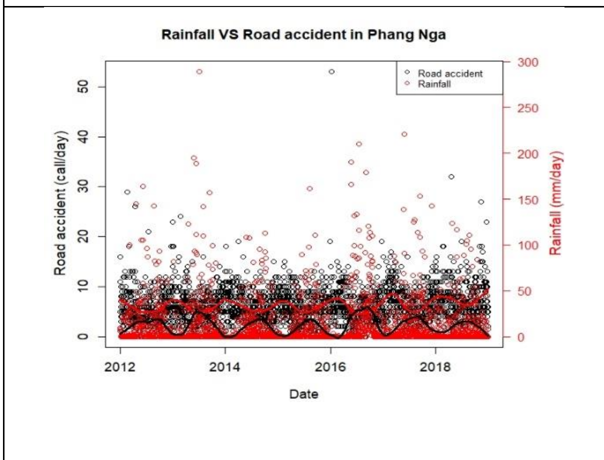
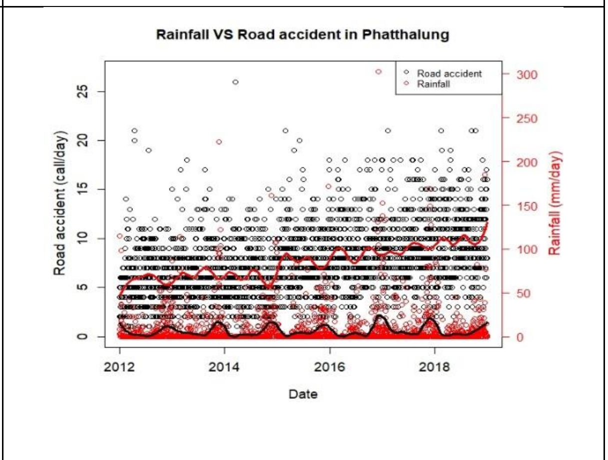
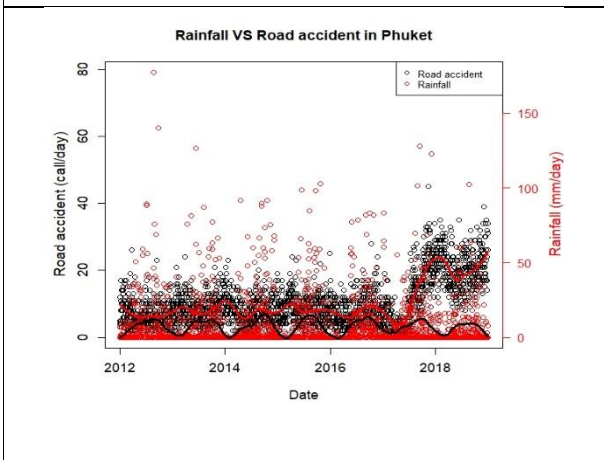
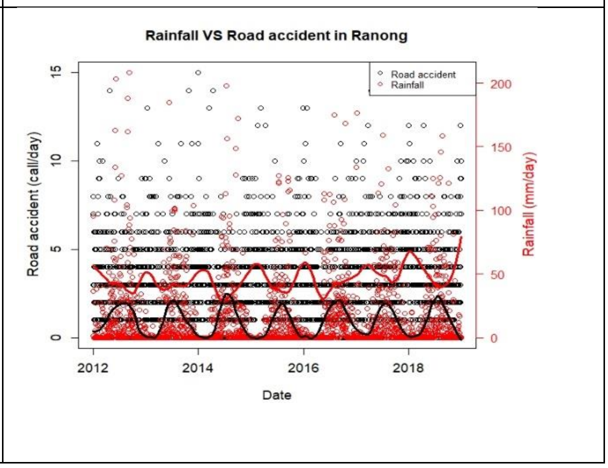
0 50 100 150 200
2012 2014 2016 2018


Rainfall VS Road accident in Phang Nga
Road accident
Rainfall
Road accident (call/day)
Rainfall (mm/day)
Date
0 10 20 30 40 50
0 50 100 150 200 250 300
2012 2014 2016 2018


Rainfall VS Road accident in Phatthalung
Road accident
Rainfall
Road accident (call/day)
Rainfall (mm/day)
Date
0 5 10 15 20 25
0 50 100 150 200 250 300
2012 2014 2016 2018


Rainfall VS Road accident in Phuket
Road accident
Rainfall
Road accident (call/day)
Rainfall (mm/day)
Date
0 20 40 60 80
0 50 100 150
2012 2014 2016 2018


Rainfall VS Road accident in Ranong
Road accident
Rainfall
Road accident (call/day)
Rainfall (mm/day)
Date
0 5 10 15
0 50 100 150 200
2012 2014 2016 2018

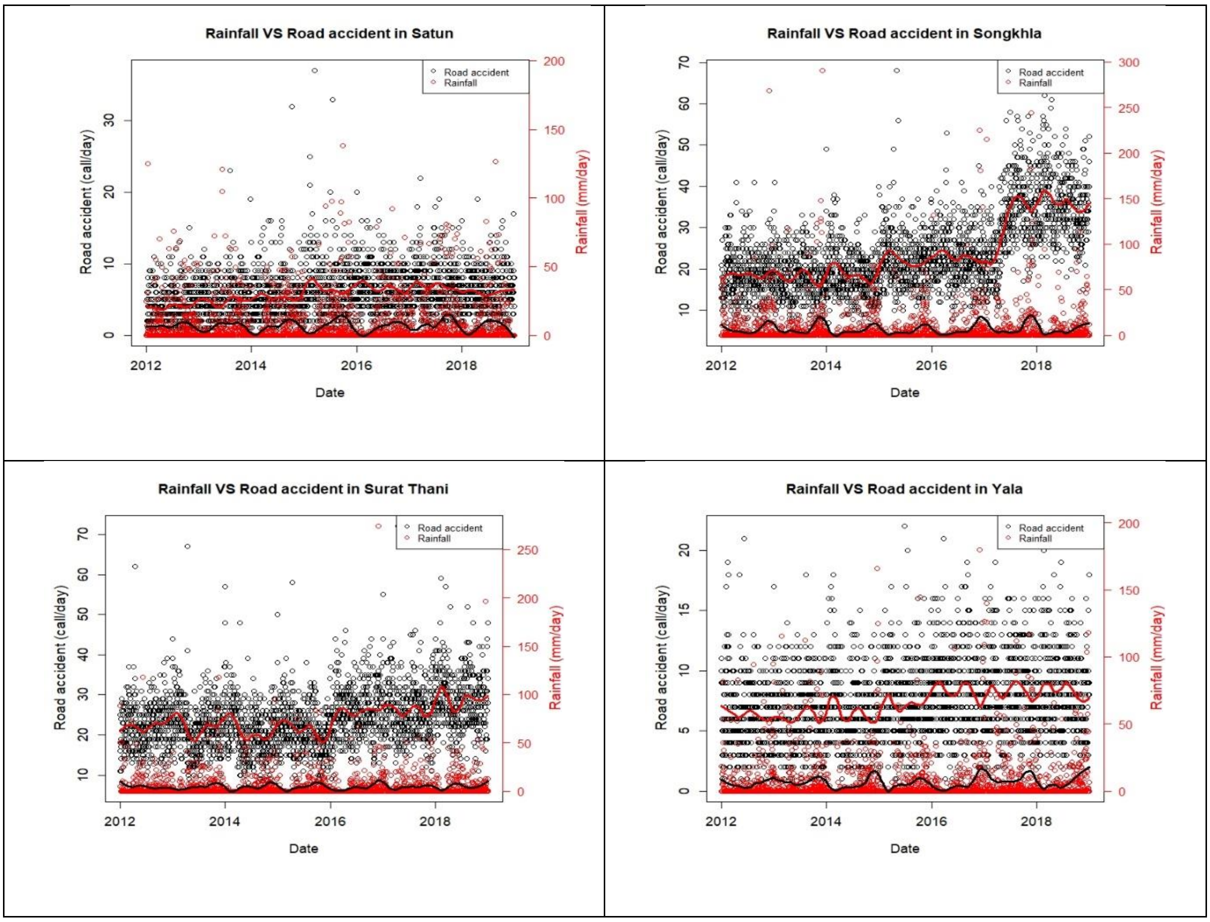


Figure 6-9 Time series plots of daily rain intensity and road accidents for each province in the Northern and South grouping (o black circle, road accident; o red circle, rainfall; red line = smoothing the curve of road accidents and black line = smoothing the curve of rainfall with 10% smoothing span

Table 6-8 Spearman correlation between total dispatches and road accident dispatches with rainfall

Region	Total dispatches			Road Accident dispatches		
	Spearman's correlation coefficient	T-test	P-value	Spearman's correlation coefficient	T-test	P-value
Northern provinces						
Chiang Rai	-0.050	-2.526	0.012	-0.109	-5.550	3.156e-08
Chiang Mai	-0.069	-3.493	<0.001	-0.154	-7.887	4.537e-15
Nan	-0.048	-2.4456	0.015	-0.087	-4.388	1.19e-05
Payao	-0.035	-1.783	0.075	-0.049	-2.469	0.014
Phrae	-0.037	-1.847	0.065	-0.035	-1.759	0.079
Mae Hong Son	-0.047	-2.383	0.017	-0.080	-4.036	5.605e-05
Lampang	-0.029	-1.461	0.010	-0.043	-2.179	-0.004
Lamphun	0.005	0.248	0.804	-0.013	-0.678	0.498
Uttaradit	-0.063	-3.211	0.001	-0.049	-2.476	0.013

Region	Total dispatches			Road Accident dispatches		
Southern provinces						
Krabi	-0.037	-1.857	0.063	-0.024	-1.232	0.218
Chumphon	-0.004	-0.207	0.836	-0.041	-2.108	0.035
Trang	-0.043	-2.192	0.028	-0.071	-3.600	<0.001
Nakhon Si Thammarat	0.021	1.071	0.284	-0.054	-2.756	0.0059
Narathiwat	0.072	3.661	<0.001	-0.033	-1.657	0.098
Pattani	0.063	3.192	0.001	-0.0007	-0.037	0.970
Phang Nga	-0.089	-4.499	7.148e-06	-0.108	-5.468	5.007e-08
Phatthalung	0.004	0.198	0.843	-0.76	-3.869	<0.001
Phuket	-0.084	-4.271	2.015e-05	-0.060	-3.024	0.002521
Ranong	-0.067	-3.419	<0.001	-0.096	-4.856	1.268e-06
Satun	-0.013	-0.637	0.524	-0.079	-4.016	6.09e-05
Songkhla	0.017	0.866	0.387	-0.026	-1.333	0.1826
Surat Thani	-0.014	-0.710	0.477	-0.041	-2.069	0.039
Yala	0.025	1.265	0.206	-0.072	-3.628	<0.001

To investigate the effect of rain on road accidents, the following variables were removed from the data: seasonality, public holiday, day of week, long-term trend and the temperature and relative humidity weather variables. Results indicate that the amount of rain is significantly associated with road accidents in most provinces (Table 6-9). Lags of 0 generated the most significant results. In the Northern Thailand, five provinces had estimated results that were significant at lag 0 for the estimated effects compared to dry rain days, the largest single estimated effect was observed when the rain amount was 1≤ rain <2 mm/day at lag 0 in Phrae province (RR = 1.159, 95% CI: 1.027-1.308). For three provinces: Chiang Mai, Phrae and Lam, the most significant results occurred when the rain was in the range 10≤ rain <20 mm, where RR =1.050 (95%CI: 1.004-1.067), RR = 1.127 (95%CI: 1.011-1.256) and RR = 1.111 (95% CI: 1.022-1.208), respectively. For rain at 5 ≤ rain < 10 mm and greater than 20 mm (rain ≥20) were associated with road accidents in two provinces. Chaing Mai's and Phrae estimated results were higher in road accidents at rain 5≤ rain <10 mm with RR =1.091 (95% CI: 1.046-1.139) and RR = 1.115 (95%CI: 1.002-1.240) respectively. Chaing Rai and Lamphun observed a significant association at high rain (rain ≥ 20 mm), RR = 1.080 (95%CI: 1.028-1.135) and RR = 1.098 (95%CI: 1.011-1.192), respectively. Four provinces including Nan, Payao, Mae Hong Son and Uttaradit did not find the significant association. In addition, there was no significant association between rain effects and road accidents for all lag 1.

In the Southern provinces, the estimated effect of the relationship rainfall was significantly associated with road accidents in ten provinces (we choose the highest effect of province if there have found a significant result more than one results); The highest estimated effect was reported in Phang Nga (RR= 1.174, 95% CI: 1.064-1.297) and the remaining were Krabi (RR = 1.113, 95% CI: 1.050-1.179), Chumphon (RR =1.119, 95% CI: 1.036-1.208), Trang (RR =1.086, 95% CI: 1.003-1.176), Nakhon Si Thammarat (RR= 1.053, 95% CI: 1.001-1.107), Pattani (RR= 1.157, 95%CI: 1.049-1.275), Phuket (RR= 1.100, 95% CI: 1.026-1.180), Songkhla (RR= 1.074, 95% CI: 1.026-1.124), Surat Thani (RR= 1.061, 95% CI: 1.010-1.114) and Yala (RR= 1.136, 95% CI: 1.055-1.223). However, there were no significant associations between rainfall and road accidents in four provinces including Narathiwat, Phatthalung, Ranong and Satun. Rainfall level at 10≤rain<20 mm and greater than or equal 20 mm have exhibited the most of significant results with five provinces. Interestingly, there was a significant estimated effect at lag 1 in Surat Thani (RR = 1.053, 95% CI: 1.014-1.3094), with no significant result at lag 0.

Table 6-9 The estimated effect of the association between rainfall and road accidents with 95 % CI by various lags

province	0<X<1 mm		1≤X<2 mm		2≤X<5 mm		5≤X<10 mm		10≤X<20 mm		≥20 mm	
	Lag 0	Lag 1	Lag 0	Lag 1	Lag 0	Lag 1	Lag 0	Lag 1	Lag 0	Lag 1	Lag 0	Lag 1
Northern												
Chiang Rai	0.960 (0.914- 1.008)	0.931 (0.887 0.978)	0.982 (0.922 1.046)	0.951 (0.894- 1.013)	1.020 (0.972- 1.071)	0.956 (0.910- 1.004)	1.000 (0.947- 1.055)	0.972 (0.921- 1.025)	1.035 (0.981- 1.092)	0.930 (0.881- 0.981)	**1.080** **(1.028-** **1.135)**	0.929 (0.883- 0.978)
Chiang Mai	1.015 0.982 1.049	1.000 0.968 1.034	1.032 0.985 1.080	0.961 0.917 1.007	**1.075** **1.032** **1.119**	1.010 0.969 1.052	**1.091** **1.046** **1.139**	1.009 0.966 1.053	**1.050** **1.004** **1.097**	1.005 0.961 1.051	0.986 0.941 1.033	0.949 0.906 0.994
Nan	1.000 0.927 1.078	1.022 0.949 1.101	1.038 0.939 1.148	0.959 0.865 1.063	1.072 0.984 1.169	1.037 0.951 1.131	1.058 0.962 1.163	1.030 0.937 1.133	1.036 0.936 1.147	0.969 0.874 1.075	1.039 0.941 1.146	0.995 0.901 1.099
Payao	0.962 0.885 1.046	0.951 0.874 1.035	0.931 0.827 1.047	1.016 0.907 1.138	1.032 0.948 1.124	1.011 0.928 1.101	1.019 0.929 1.117	1.033 0.943 1.132	1.035 0.937 1.144	1.005 0.908 1.112	1.002 0.906 1.108	1.095 0.993 1.207
Phrae	1.086 0.999 1.180	1.054 0.970 1.146	**1.159** **1.027** **1.308**	1.056 0.932 1.197	1.027 0.926 1.139	1.035 0.934 1.147	**1.115** **1.002** **1.240**	1.083 0.974 1.206	**1.127** **1.011** **1.256**	1.095 0.982 1.222	1.105 0.990 1.233	0.943 0.840 1.058
Mae Hong Son	0.988 0.880 1.109	0.953 0.847 1.078	1.109 0.966 1.274	1.021 0.882 1.182	1.016 0.894 1.154	1.025 0.902 1.166	1.086 0.962 1.227	1.087 0.962 1.229	1.023 0.888 1.179	1.104 0.960 1.270	1.013 0.870 1.179	1.029 0.884 1.199
Lampang	**1.086** **1.003** **1.176**	0.975 0.900 1.058	1.022 0.918 1.138	0.974 0.875 1.084	1.053 0.966 1.147	0.985 0.903 1.073	1.039 0.948 1.138	0.959 0.875 1.052	1.062 0.963 1.172	0.935 0.845 1.034	1.040 0.940 1.151	0.933 0.842 1.035
Lamphun	0.990 0.926 1.058	1.048 0.982 1.118	0.990 0.900 1.089	0.983 0.895 1.080	1.042 0.963 1.127	0.957 0.884 1.037	1.010 0.927 1.101	0.951 0.872 1.037	**1.111** **1.022** **1.208**	0.966 0.886 1.053	**1.098** **1.011** **1.192**	0.952 0.875 1.037
Uttaradit	1.009 0.937 1.086	1.004 0.932 1.080	1.045 0.959 1.139	0.976 0.894 1.066	0.982 0.909 1.060	0.968 0.896 1.045	1.000 0.919 1.088	0.950 0.872 1.034	1.023 0.929 1.125	0.968 0.878 1.066	1.010 0.934 1.093	1.022 0.945 1.105
Southern												
Krabi	1.056 0.986	1.019 0.951	1.077 0.997	0.991 0.915	**1.068** **1.002**	0.993 0.931	1.058 0.989	1.007 0.941	1.034 0.968	0.977 0.913	**1.113** **1.050**	0.987 0.929

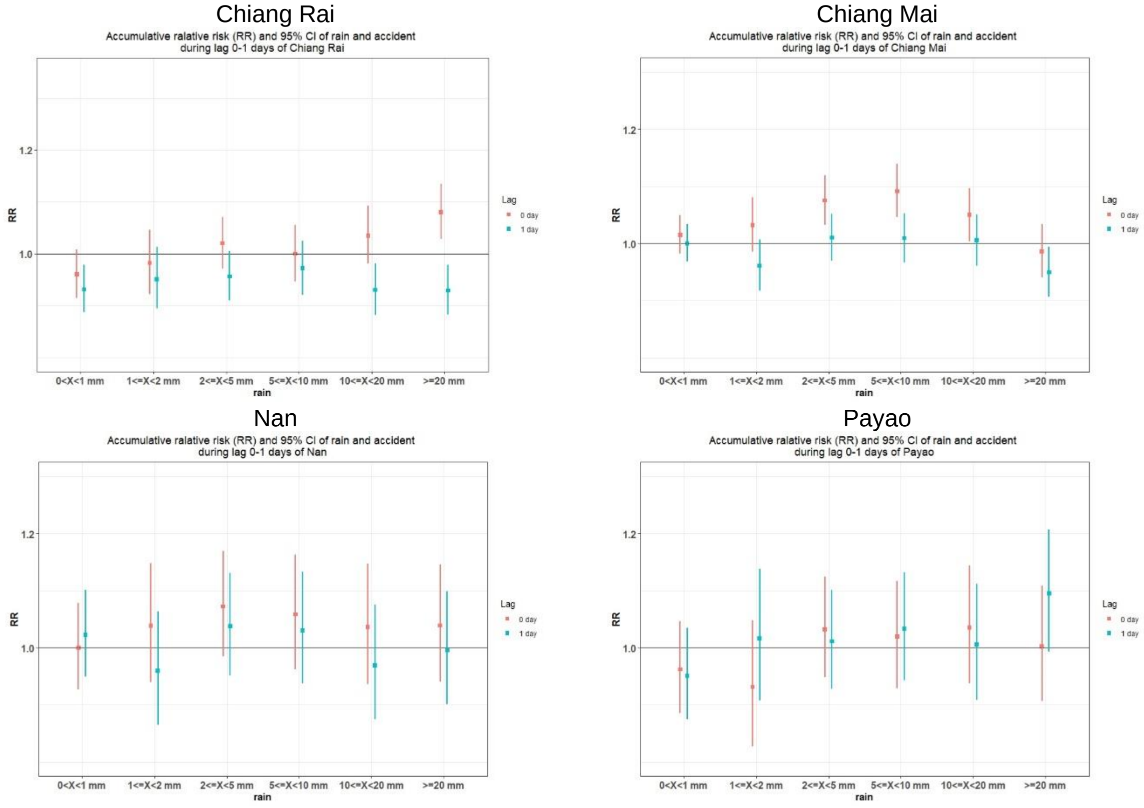
province	0<X<1 mm		1≤X<2 mm		2≤X<5 mm		5≤X<10 mm		10≤X<20 mm		≥20 mm	
	Lag 0	Lag 1	Lag 0	Lag 1	Lag 0	Lag 1	Lag 0	Lag 1	Lag 0	Lag 1	Lag 0	Lag 1
	1.130	1.092	1.163	1.073	**1.138**	1.060	1.132	1.078	1.104	1.044	**1.179**	1.049
Chumphon	1.015 0.956 1.078	0.993 0.935 1.054	1.084 0.999 1.176	0.948 0.871 1.032	1.036 0.966 1.111	0.982 0.916 1.054	1.055 0.980 1.136	0.942 0.873 1.016	**1.119** **1.036** **1.208**	1.018 0.942 1.100	1.044 0.966 1.129	1.026 0.950 1.109
Trang	1.027 0.951 1.108	0.989 0.916 1.069	1.068 0.976 1.168	1.026 0.937 1.123	1.004 0.927 1.086	0.973 0.899 1.053	**1.086** **1.003** **1.176**	1.006 0.927 1.090	1.044 0.957 1.140	0.935 0.855 1.021	1.023 0.939 1.116	0.918 0.841 1.002
Nakhon Si Thammarat	1.031 0.988 1.075	1.001 0.959 1.044	1.042 0.988 1.100	0.969 0.918 1.024	1.021 0.975 1.069	1.011 0.965 1.058	1.001 0.953 1.052	1.003 0.955 1.053	**1.053** **1.001** **1.107**	0.988 0.939 1.040	1.034 0.981 1.090	0.993 0.941 1.046
Narathiwat	1.028 (0.947- 1.115)	1.024 (0.944- 1.110)	1.097 (0.991- 1.214)	1.030 (0.929- 1.142)	0.970 (0.891- 1.055)	1.016 (0.936- 1.103)	1.020 (0.939- 1.108)	0.987 (0.908- 1.073)	1.056 (0.970- 1.150)	0.984 (0.902- 1.073)	1.076 (1.000- 1.160)	0.996 (0.923- 1.075)
Pattani	1.023 (0.932- 1.123)	1.045 (0.954- 1.146)	1.078 (0.962- 1.209)	1.003 (0.893- 1.126)	1.061 (0.973- 1.157)	0.993 (0.910- 1.084)	1.057 (0.957- 1.167)	0.958 (0.866- 1.061)	1.098 (0.996- 1.210)	1.043 (0.946- 1.149)	**1.157** **(1.049-** **1.275)**	0.984 (0.889- 1.090)
Phang Nga	1.039 0.951 1.135	1.029 0.944 1.121	**1.174** **1.064** **1.297**	1.017 0.918 1.126	**1.122** **1.034** **1.218**	0.998 0.919 1.084	**1.127** **1.032** **1.230**	0.969 0.885 1.060	1.054 0.967 1.149	0.926 0.849 1.010	**1.097** **1.013** **1.187**	0.897 0.827 0.973
Phatthalung	1.057 0.993 1.124	0.962 0.903 1.025	0.980 0.897 1.070	1.003 0.920 1.094	1.068 0.997 1.143	0.987 0.921 1.058	1.014 0.940 1.093	0.977 0.906 1.054	1.092 1.013 1.177	1.001 0.927 1.081	0.969 0.896 1.048	0.951 0.879 1.029
Phuket	1.038 0.971 1.110	0.966 0.903 1.034	1.011 0.928 1.100	0.982 0.902 1.069	1.066 0.996 1.141	0.992 0.926 1.063	1.070 0.998 1.147	0.961 0.895 1.032	**1.096** **1.026** **1.171**	0.917 0.855 0.982	**1.100** **1.026** **1.180**	0.934 0.869 1.004
Ranong	1.018 0.916 1.132	1.021 0.919 1.135	1.129 0.979 1.303	1.086 0.939 1.255	1.074 0.958 1.205	1.021 0.909 1.148	1.017 0.901 1.149	1.046 0.926 1.181	0.960 0.846 1.089	1.047 0.925 1.184	1.054 0.938 1.185	1.042 0.926 1.172
Satun	1.007 0.925 1.096	0.948 0.870 1.034	0.960 0.861 1.071	1.008 0.907 1.121	1.032 0.947 1.125	0.985 0.903 1.075	1.030 0.937 1.132	0.974 0.885 1.072	1.079 0.982 1.185	0.999 0.908 1.099	1.043 0.949 1.147	0.996 0.905 1.095
Songkhla	1.033 0.991	1.015 0.974	**1.055** **1.002**	0.968 0.918	1.035 0.993	1.008 0.966	1.015 0.971	0.989 0.947	**1.060** **1.012**	0.986 0.941	**1.074** **1.026**	0.991 0.946

province	0<X<1 mm		1≤X<2 mm		2≤X<5 mm		5≤X<10 mm		10≤X<20 mm		≥20 mm	
	Lag 0	Lag 1	Lag 0	Lag 1	Lag 0	Lag 1	Lag 0	Lag 1	Lag 0	Lag 1	Lag 0	Lag 1
	1.077	1.059	**1.110**	1.020	1.079	1.051	1.060	1.033	**1.110**	1.034	**1.124**	1.038
Surat Thani	1.002 0.964 1.042	**1.053** **1.014** **1.094**	1.003 0.954 1.055	1.043 0.993 1.096	1.025 0.984 1.068	1.041 0.999 1.084	1.015 0.969 1.062	1.025 0.979 1.073	**1.056** **1.006** **1.109**	**1.061** **1.010** **1.114**	1.052 0.999 1.108	1.031 0.978 1.086
Yala	1.051 0.984 1.122	1.043 0.977 1.113	1.064 0.977 1.159	0.969 0.888 1.058	1.060 0.990 1.135	0.993 0.926 1.064	**1.136** **1.055** **1.223**	1.003 0.929 1.082	1.048 0.972 1.130	0.963 0.892 1.039	1.077 0.998 1.161	0.980 0.908 1.058

Bold = Statistically significant at 95% CI

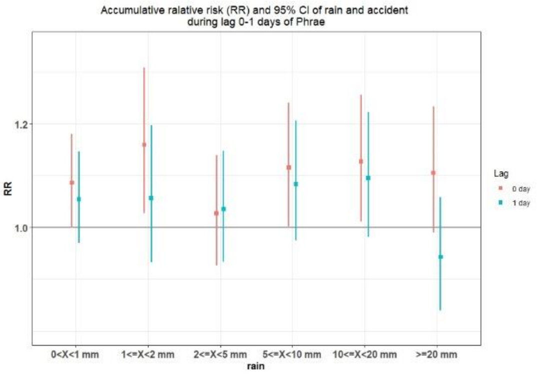
Figure 6-10 presents the estimated effect at different lag (lag 0 and lag 1) for the rain groups in each province. All results did not show delayed effects except Surat Thani for which the result at lag 1 was higher than the results at lag 0. There were different patterns of the impact of rainfall in different provinces. Firstly, certain provinces showed significant increases in road accidents due to a rising rain volume, for example, Chiang Rai and Phuket. Secondly, the effect was increased when the volume of rainfall increased then the number of road accidents declined even though the amount of rainfall was still rising. This pattern is clearly observed in Chiang Mai, Nan and Payao. Thirdly, some provinces showed an increase initially then a decline followed by a rise again such as Phrae, Mae Hong Son, Lampang, Lamphun, Uttaradit, Krabi, Chumphon, Trang, Nakhon Si Thammarat, Narathiwat, Pattani, Phang Nga, Phattalung, Ranong, Satun, Songkhla, Surat Thani and Yala.

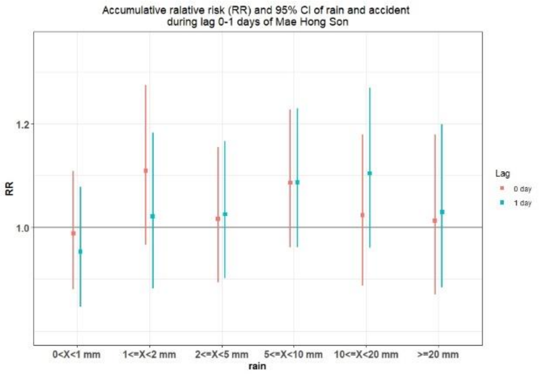
Northern provinces



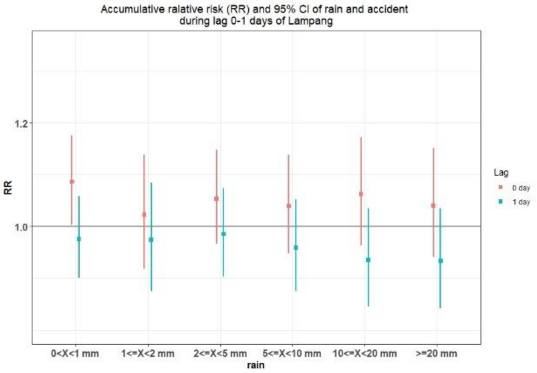
Phrae

Mae Hong Son

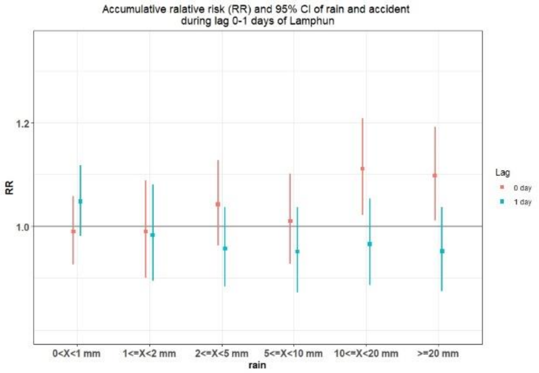




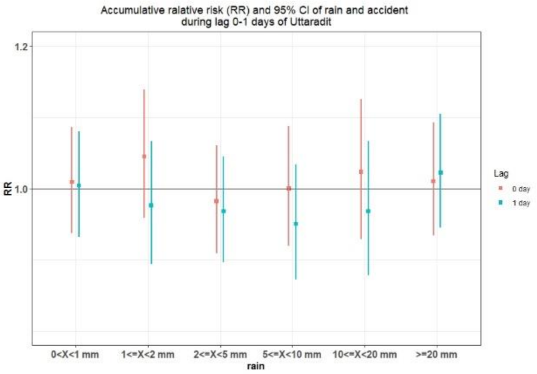
Lampang



Lamphun

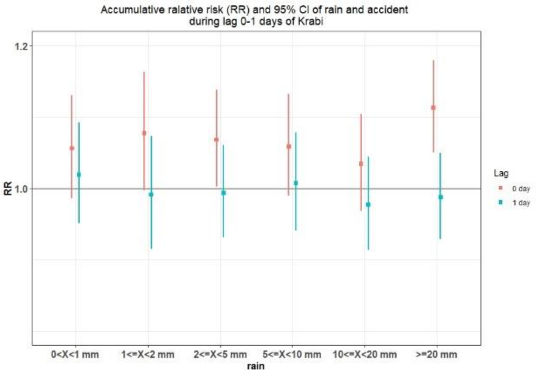


Uttaradit

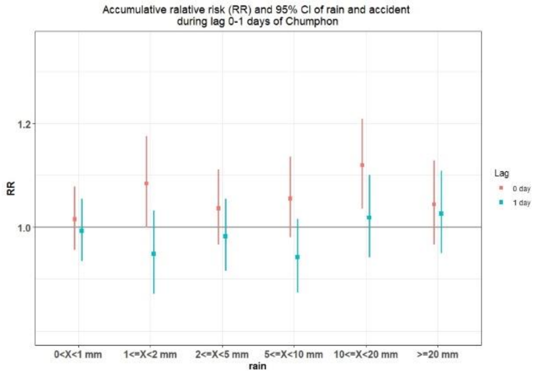


Southern provinces

Krabi

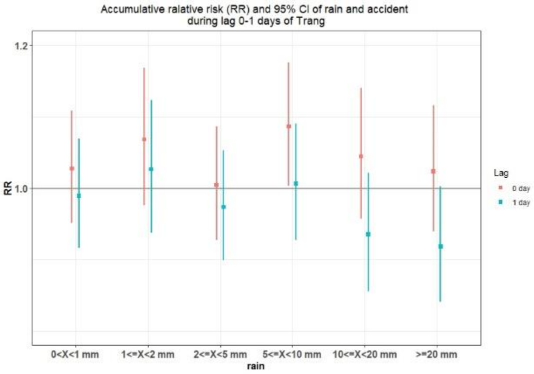


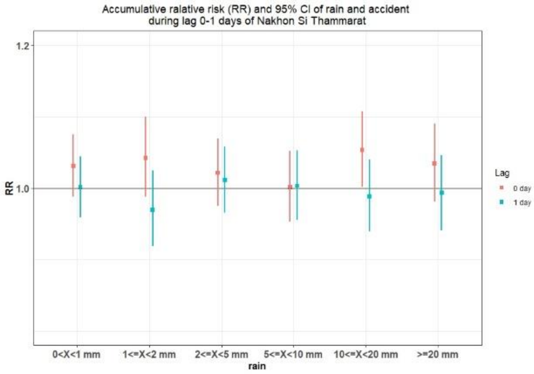
Chumphon



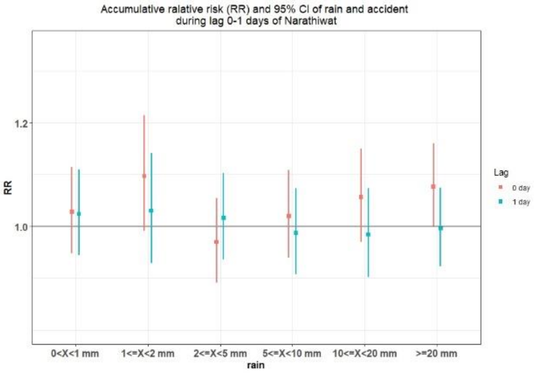
Trang

Nakhon Si Thammarat

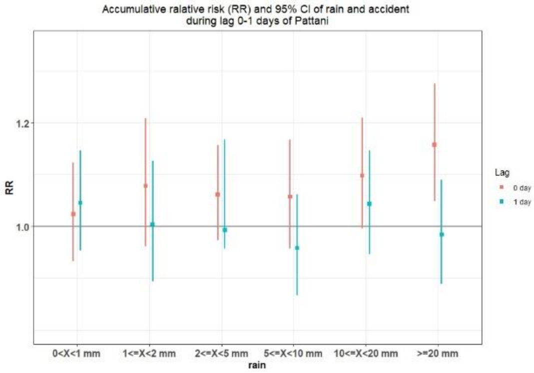




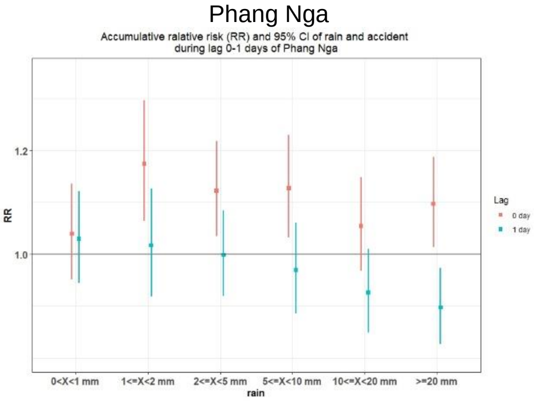
Narathiwat



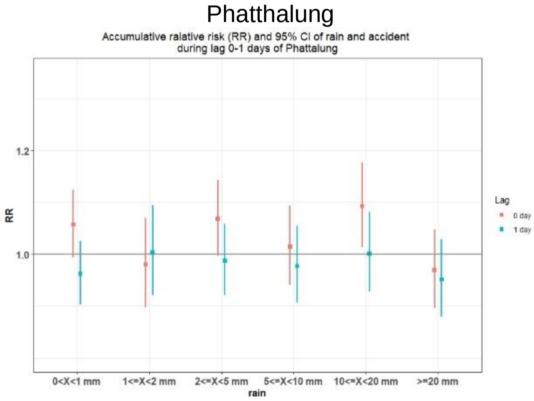
Pattani



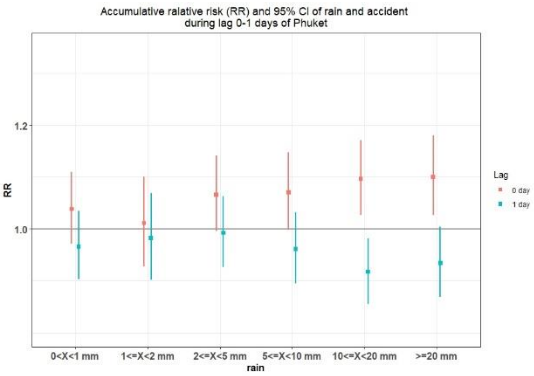
Phang Nga



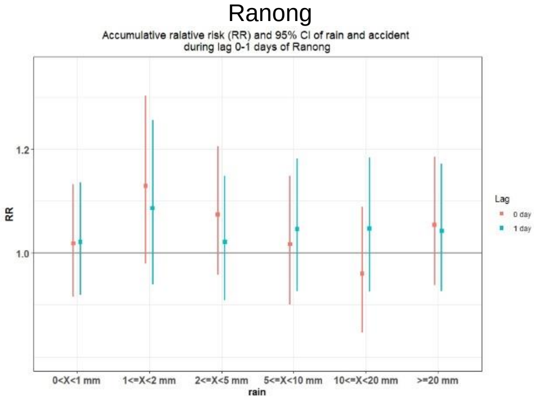
Phatthalung



Phuket



Ranong



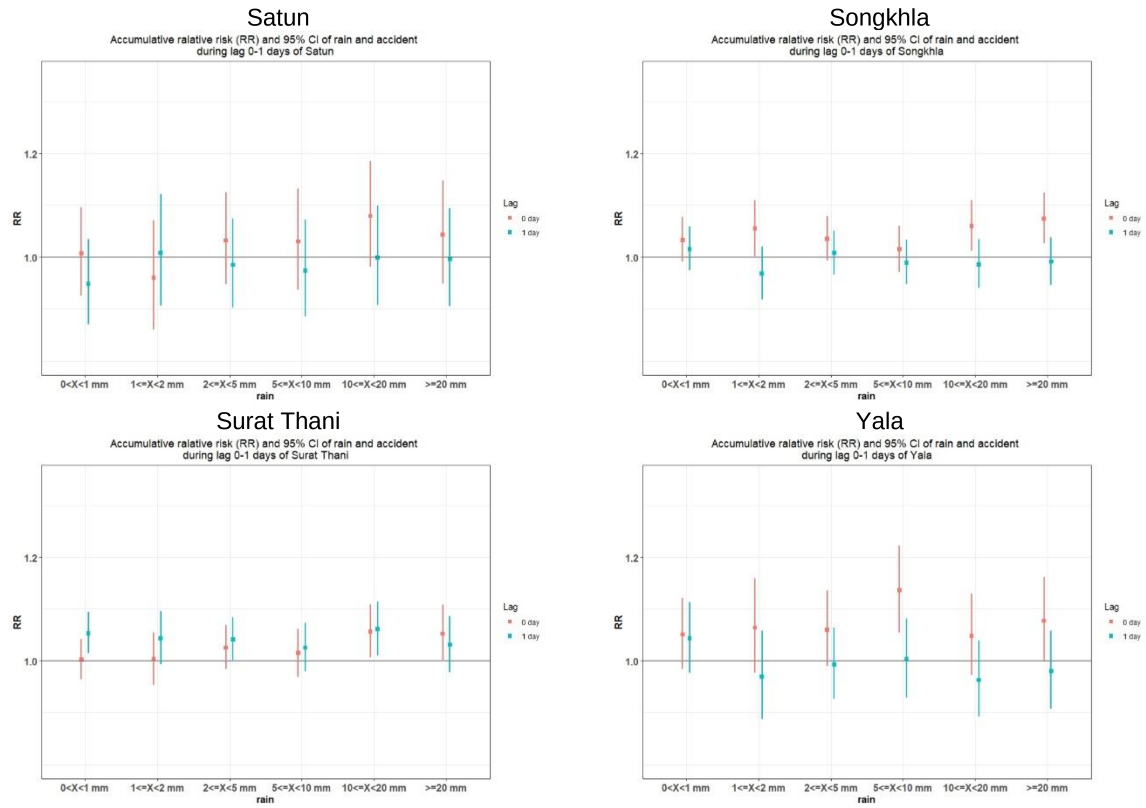
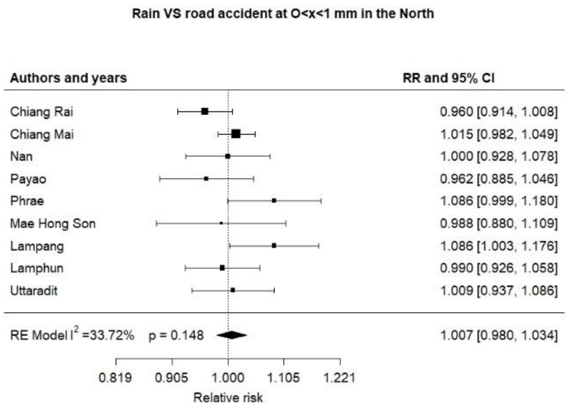


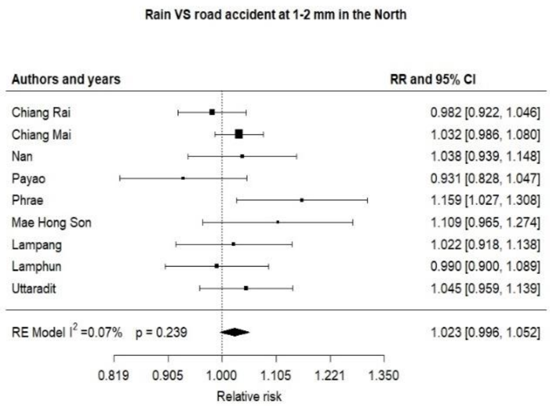
Figure 6-10 Forest plot of the relative risk with 95% CI for road accidents with different rain group groups and different lagged days of province in the Northern and the Southern provinces of Thailand. Red color is lag 0 and blue color is lag 1.

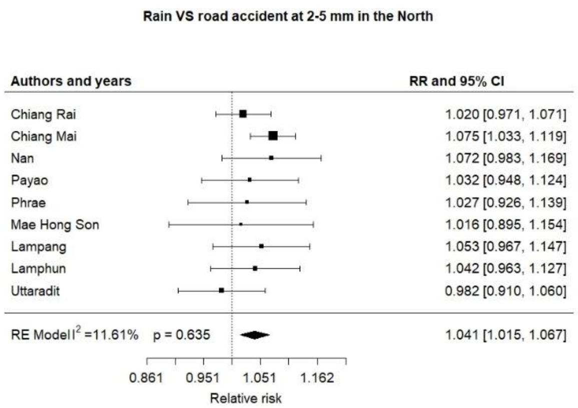
6.3.3 Meta-analyses for pooled estimated risks of the association between rainfall and road accidents

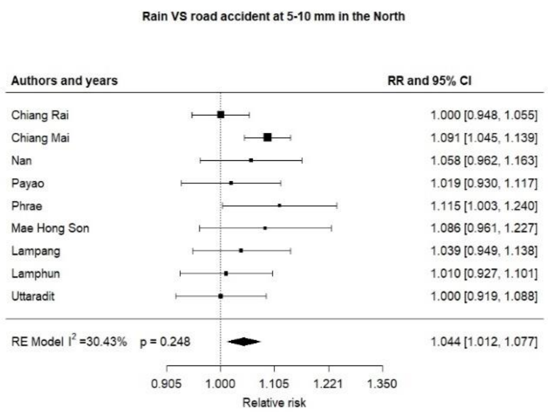
The estimated effect from different provinces were pooled by regions and stratified by rain groups as shown in Figure 6-11 and Figure 6-12. Rain groups are associated with an increase in road accidents in the Northern provinces for 2≤rain<5 mm (RR = 1.041, 95%CI: 1.015-1.067), 5≤rain<10 mm (RR= 1.044, 95%CI: 1.012-1.077), 10≤rain<20 mm (RR= 1.052, 95%CI: 1.026-1.079) and greater than 20 mm (rain ≥ 20) (RR= 1.039, 95%CI: 1.005-1.075). However, there were not found a significant association for rain group at 0<rain<1 mm and 1≤rain<2 mm. Northern's estimated results were different with the Southern' s results at rain group 0<rain<1 mm and 1≤rain<2 mm which revealed a significant estimated effects at RR=

1.028 (95% CI: 1.012-1.045) and RR = 1.049 (95%CI: 1.025-1.073). The combined effects for rain 2≤rain<5 mm and 5≤rain<10 mm were slightly less than the Northern's results with RR=1.040, 95% CI: 1.023-1.058) and RR= 1.043, 95%CI: 1.021-1.600 respectively. Conversely, the pooled RR for 10-20 mm and greater than 20 mm were larger than the Southern provinces with 1.062 (95%CI: 1.043-1.082) and 1.062 (95%CI: 1.040-1.084).









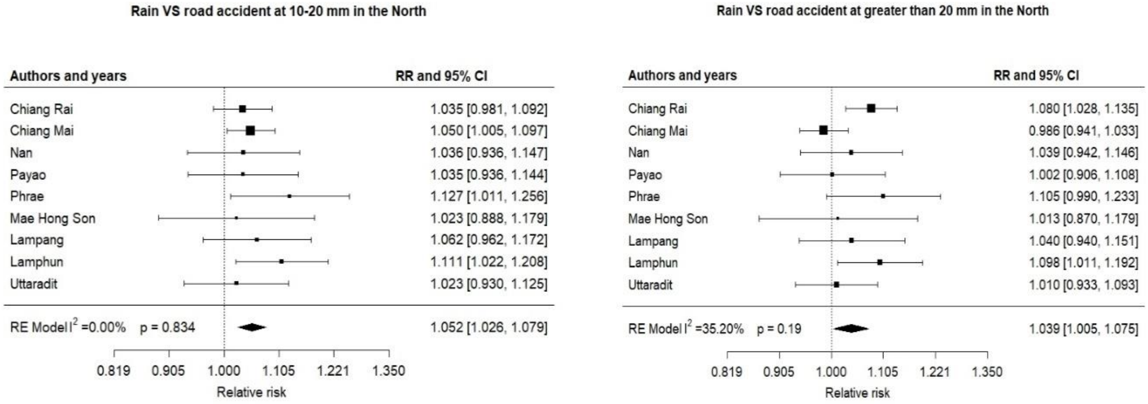
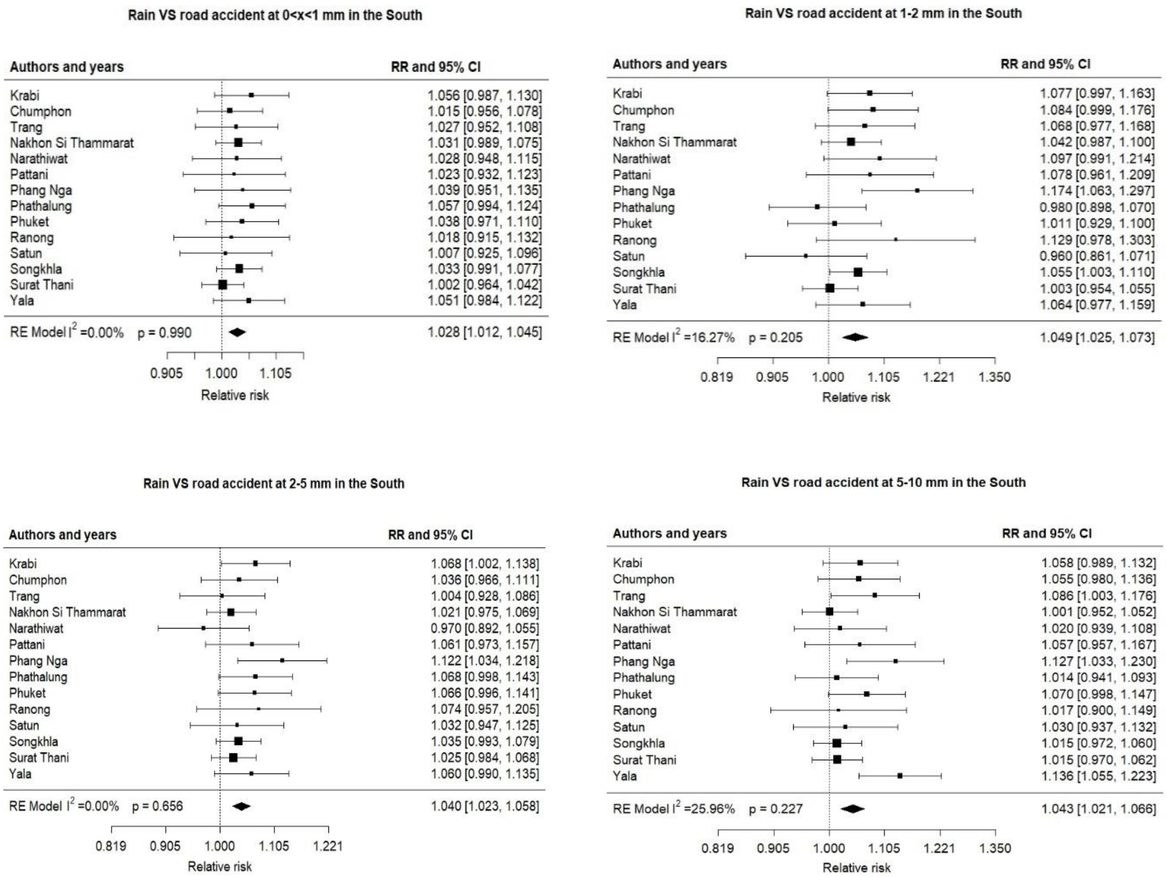


Figure 6-11 Forest plot for rainfall and road accidents at different rain volume (rain group) in the Northern provinces of Thailand.

The I^2 statistic (Higgins's I^2 test statistic) is an explanation of the inconsistency of publications from heterogeneity by showing the proportion of percentage of variation. I^2 = 0-30%, ≥ 30-50% and ≥ 50% were defined as low, moderate and high heterogeneity respectively. The p-value from Cochran's Q test reports a significant level at 0.10 (10%).



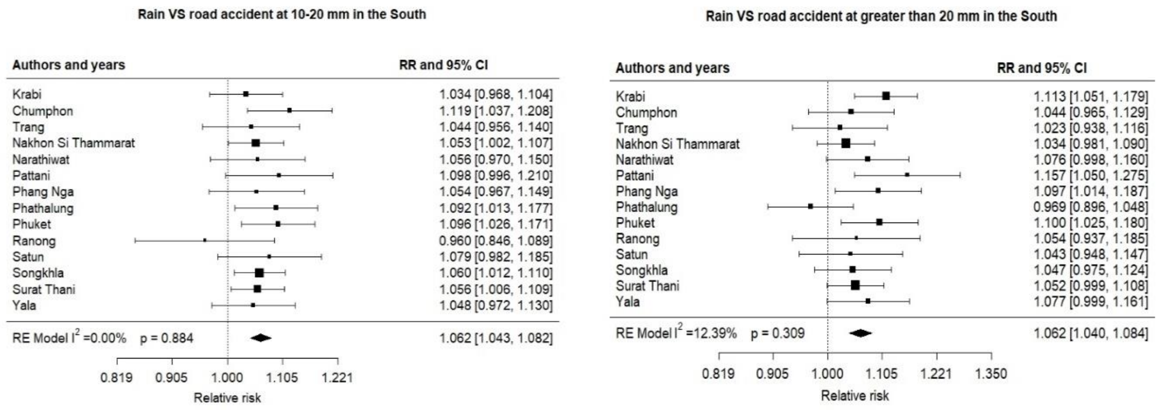


Figure 6-12 Forest plot for rainfall and road accidents at different rain volume (rain group) in the Southern provinces of Thailand.

The I^2 statistic (Higgins's I^2 test statistic) is an explanation of the inconsistency of publications from heterogeneity by showing the proportion of percentage of variation. I^2 = 0-30%, ≥ 30-50% and ≥ 50% were defined as low, moderated and high heterogeneity respectively. The p-value from Cochran's Q test reports a significant level at 0.10 (10%).

6.4 Discussion

This time-series study investigated the effect of extreme temperatures (low and high temperature) and rainfall on ambulance dispatches in the Northern and the Southern provinces of Thailand between 2012 and 2018. Our findings report the association between extreme temperatures and ambulance dispatches in both total dispatches and road accident dispatches. Results report estimated effects in RR with 95% CIs of the association between extreme temperature and ambulance dispatches compared to a threshold temperature. Our findings show a significant cumulative risk for associations between daily mean temperature and ambulance dispatches both in the Northern provinces for Chiang Rai and Chiang Mai and the Southern provinces in Nakhon Si Thammarat. But results did not have a U-shape similar to previous studies (Guo et al., 2018; Zhan et al., 2018). Hence, estimated relative risks explained how impact of low or high temperatures with ambulance dispatches compared to the minimum risk relationship at T_{MADT}.

The previous studies presented the significant association at low and high temperature with total ambulance dispatches. For example, study in Shenzhen, China have found the cumulative RR for ambulance emergency call-outs (AECOS) at 95% CI at cold effect by comparing the 1st and 5th percentile of temperature with the reference temperature (19.5 degree), RR=1.23 (95% CI: 1.10-1.38) and 1.25 (95% CI: 1.15-1.35) respectively. The risk for high temperature were RR= 1.19 (95% CI: 1.14-1.23) and RR =1.21 (95% CI: 1.16-1.26) when compared with the 95th and 99th percentile of temperature (Zhan et al., 2018). Previous studies reported that a rise in temperature was significantly associated with an increase of ambulance dispatches for lag 0-5, 27% (95%CI: 12-44) (Cheng et al., 2016). Additionally, cause-specific risks reported the association due to cardiovascular and respiratory categories. The emergency dispatches increased for 6.94% (95%CI: 5.93-7.70), 17.93 (95%CI: 16.10-19.25) and 12.19% (95%CI: 9.90-13.66) of all causes, cardiovascular disease and respiratory disease respectively when exposure to low temperature. Whereas high temperature also reported a significant effect for all causes, cardiovascular diseases and respiratory but small fraction compared with exposing to low temperature (Onozuka and Hagihara, 2015). All ambulance dispatches in London between 2010 and 2014 were significantly associated with low and high temperature at the 5th and the 95th percentile of temperature distribution, see Chapter 5. The specific causes of a respiratory group reported RR ranged from 1.392 (95% CI: 1.161-1.699) to 2.075 (95% CI: 1.673-2.574) for asthma and respiratory chest infection respectively. For cardiovascular categories, only exposure to high temperature for chest pain symptom had a significant association (RR= 1.684, 95% CI: 1.320-2.150). Mechanisms in the human body is one possible reason that can be related to extreme low temperature, because blood pressure, heart rate and blood cholesterol will increase, while exposure to high temperature is associated with sweating, vasodilatation and vasoconstriction of blood vessels (Ballester et al., 1997; Carder et al., 2005; Keatinge and Donaldson, 2001; Woodhouse et al., 1994)

Lag pattern for the association between ambulance dispatches and temperature findings for low temperature were presented until 3-4 days while the effect persisted until 3-4 weeks. These results are in agreement with a previous studies by (Bao et al., 2016; Guo et al., 2012; Onozuka and Hagihara, 2017; Yang et al., 2012; Zhan et al., 2018).

A possible explanation why our results differ from previous studies might be the source of ambulance dispatches which have different methods for diagnosis following confirmation by ambulance dispatch, paramedics and physicians (Johnston et al., 2019; Sangkharat et al., 2019). Moreover, the impact of geographic areas, demographic, economic and health condition can be affected to the response (Basu, 2009; Berko et al., 2014; Guo et al., 2012; Kragholm et al., 2017; Onozuka et al., 2018; Shah et al., 2013; Zhao et al., 2017).

The rainfall results were different from the association between ambulance dispatches and temperature. Results reported a significant increase in ambulance dispatches due to road accident dispatches both in the Southern and the Northern provinces. Our findings supports evidence from the previous studies (Bergel-Hayat et al., 2013). The pooled estimated risk rising in road accident dispatches due to rain in the Southern provinces was higher than the provinces in the North. The pooled estimated from nine provinces in the Norther had a significant association at rainfall level 2≤rain<5 mm, 5≤rain<10 mm, 10≤rain<20 mm and rain > 20 mm per day, but not for lower rain at 0<rain<1 mm and 1≤rain<2 mm per day. The largest pooled estimated RR is 1.052 (95%CI: 1.026-1.079) at rainfall 10-20 mm per day.

The result from the Northern provinces was different from the Southern findings, with an increase in road accident dispatches associated with all rain groups. The group of rain with

10-20 mm per day result also was noted the highest pooled estimated risk (RR= 1.062, 95% CI: 1.043-1.082). These differences between areas can be explained in term of geographic location (Guo et al., 2012) which is consistent with our findings that reported the amount of rainfall in the Southern province was higher than the Northern province because Southwest monsoon.

Interestingly, our results reported that the association between road accident dispatches and rainfall did not have a linear relationship. The estimated effects for the heavy rain group (more than 20 mm/day) was lower than the rain volume 10-20 mm/day. These result are consistent with Bergel-Hayat et al (2013) and Yannis and Karlaftis (2010) who reported the negative relationship between precipitation and accident on the road. The results are likely to be related to the behaviour of drivers due to the decline of traffic volume during heavy rain. In heavy rain, people are likely to change activity plans; and this behaviour is likely to be related to geographic areas. Previous studies mentioned that drivers change their behaviour on the following days of rainfall resulting in a reduction of motorcycle risks (Brijs et al., 2008; Eisenberg, 2004).

Our findings can be advantageous for the surveillance system about extreme temperatures and rain event, which are found to be associated with total ambulance dispatches and especially road accident dispatches. Policymakers should consider environmental factors, when creating a strategy to improve the ambulance service and public health in general. The prediction of the volume of ambulance calls due to changing environmental factors can improve the effectiveness of ambulance services. Raising people's awareness about the safety of driving under extreme weather conditions can help mitigate the associated risks. Adaptation techniques could include checking the maintenance of vehicles regularly, driving carefully with reduced speed and using helmet if on a bike. System warning and system surveillance need to be further developed in the future. WHO (2018) stressed that low and middle income countries need to take advantage of the experience of high income countries regarding safety road policies, road designs and good standard of driving behaviours.

This study has several limitations. First, Thai ambulance dispatch data did not contain demographic data and geographical data disaggregated further than the province level. In addition, the road accident model could be further refined to investigate the association between rainfall and road accident by adding related factors such as the traffic volume, type of road, type of cars and speed of vehicle. Hence, further studies should take these variables into account to provide a more nuanced explanation of risk factors for the public health sector. Second, we could not investigate data from Bangkok metropolitan which is the capital in Thailand because the data is collected by The Erawan Medical Center Bangkok and is outside the jurisdiction of the data providers used in this study. Data from Bangkok metropolitan area will contain a high density of people and thus is likely to produce good statistics, similar to that observed in the London study reported in Chapter 5.

6.5 Conclusion

This study provides clear evidence of the association between an increase in road accident and rainfall in the range between 5-20 mm/day of rain. The results did not report a delay effect or the impact of lagged days. Moreover, few findings presented the significant association between temperature and ambulance dispatch at lag 0-21 days. These results suggest the surveillance system for the association between environmental factors, for both rainfall and temperature, need to be set up in Thailand. This can be a prevention measure from the environmental impact. With this information, the Thai emergency services can improve the effectiveness of both staff and equipment. For this to be effective, health education about the impact of environmental factor is required. The outcomes from this study on Thai data is likely applicable to other countries at similar stages of development and meteorology.

6.6 References

Ballester, F., Corella, D., Pérez-Hoyos, S., Sáez, M., Hervás, A., 1997. Mortality as a function of temperature. A study in Valencia, Spain, 1991-1993, International Journal of Epidemiology. https://doi.org/10.1093/ije/26.3.551

Bao, J., Wang, Z., Yu, C., Li, X., 2016. The influence of temperature on mortality and its Lag effect: A study in four Chinese cities with different latitudes. BMC Public Health 16. https://doi.org/10.1186/s12889-016-3031-z

Basu, R., 2009. Environmental Health High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008. https://doi.org/10.1186/1476-069X-8-40

Bergel-Hayat, R., Debbarh, M., Antoniou, C., Yannis, G., 2013. Explaining the road accident risk: Weather effects. Accid. Anal. Prev. https://doi.org/10.1016/j.aap.2013.03.006

Berko, J., Ingram, D.D., Saha, S., Parker, J.D., 2014. Deaths attributed to heat, cold, and other weather events in the United States, 2006-2010. Natl. Health Stat. Report. 1–15.

Bernardin, F., Bremond, R., Ledoux, V., Pinto, M., Lemonnier, S., Cavallo, V., Colomb, M., 2014. Measuring the effect of the rainfall on the windshield in terms of visual performance. Accid. Anal. Prev. 63, 83–88. https://doi.org/10.1016/j.aap.2013.10.008

Brijs, T., Karlis, D., Wets, G., 2008. Studying the effect of weather conditions on daily crash counts using a discrete time-series model. Accid. Anal. Prev. https://doi.org/10.1016/j.aap.2008.01.001

Brodsky, H., Hakkert, A.S., 1988. Risk of a road accident in rainy weather. Accid. Anal. Prev. https://doi.org/10.1016/0001-4575(88)90001-2

Camel Travel, 2017. Thailand Fact Sheet For Travellers - Camel Travel [WWW Document]. URL https://cameltravel.co.uk/thailand-fact-sheet-travellers/ (accessed 1.30.20).

Carder, M., McNamee, R., Beverland, I., Elton, R., Cohen, G.R., Boyd, J., Agius, R.M., 2005. The lagged effect of cold temperature and wind chill on cardiorespiratory mortality in Scotland. Occup. Environ. Med. 62, 702–710. https://doi.org/10.1136/oem.2004.016394

Cavanagh, R., 2008. When is the Rainy Season in Thailand? [WWW Document]. URL https://www.thaizer.com/weather/when-is-the-rainy-season-in-thailand/ (accessed 11.19.19).

Cheng, J., Xu, Z., Zhao, D., Xie, M., Yang, H., Wen, L., Li, K., Su, H., 2016. Impacts of temperature change on ambulance dispatches and seasonal effect modification. Int. J. Biometeorol. 60, 1863–1871. https://doi.org/10.1007/s00484-016-1173-4

Eisenberg, D., 2004. The mixed effects of precipitation on traffic crashes. Accid. Anal. Prev. 36, 637–647. https://doi.org/10.1016/S0001-4575(03)00085-X

Guo, Y., Li, S., Zhang, Y., Armstrong, B., Jaakkola, J.J.K., Tong, S., Pan, X., 2012. Extremely cold and hot temperatures increase the risk of ischaemic heart disease mortality: epidemiological evidence from China. https://doi.org/10.1136/heartjnl-2012

Guo, Y., Ma, Y., Ji, J., Liu, N., Zhou, G., Fang, D., Huang, G., Lan, T., Peng, C., Yu, S., 2018. The relationship between extreme temperature and emergency incidences: a time series analysis in Shenzhen, China. Environ. Sci. Pollut. Res. 25, 36239–36255. https://doi.org/10.1007/s11356-018-3426-8

Hermans, E., Wets, G., Van Den Bossche, F., 2006. Hermans, Wets and Van den Bossche Frequency and Severity of Belgian Road Traffic Accidents Studied by State Space Methods.

ITEMS, 2018. Information Technology for Emergency Medical System [WWW Document]. URL https://ws.niems.go.th/items_front/index.aspx (accessed 1.30.20).

Johnston, F.H., Salimi, F., Williamson, G.J., Henderson, S.B., Yao, J., Dennekamp, M., Smith, K., Abramson, M.J., Morgan, G.G., 2019. Ambient Particulate Matter and Paramedic Assessments of Acute Diabetic, Cardiovascular, and Respiratory Conditions. Epidemiology 30, 11–19. https://doi.org/10.1097/EDE.0000000000000929

Keatinge, W.R., Donaldson, G.C., 2001. Mortality related to cold and air pollution in London after allowance for effects of associated weather patterns. Environ. Res. 86, 209–216. https://doi.org/10.1006/enrs.2001.4255

Keay, K., Simmonds, I., 2006. Road accidents and rainfall in a large Australian city. Accid. Anal. Prev. https://doi.org/10.1016/j.aap.2005.06.025

Kragholm, K., Wissenberg, M., Mortensen, R.N., Hansen, S.M., Hansen, C.M., Thorsteinsson, K., Rajan, S., Lippert, F., Folke, F., Gislason, G., Kober, L., Fonager, K., Jensen, S.E., Gerds, T.A., Torp-Pedersen, C., Rasmussen, B.S., 2017. Bystander Efforts and 1-Year Outcomes in Out-of-Hospital Cardiac Arrest. N. Engl. J. Med. 376, 1737–1747. https://doi.org/10.1056/NEJMoa1601891

Onozuka, D., Hagihara, A., 2017. Spatiotemporal variation in heat-related out-of-hospital cardiac arrest during the summer in Japan. Sci. Total Environ. 583, 401–407. https://doi.org/10.1016/j.scitotenv.2017.01.081

Onozuka, D., Hagihara, A., 2015. All-Cause and cause-specific risk of emergency transport attributable to temperature: A nationwide study. Med. (United States) 94. https://doi.org/10.1097/MD.0000000000002259

Onozuka, D., Nishimura, K., Hagihara, A., 2018. Full moon and traffic accident-related emergency ambulance transport: A nationwide case-crossover study. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2018.07.053

Sangkharat, K., Fisher, P., Thomas, G.N., Thornes, J., Pope, F.D., 2019. The impact of air pollutants on ambulance dispatches: A systematic review and meta-analysis of acute effects. Environ. Pollut. 254, 112769. https://doi.org/10.1016/j.envpol.2019.06.065

Shah, A.S. V, Langrish, J.P., Nair, H., Mcallister, D.A., Hunter, A.L., Donaldson, K., Newby, D.E., Mills, N.L., 2013. Global association of air pollution and heart failure: a systematic review and meta-analysis. www.thelancet.com 382, 1039. https://doi.org/10.1016/S0140-6736(13)60898-3

WHO, 2018. GLOBAL STATUS REPORT ON ROAD SAFETY 2018 SUMMARY.

Woodhouse, P.R., Khaw, K.T., Plummer, M., Meade, T.W., Foley, A., 1994. Seasonal variations of plasma fibrinogen and factor VII activity in the elderly: winter infections and death from cardiovascular disease. Lancet 343, 435–439. https://doi.org/10.1016/S0140-6736(94)92689-1

Xu, Q., Wang, S., Guo, Y., Wang, C., Huang, F., Li, X., Gao, Q., Wu, L., Tao, L., Guo, J., Wang, W., Guo, X., 2017. Acute exposure to fine particulate matter and cardiovascular hospital emergency room visits in Beijing, China. Environ. Pollut. 220, 317–327. https://doi.org/10.1016/J.ENVPOL.2016.09.065

Yang, J., Ou, C.Q., Ding, Y., Zhou, Y.X., Chen, P.Y., 2012. Daily temperature and mortality: A study of distributed lag non-linear effect and effect modification in Guangzhou, Environmental Health: A Global Access Science Source. https://doi.org/10.1186/1476-069X-11-63

Yannis, G., Karlaftis, M.G., 2010. Weather Effects on Daily Traffic Accidents and Fatalities: A Time Series Count Data Approach, Transportation Research Board 89th Annual Meeting.

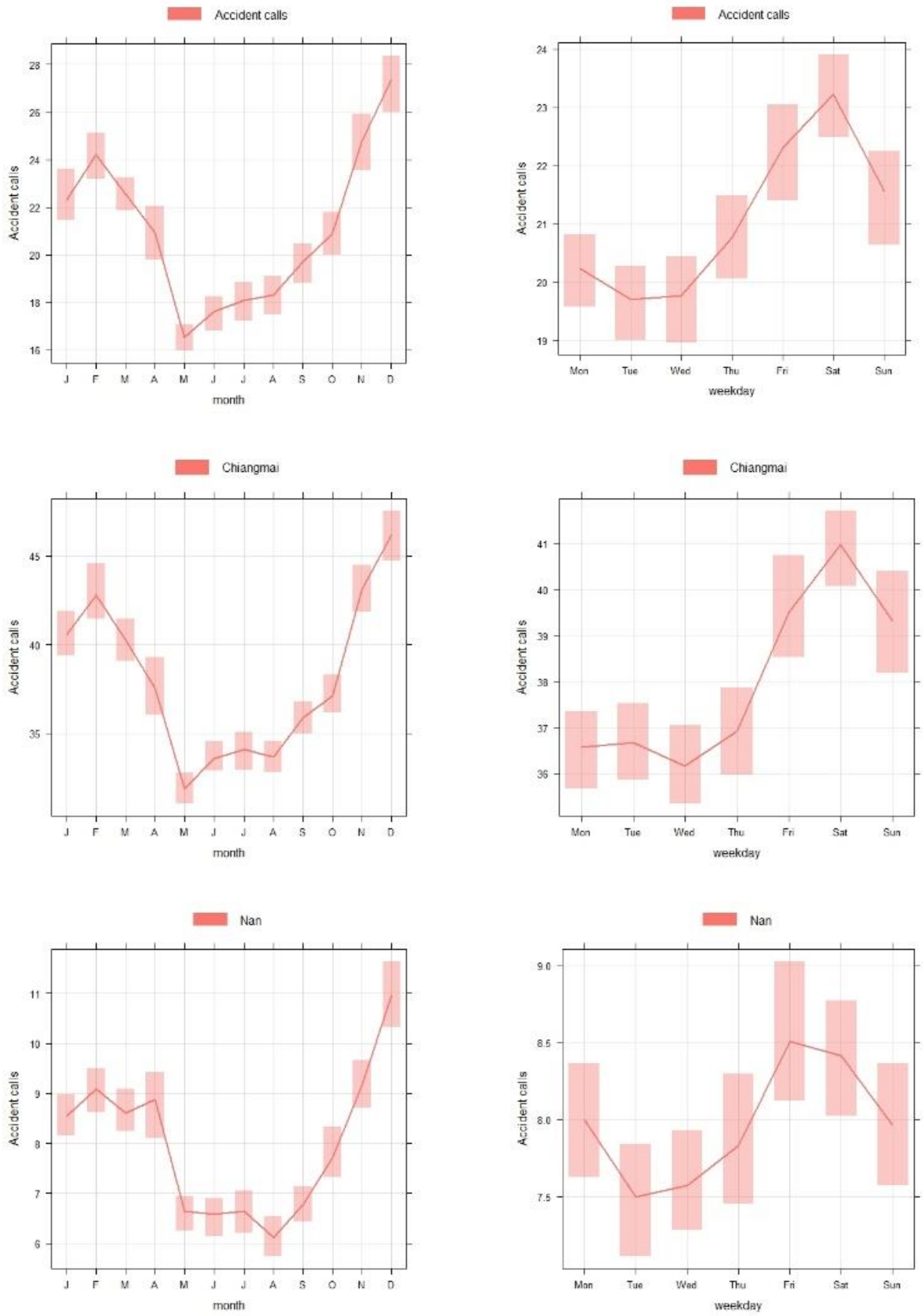
Zhan, Z.Y., Yu, Y.M., Qian, J., Song, Y.F., Chen, P.Y., Ou, C.Q., 2018. Effects of ambient temperature on ambulance emergency call-outs in the subtropical city of Shenzhen, China. PLoS One 13, e0207187. https://doi.org/10.1371/journal.pone.0207187

Zhao, R., Chen, S., Wang, W., Huang, J., Wang, K., Liu, L., Wei, S., 2017. The impact of short-term exposure to air pollutants on the onset of out-of-hospital cardiac arrest: A systematic review and meta-analysis. Int. J. Cardiol. 226, 110–117. https://doi.org/10.1016/j.ijcard.2016.10.053

6.7 Supplementary

Figure 6-13 Monthly time variation (right side) of total dispatches and weekday time (left side) variation as shown in x-axis of ambulance dispatches caused by road accidents (calls) (y-axis)

Monthly Weekly



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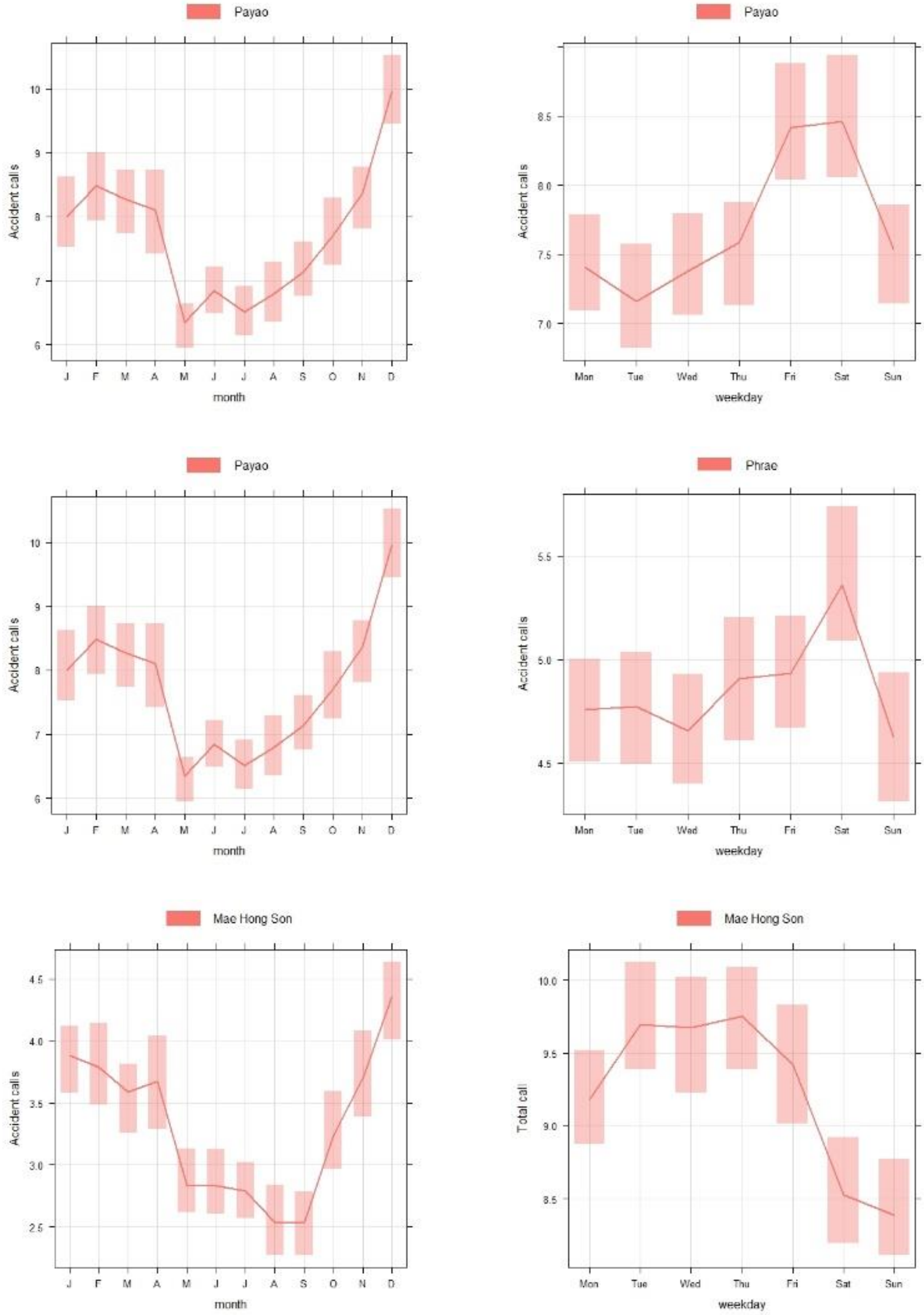

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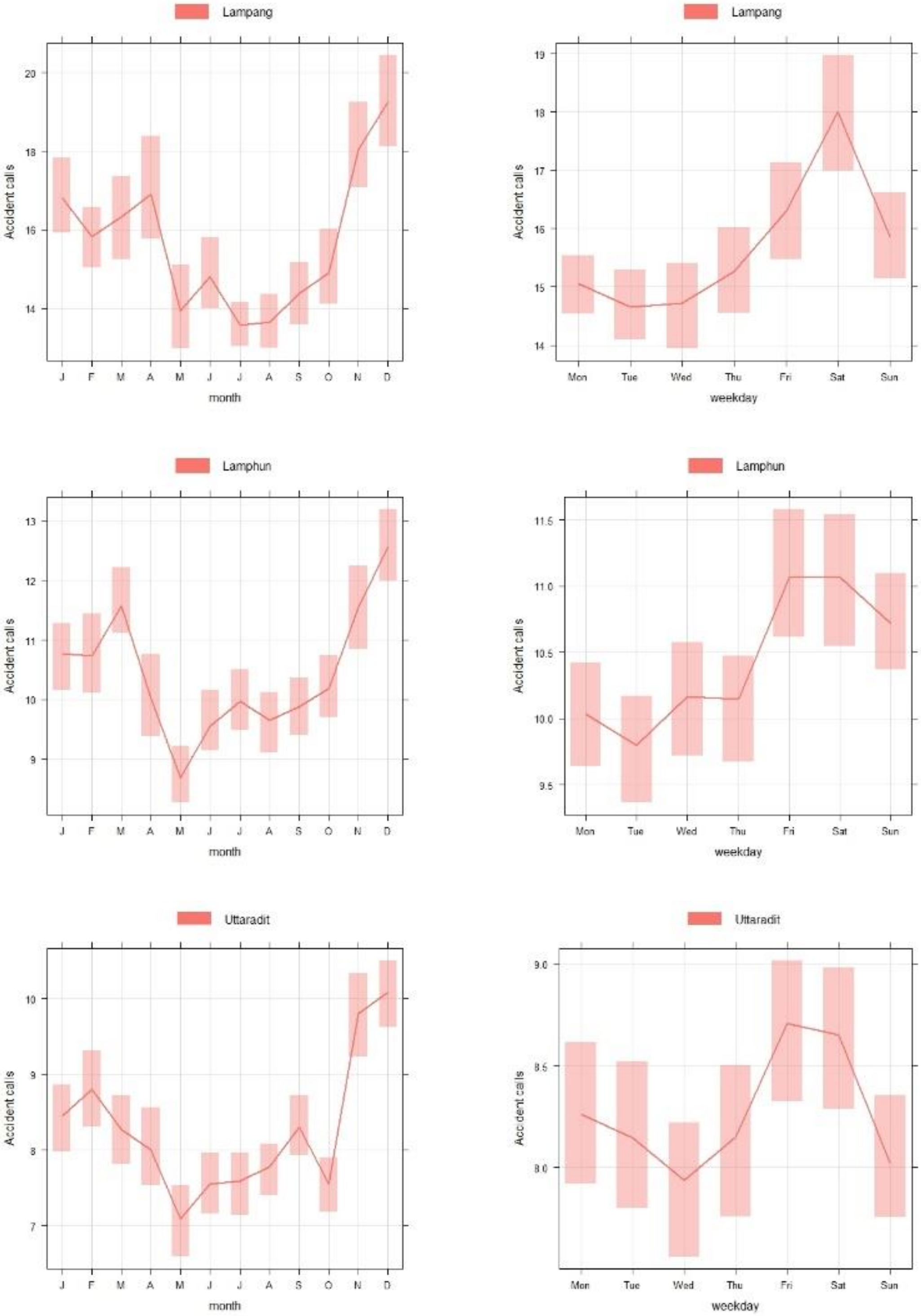

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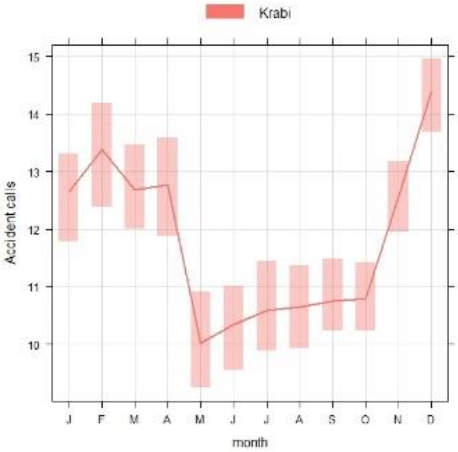

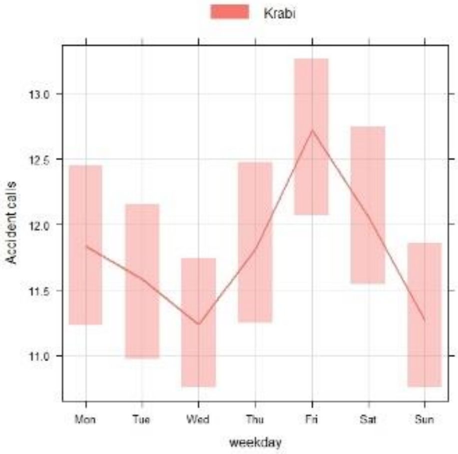

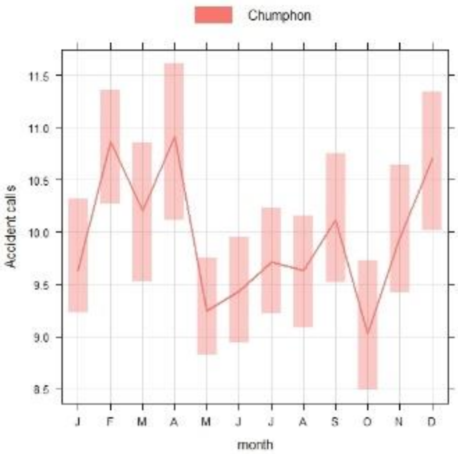

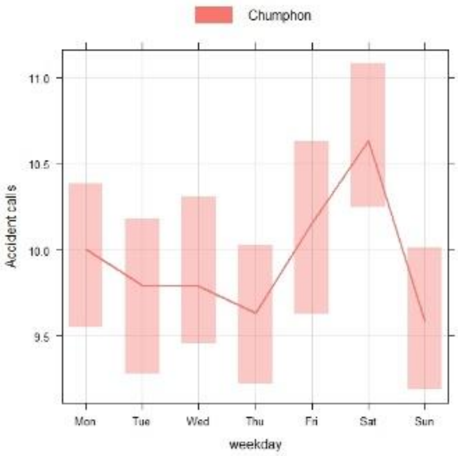

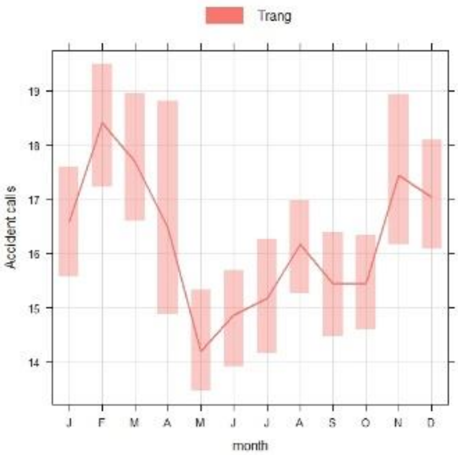

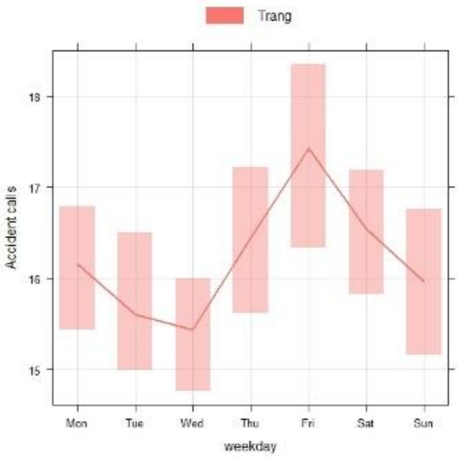

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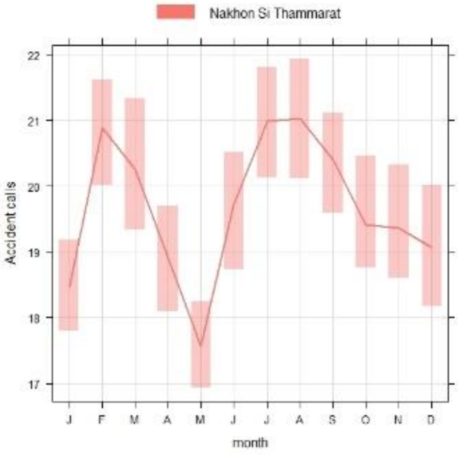

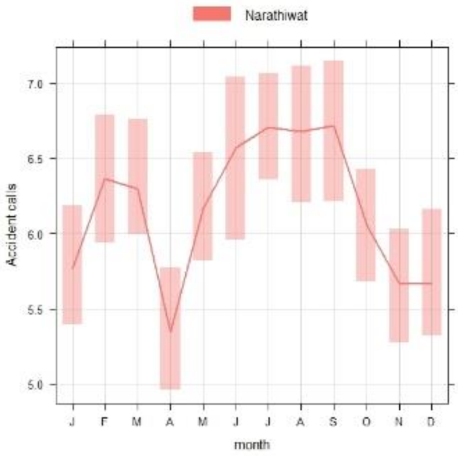

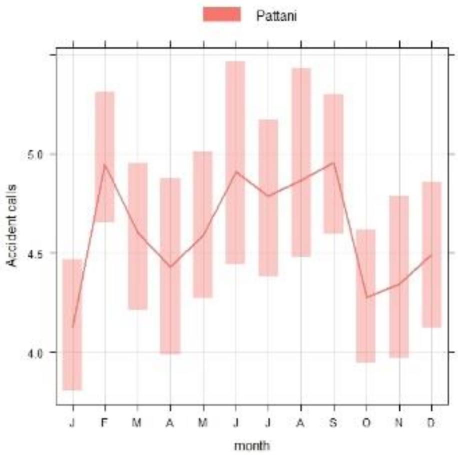

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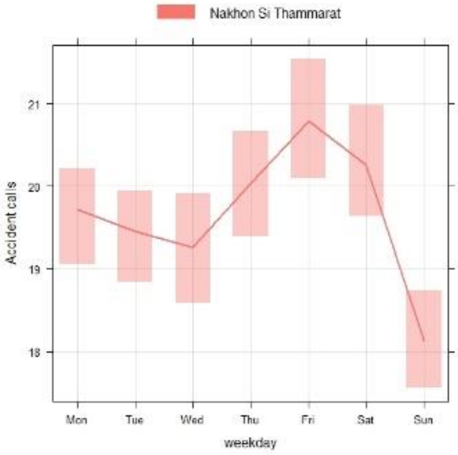

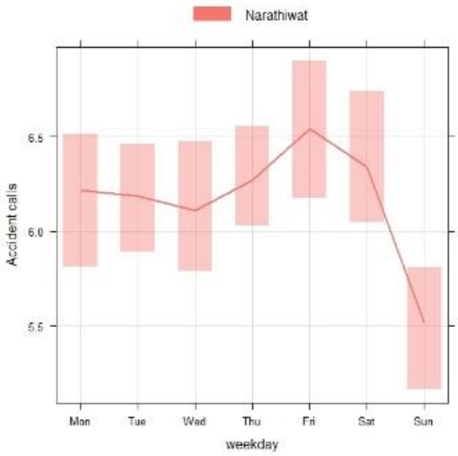

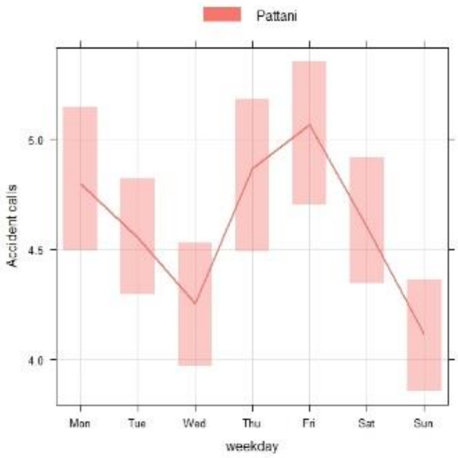

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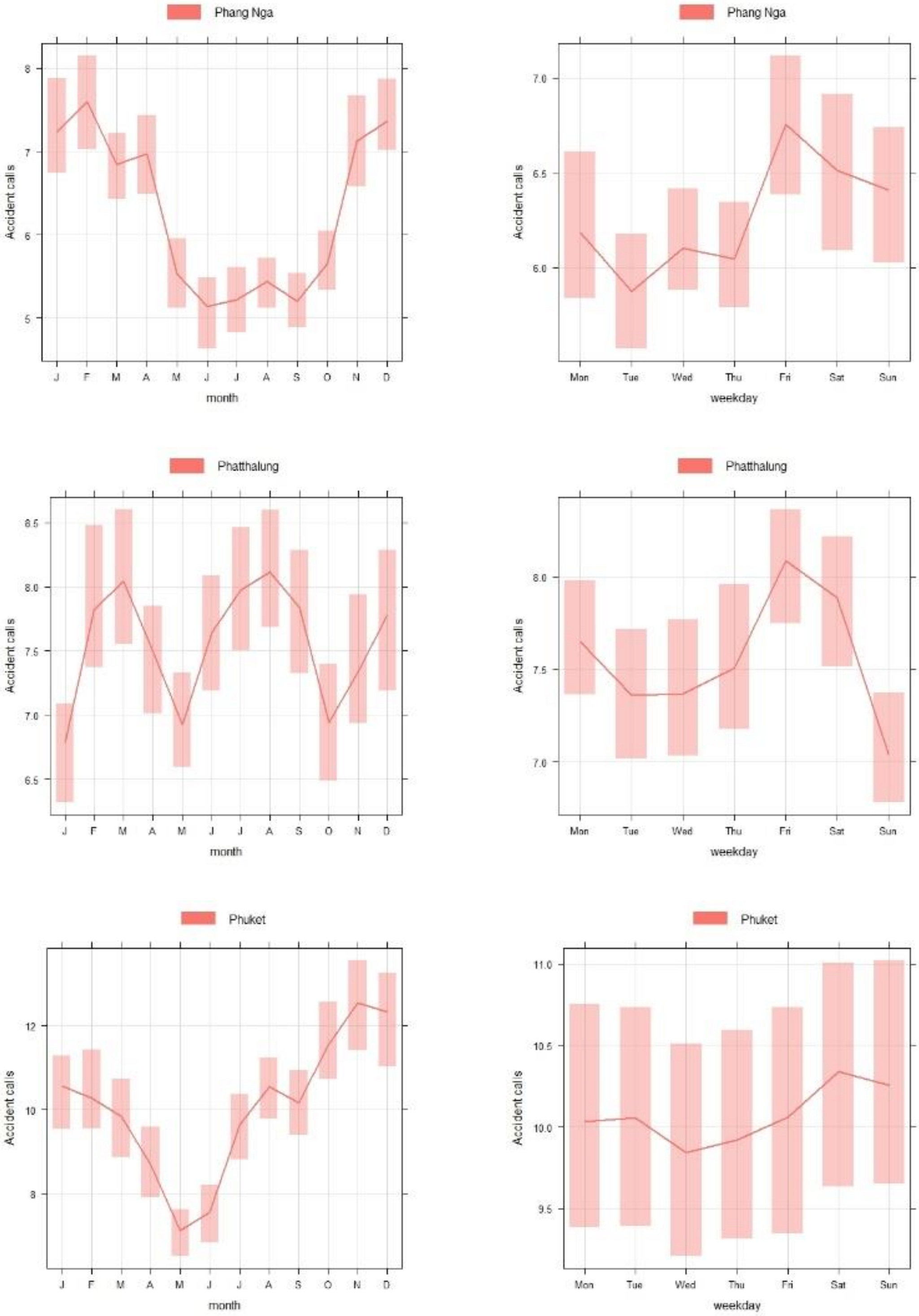

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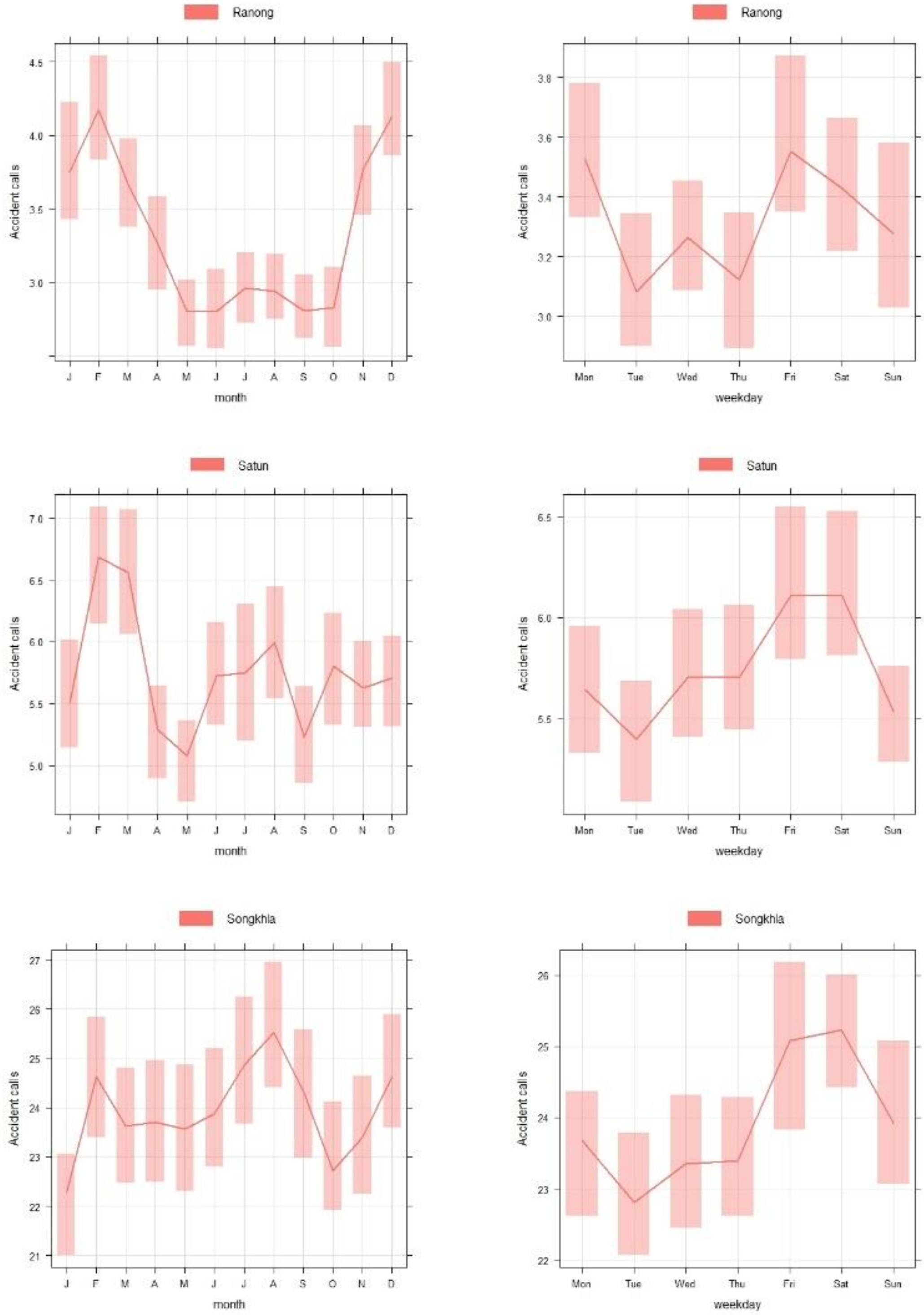

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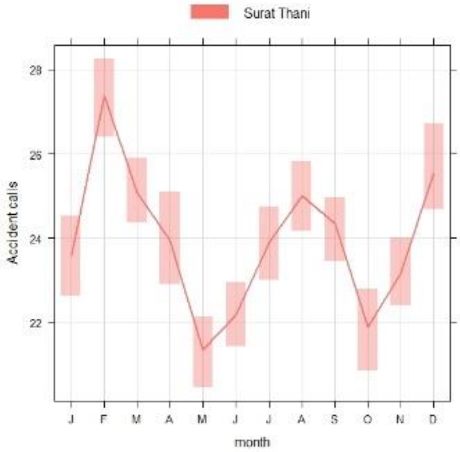

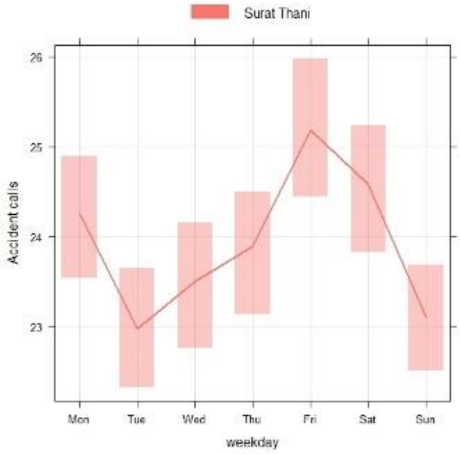

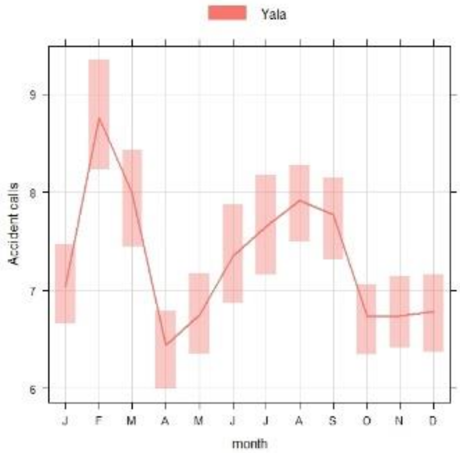

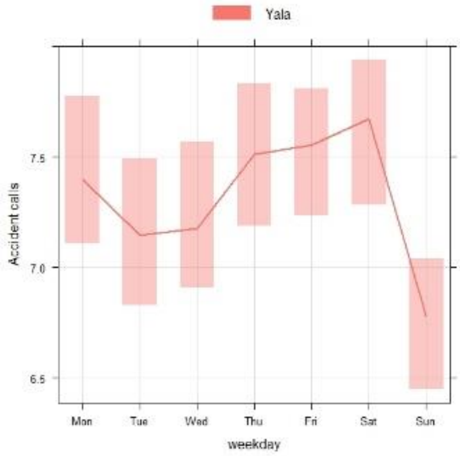

CHAPTER 7 : GENERAL DISCUSSION

This chapter provides a summary of the main findings and key discussion points from the three results chapters. Firstly, the main results have been summarised. Secondly, the strengths and limitations of the outputs are discussed. Thirdly, the implications on the Thai public health service have been outlined. Finally, recommendations for future work are suggested.

7.1 Summary of main results

7.1.1 The impact of air pollutants on ambulance dispatches: A systematic review and meta-analysis of acute effects

7.1.1.1 The ambulance data in each country have different methods for assessments. Hence, these meta-analysis results of association between air pollutants and health outcomes can be divided into three group sources: 1) ambulance dispatches with diagnosis made over phone prior to ambulance dispatch, 2) ambulance dispatch with paramedic assessment and 3) ambulance dispatches with subsequent physician diagnosis at hospital.

7.1.1.2 There were five categories of health outcomes that previous studies had investigated: two non-specific causes, such as all-respiratory (n=10) and all-cardiovascular; and three specific causes: cardiac arrest, asthma and chest pain. Interestingly, only cardiac arrest was reported for paramedic assessment, no other category was reported. Variation categories could be found from phone diagnoses and physician diagnoses.

7.1.1.3 The risk of the impact of air pollution on health is indicated by a concentration-response role. This study uses relative risk (RR) to get estimated risk from ecological study. The RR shows health outcomes of population when exposed to high level of pollutant compared to lower exposures. The increment in pollutant could be described in different unit. Hence, each pollutant was standardized to the same unit. Some reported 10 μg/m^3, while others reported in 1 μg/m^3 for PM. For gases, they reported relative risk per interquartile (IQR) increment for O_3, SO_2 and NO_2 in both μg/m^3 and parts per billion (ppb). Bbefore pooling, all results were standardised to 10 ppb and 1 parts per million (ppm) of CO. We assumed the association between pollutants and health outcomes is linear.

7.1.1.4 The pooled effect for pollutants and health outcomes was different depending on the method of assessments. For instance, for ambulance phone dispatch data, exposure $PM_{2.5}$ for a 10 μg/m^3 i was associated with an increase in all respiratory dispatches. An increase in 10 ppb of NO_2 was positively associated with asthma dispatches. For paramedic assessment, both an increase in 10 ppb of $PM_{2.5}$ and coarse particulate and exposure to a 1 ppm of CO were associated with cardiac arrest dispatches. The results did not show any significant association between cardiac arrest dispatches and PM_{10}, SO_2, NO_2 and O_3. For physician diagnosis data, it was estimated each 10 μg/m^3 of $PM_{2.5}$ that increase in all-respiratory categories.

7.1.1.5 The results from subgroup analysis by regions were not consistent. For example, cardiac arrest – $PM_{2.5}$ results were not significant when we analysed only European countries, while results became significant between exposure to PM_{10} and O_3 and cardiac arrest dispatches for paramedic assessments when including only European countries.

7.1.1.6 Sensitivity analysis results decreased heterogeneity and became significant and non-significant results when some publications were removed. This means the findings were not robust. For instance, when one publication from phone assess was removed for cardiac arrest-$PM_{2.5}$ association, the result became significant. However, some results remained consistent whichever paper was removed.

7.1.1.7 The role of heterogeneity decreased when doing sensitivity analyses or subgroup analyses. This can reduce the problem when we attempt to do a meta-analysis because heterogeneity refers to the variation of outcomes. The reason of heterogeneity could be explained by different areas or different studies. Hence, the interpretation of results needs careful explanation.

7.1.1.8 The previous studies only have two systematic review and did only once a meta-analysis for OHCA and air pollution. Hence, this is the first publication that analysed both systematic review and meta-analysis focusing on various ambulance dispatches and outdoor pollutants. Moreover, we managed ambulance data to reduce the problem of misclassification bias by analysing them based on group sources.

7.1.2 Impact of extreme temperature on ambulance dispatches

7.1.2.1 Most previous studies on the association between extreme temperatures and health outcomes have used either mortality or hospital data for the health outcome. Only a few studies have investigated the association between temperature and ambulance dispatches for non life-threatening cases. This study provided evidence for 14 dispatch categories related to extreme hot and cold effects. The 14 categories investigated were asthma, dyspnoea, RCI, respiratory arrest and COPD, chest pain, cardiac chest pain, cardiac arrhythmia and 'other cardiac problems', dizzy, alcohol-related, vomiting and 'generally unwell'. The previous studies investigated the role of extreme weather on total ambulance dispatches (Cheng et al., 2016; Zhan et al., 2018) or only investigated one symptom (Kotani et al., 2018).

7.1.2.2 The result indicated the Minimum Ambulance Dispatch Temperature (T_{MADT}) at minimum dispatches percentile (MDP) of each category. The T_{MADT} is similar to Minimum Mortality Temperature (MMT) (Fu et al., 2018; Gasparrini et al., 2015), which reflects the specific temperature associated with the lowest risk. The T_{MADT} is used for the reference temperature when investigating the effect of low (below T_{MADT}) and high (above T_{MADT}) temperature. The association between temperature and health outcomes exhibited an U-, V- and J- shapes. The existing MMT or T_{MADT} were based on each data in different areas. The different number of T_{MADT} related to how people can adapt under climate changing and the MMT varied considerably across geographic and average temperature (Kinney, 2012; Watts et al., 2015; Yang et al., 2015; Yin et al., 2019). Therefore, it is important to understand the change in T_{MADT}. Now only a few studies have reported the response of the temperature and ambulance dispatches. This information can inform policymakers, especially as it has public health implication for mitigating the impacts of climate change.

7.1.2.3 Some categories showed a U-shaped pattern for the association between temperature and dispatch category, such as RCI, cardiac arrest, 'generally unwell', vomit and dizzy dispatch. While COPD, chest pain, cardiac arrhythmia and alcohol-related have a J- shape with only high temperature leading to increased health effects compared to the T_{MADT}. In addition, dyspnoea, respiratory arrest, cardiac chest pain and 'other cardiac problem' dispatches also exhibited J-shape behaviour, albeit for extreme low temperatures as opposed to high temperatures.

7.1.2.4 The result is in line with previous studies (Gasparrini et al., 2015; Onozuka and Hagihara, 2015; Zhan et al., 2018) showing that exposure to high temperatures typical exhibit a shortage lag period. For example, 999 or Red dispatches showed a highest relative risk on the same day (lag 0) and decreased in two or three days. In contrast, low temperatures typically were associated with a slight increase and persistence for longer lags reaching up to 3-4 weeks. Hence, it is useful for public health authorities to consider the delay effect when issuing public health warnings.

7.1.2.5 Extreme low temperature at the 1st percentile of the whole temperature distribution was significantly associated with dispatches caused by 999 dispatches, RCI, asthma, dyspnoea and 'generally unwell' dispatches compared with the threshold temperature at T_{MADT} over 21 lagged days.

7.1.2.6 Extreme high temperature at the 99th percentile of temperature distribution was positively associated with 999, Red, dizzy, alcohol-related, vomiting and 'generally unwell' with the threshold temperature at T_{MADT} over 21 lagged days.

7.1.2.7 A harvesting effect or mortality displacement is the phenomenon to observe people who have died shortly from environmental exposure or bringing forward of mortality. A number of studies suggested that the association between temperature and health occurs mostly with frail people (Basu, 2009; Carder et al., 2005; Le et al., 2014). Our findings found at high temperature for the dispatch categories COPD and cardiac arrhythmia, but no such effect was observed at low temperatures. It is important for public health authorities to investigate the mortality displacement from long exposure days around 20 to 40 days by checking whether there is a positive association in the first few days and a subsequent decline by a negative association in the following days (Basu, 2009). Normally, the harvesting effect is considered to cause an exacerbation of medical condition in frail person.

7.1.3 The association between rainfall and road accidents in Thailand

7.1.3.1 There are a difference of the meteorology and climatology between the UK and Thailand. For example, the annual average temperature around 11.8±5.5 °C (Mean ± SD) in UK with minimum was -2.2 °C and maximum was 25.4 °C while the average temperature in Northern region was 26.6 ±2.9 °C with the minimum was 10.9 °C and maximum was 35.2 °C. In the Southern Thailand, the average temperature was 27.7 °C with the minimum at 23.2 °C and the maximum was 32.0 °C. The relative humidity in the UK (75.2±10.5) was similar to Thailand, ranging from 70.1±10.6 % to 83.8 ±5.7%. Moreover, the seasons between the two countries are different. The association between meteorological exposures and health outcomes could be different depending on these geographical factors. Therefore, it is important for the public health sector to understand the response of associations in specific areas.

7.1.3.2 In Thailand, there is no clear effect of temperature on total ambulance dispatches. A few provinces displayed a J-shaped pattern association, indicating either a high or low-temperature effect.

7.1.3.3 There was an apparent effect of rainfall upon road accidents in 15 provinces out of the 23 provinces in the North (n=5) and South (n=10). However, no significant relationships between rainfall and road accidents were observe in eight provinces.

7.1.3.4 Only one province showed higher estimated risks at lag 1 compared to lag 0. The reason could be explained in term of related factors that leading to more accidents such as reduced visibility, increased-wind speeds and long holidays. This finding is contrary which most studies that the risk of road accidents is decline after rainfall because people have driving behaviour adjustments or people changed the plan due to rainfall (Brijs et al., 2008; Eisenberg, 2004; Keay and Simmonds, 2006).

7.1.3.5 The Southern provinces results have a higher risk compared to the Northern ones for all rain groups. These findings could be explained in terms of geographic variables (Guo et al., 2012). Our results confirm rainfall volume in the Southern provinces was higher than the Northern parts. This is important as it has public health implications for setting up a surveillance system and preparing an effective health service.

7.1.3.6 Surprisingly, both the Northern and Southern provinces indicated that the rain group with 10-20 mm/day had the highest pooled estimated risk while the heaviest rain category, with more than 20 mm/day, reported a reduction of risks. This result are consistent with previous research that indicated the heavy rain causes a decrease in traffic volume, driving behaviours and cancelling travel plans (Brijs et al., 2008; Eisenberg, 2004).

7.2 Strengths of this study

7.2.1 This study used ambulance dispatches which have only a few studies until now to investigate the association with environmental factors and ambulance data have not been fully utilized in many countries. Recently, the number of studies looking at the association between environmental factors and ambulance dispatches has been increasing, but there is still a gap of knowledge.

7.2.2 Ambulance service is a primary aid treatment for patients subject to life-threatening or urgent problems. Ambulance dispatch data provides a real-time data source, which has greater data density than mortality statistics. Moreover, ambulance dispatch data can be used for spatial analyses because the location of call is available via the postcode.

7.2.3 These findings support how environmental factors can have an adverse effect on health. Firstly, the systematic review highlighted the role of pollution upon human health. Secondly, whether there is the association between temperature (extreme low and high) and ambulance dispatches by using London Ambulance Service data. Thirdly, the role of rainfall was highlighted how does it affect road accidents. Thai ambulance dispatches caused from road accident were associated with rainfall. The findings have several important implications for public health in many aspects, including about the consideration of the impact of climate change when planning, setting an effective environmental surveillance system, and communicating with people by using early warning system. The benefits of these implications can lead to a reduction in health cost and the number of patients.

7.2.4 The ambulance data can be developed for an effective and real-time surveillance system as found in England and Wales. The NHS Direct syndromic surveillance system such as fever, difficulty breathing and vomiting calls is used for early warning due to the impact of an increase in temperature (heat-wave). The real-time response on changing in environmental factors is a good example of health surveillance. Many cities in Europe take it into account to develop health surveillance and predict the temperature effects (Leonardi et al., 2006). The implication of our findings on Thailand ambulance service or Low-Middle-income countries can bring more benefits because the ambulance service in Thailand was established in 2012. Therefore, there are several important opportunities to contribute to a more effective both management and planning.

7.2.5 In Chapter 4, we used meta-analysis to perform a pooled effect. This method can reduce a variation from individual study. This is a first systematic review and meta-analysis between the association between air pollutants (PM and gases) and various ambulance dispatches.

7.2.6 A distributed lag non-linear model (DLNM) is a famous model to investigate the association between health outcomes and environmental factors. The DLNM explains the non-linear association and delayed effects of environmental factors and associated health outcome. A cross basis function is used to investigate the effect of temperature at different days (lags). We have investigated not only exposure to high temperature, but also studied exposure to low temperature. Both have a different pattern of lags and they showed a significant association with neighbouring days. The findings should be considered when setting up a warning system and public health strategies. The effect from exposure to extreme temperature shows estimated risks not only on the same day but also on the following days. Hence, understanding the pattern of lagged days is important for public health because exposure to low and high temperature have different patterns. The highest risk is observed on the concurrent day (lag 0) and the RR declines in following few days, whilst the RR slightly increases after two or three days.

7.2.7 Temperature and rainfall analyses using the DLNM model, is a useful tool for assessing the impact of environmental factors on health outcomes. We did not focus only temperature or rainfall effects, but we also adjusted for a long-term trend effect, seasonality and other confounding variables such as day of the week, holidays, infectious disease (influenza) and meteorological factors in the model.

7.2.8 A sensitivity analysis was conducted to check the robustness of the model. For instance, we removed one study from the group re-analysed the pooled estimates in chapter 4 and we added some pollutants in the model in chapter 5. The usefulness of sensitivity analyses is checking whether results were changed when we changed selected inputs. For example, in chapter 5 the estimated risks were not changed after adding air pollutants in the model. Hence, the core model in this study had not included air pollutants.

7.2.9 The study used the London Ambulance Services (LAS) which provides a larger number of people and LAS is the busiest service in the European countries. We analysed the estimated risk between temperature and specific-14 category outcomes.

7.2.10 The mortality displacement or harvesting effect was investigated in chapter 5. The finding is important for public health policies especially vulnerable groups. For example, in chapter 5, some patients were affected by heatwave because of exacerbation of history of medical conditions.

7.2.11 In chapter 7, the Thai study has been analysed across the Northern (n=9) and Southern (n=14) regions which may help to understand the effect of geographical factors. Moreover, a meta-analysis was analysed to get a pooled estimate for each rain level compared with different geographical areas.

7.3 Limitations

7.3.1 It could be a problem of misclassification from diagnoses. It could be from telephone interviewers, paramedic assessments and physician diagnoses. Hence, in chapter 4 we reported a result by group sources of ambulance data which are phone interview, paramedic assessment and physician diagnosis at hospital to reduce the bias. However, it could be a problem when we would like to compare results which other studies due to different grouping systems.

7.3.2 Another limitation of this study is air pollutant data, which was taken from monitoring stations and did not allow the evaluation for individual levels in chapter 5 and 6. This issue should be tackled by using personal exposure level.

7.3.3 The study is limited to personal characteristics such as age, gender, race and socioeconomic status because of the lack of access to data both chapter 5 and 6. For example, the risk form exposure to $PM_{2.5}$ was associated with out-of-hospital cardiac arrest in elderly group (aged > 65) than other groups (Ensor et al., 2013; Guo et al., 2013). Elderly women found the higher risk of the relationship between stroke and PM_{10} (Hong et al., 2002). The association between increased mortality and temperature showed the higher rate in low-income countries (Berko et al., 2014; Stafoggia et al., 2006). These factors are important to make plans in public health related to vulnerable groups.

7.3.4 In chapter 5, results have not been examined during heatwave (very extreme temperature) with normal periods. To understand how estimated risks differ between heatwave and non-heatwave.

7.3.5 In chapter 6, Bangkok data was not included in this study because the data is collected by The Erawan Medical Center Bangkok. Bangkok is a capital city of Thailand and have likely increased population. Urban Heat Island is related rapid urbanization and population growth which leads to an increase in temperature due to absorbing and storing in urban than rural areas (Shahmohamadi et al., 2011).

7.4 Implications from this study

7.4.1 There are few studies using ambulance data up to now but they have been increasing recently. Hence, this is a new vision to understand the role of environmental factor upon adverse health. The effect of climate change is more frequent and extreme. The most important health effects are an increase in air pollution and change in temperature (exposure to low or high temperature). The previous studies focused on the mortality or morbidity utilisation, while this study investigated the potential role of ambulance dispatch, which is real-time and more sensitive than hospital admission for incorporating the health surveillance in public health and effective ambulance services. The outcome from ambulance dispatches is similar to the association from previous studies that used hospital data.

7.4.2 The findings of this research suggest a role for environmental factors to be further incorporated into health surveillance systems and environment warning systems in response to climate change. The environmental surveillance and warning system in response to exposure to an increasingly changing environment should consider the following:

- Establishing a surveillance system from validated ambulance dispatches consisting of syndromic related-health.
- Monitoring the health effects not only on all population but also on vulnerable groups, such as children, elderly, low income people and history of medical condition.

- Preparing effective medical services, such as hospital admission or ambulance services during extreme conditions
- Communicating with people for preparing themselves to climate change effects.
- Giving knowledge and raising awareness about how to prepare to climate change effects.

7.4.3 These findings have a significant implication for preparing an efficient service under a changing climate in term of harvesting effects, cold and hot effects and delayed effects. IPCC (2014) indicated the Earth's global mean temperature will rise by 0.3-4.8 °C depending on the emission of greenhouse gases (GHGs) by 2100. Moreover, a significant increase in the frequency of extreme temperatures like heatwave has been reported in previous publications (WHO, 2018). Moreover, climate change is linked to air pollution, because some types of air pollution leading to getting warm or cold. Therefore, the Sustainable Development Goal (SDGs) required member countries to take action plans to reduce the impacts of air pollution and temperature (United Nations, 2015). Presently, the air quality in Bangkok, which is the capital in Thailand has increased in the level of with diameters less than 2.5 micrometres ($PM_{2.5}$) leading to poor air quality and unhealthy pollution level in some days. Even though the government has made a big effort to reduce problems such as a decline of burning or reducing a traffic but it looks failure (BBC, 2019). Our findings can contribute to public health policymakers and health services for implementing climate change strategies to decrease health cost and increase the number of survival rates. Therefore, leaders and policymakers need to pay attention to climate change strategies and policies.

7.4.4 This is the first study in Thailand using the ambulance data to investigate whether there is any association with environmental factors. The ambulance service in Thailand is new and only started in 2012. The number of calls have been increasing significantly every year. Efforts to improve the ambulance system in these early days will be cheaper and easier to enact before the system becomes bigger. These results can be used to develop ambulance service in worldwide country and especially ambulance services in Thailand. During extreme episodes, emergency service should be equipped ahead of severe effects to arrive at the scene as fast as possible and increase survival rate. Meanwhile, the trend of elderly people who are vulnerable has increased in Thailand. Increasing in ageing population will be a problem both UK and Thailand. The age structure of UK people in August 2019 shows that the population aged 65 years and over is growing faster than other groups. From the prediction, it is expected that this category will reach around 8.2 million people by 2068, i.e. corresponding to 26.4% of the estimated population (Office for National Statistics, 2019). The same situation is experienced in Thailand which exhibits a rapidly increasing trend of the ageing group that, going from 11% (7.5 million) of the population in 2016 to 25 % of the population (17 millions) estimated in 2040.

7.4.5 In chapter 4, the outcome from the meta-analysis show significant similarities to results which were conducted for hospitals or mortality. This provides the required confidence to use ambulance data as a health indicator to be used in health surveillance system.

7.4.6 Policymakers should consider environmental factors, especially the predicted changes in temperature, increases in pollutants, and changing rainfall patterns when doing a policy implication for preparing critical episodes.

7.4.7 Not only public health sectors but also relevant sectors like schools or government should take into account the priority or practical implications for local policymakers to increase survival rates and reduce costs.

7.4.8 Most results indicate that the old and the young people have higher risk factors compared to other age categories (Ensor et al., 2013; Guo et al., 2013; Kovats et al., 2004; Zeng et al., 2017). The way how to protect themselves from environmental harm is important to vulnerable group. Social media is a crucial mean of communication with people to disseminate knowledge and warn them in case of emergency

7.5 Recommendations for future work

7.5.1 Further study should be undertaken to investigate the association between environmental factors and adverse health outcomes in other Low Middle Incomes countries (LMICs). To date, there has been little research conducted in LMICs.

7.5.2 Greater spatial analysis would be beneficial, because of the variety of causes in different regions, physiology and behaviour. The differences between rural and urban areas should be studied to investigate any difference in associations. This will help to understand the effect of Urban Heat Island (UHI), which by definition is predominantly an urban effect.

7.5.3 Further work need to study the effect from particulate matter composition, because the findings are not consistent and it further examination is needed between PM component and health outcomes (Cao et al., 2012; Lin et al., 2016; Qiao et al., 2014) The size effect of PM upon its health effects has only been addressed in few studies. A further study should assess the association of PM size fractions and health outcomes (Perez et al., 2009).

7.5.4 Investigating the association between environmental factors and ambulance dispatches should take into account personal characteristics and socioeconomic factors to understand implications on specific groups.

7.5.5 This issue should be carried out by using personal exposure level as air pollution data because we can investigate the individual risk level related to real exposure.

7.6 Conclusion

This study provides key evidence on the role of environmental factors (pollutants, extreme temperature and rainfall) upon ambulance dispatches. The evidence suggests many implications need to be made. First, public health interventions should take into consideration setting up an effective surveillance system and early warning systems, giving knowledge and raising awareness. Second, the emergency services need to ensure their infrastructure and capacity is appropriate for the environment, both now and under future changes. In particular, preparations for the climate change predicted scenarios are required. These finding are important for worldwide ambulance service and public health sectors in term of making strategies, policies, preparing the public health service units (hospitals and ambulance services) in response to climate change, and encourage the education to understand the adverse impact of changing environmental factors on health. All these actions can help the United Nations Member (around 170 countries) meet the SDGs goal to reduce the climate change impact from air pollution and temperature by 2030.

7.7 References

Basu, R., 2009. High ambient temperature and mortality: A review of epidemiologic studies from 2001 to 2008. Environ. Heal. A Glob. Access Sci. Source 8. https://doi.org/10.1186/1476-069X-8-40

BBC, 2019. Bangkok schools closed over "unhealthy" pollution levels [WWW Document]. BBC News. URL https://www.bbc.com/news/world-asia-pacific-47057128 (accessed 1.17.20).

Berko, J., Ingram, D.D., Saha, S., Parker, J.D., 2014. Deaths attributed to heat, cold, and other weather events in the United States, 2006–2010. Natl. Health Stat. Report. 2014, 1–15.

Brijs, T., Karlis, D., Wets, G., 2008. Studying the effect of weather conditions on daily crash counts using a discrete time-series model. Accid. Anal. Prev. https://doi.org/10.1016/j.aap.2008.01.001

Cao, J., Xu, H., Xu, Q., Chen, B., Kan, H., 2012. Fine Particulate Matter Constituents and Cardiopulmonary Mortality in a Heavily Polluted Chinese City. Environ. Health Perspect. 120, 373–378. https://doi.org/10.1289/ehp.1103671

Carder, M., McNamee, R., Beverland, I., Elton, R., Cohen, G.R., Boyd, J., Agius, R.M., 2005. The lagged effect of cold temperature and wind chill on cardiorespiratory mortality in Scotland. Occup. Environ. Med. 62, 702–710. https://doi.org/10.1136/oem.2004.016394

Cheng, J., Xu, Z., Zhao, D., Xie, M., Yang, H., Wen, L., Li, K., Su, H., 2016. Impacts of temperature change on ambulance dispatches and seasonal effect modification. Int. J. Biometeorol. 60, 1863–1871. https://doi.org/10.1007/s00484-016-1173-4

Eisenberg, D., 2004. The mixed effects of precipitation on traffic crashes. Accid. Anal. Prev. 36, 637–647. https://doi.org/10.1016/S0001-4575(03)00085-X

Ensor, K.B., Raun, L.H., Persse, D., 2013. A case-crossover analysis of out-of-hospital cardiac arrest and air pollution. Circulation 127, 1192–1199. https://doi.org/10.1161/CIRCULATIONAHA.113.000027

Fu, S.H., Gasparrini, A., Rodriguez, P.S., Jha, P., 2018. Mortality attributable to hot and cold ambient temperatures in India: a nationally representative case-crossover study. PLOS Med. 15, e1002619. https://doi.org/10.1371/journal.pmed.1002619

Gasparrini, A., Guo, Y.-L.L.Y., Hashizume, M., Lavigne, E., Zanobetti, A., Schwartz, J., Tobias, A., Tong, S., Rocklöv, J., Forsberg, B., Leone, M., De Sario, M., Bell, M.L., Guo, Y.-L.L.Y., Wu, C.-F., Kan, H., Yi, S.-M., de Sousa Zanotti Stagliorio Coelho, M., Saldiva, P.H.N., Honda, Y., Kim, H., Armstrong, B., De, M., Zanotti, S., Coelho, S., Hilario, P., Saldiva, N., Honda, Y., Kim, H., Armstrong, B., 2015. Mortality risk attributable to high and low ambient temperature: a multicountry observational study. Lancet 386, 369–375. https://doi.org/10.1016/S0140-6736(14)62114-0

Guo, Y., Li, S., Tian, Z., Pan, X., Zhang, J., Williams, G., 2013. The burden of air pollution on years of life lost in Beijing, China, 2004-08: Retrospective regression analysis of daily deaths. BMJ 347. https://doi.org/10.1136/bmj.f7139

Guo, Y., Li, S., Zhang, Y., Armstrong, B., Jaakkola, J.J.K., Tong, S., Pan, X., 2012. Extremely cold and hot temperatures increase the risk of ischaemic heart disease mortality: epidemiological evidence from China. https://doi.org/10.1136/heartjnl-2012

Hong, Y.C., Lee, J.T., Kim, H., Ha, E.H., Schwartz, J., Christiani, D.C., 2002. Effects of air pollutants on acute stroke mortality. Environ. Health Perspect. 110, 187–191. https://doi.org/10.1289/ehp.02110187

IPCC, 2014. Climate Change 2014 Synthesis Report Summary for Policymakers, IPCC 5th Assessment Report.

Keay, K., Simmonds, I., 2006. Road accidents and rainfall in a large Australian city. Accid. Anal. Prev. https://doi.org/10.1016/j.aap.2005.06.025

Kinney, P.L., 2012. Health: A new measure of health effects. Nat. Clim. Chang. https://doi.org/10.1038/nclimate1460

Kotani, K., Ueda, K., Seposo, X., Yasukochi, S., Matsumoto, H., Ono, M., Honda, A., Takano, H., 2018. Effects of high ambient temperature on ambulance dispatches in different age groups in Fukuoka, Japan. Glob. Health Action 11, 1437882. https://doi.org/10.1080/16549716.2018.1437882

Kovats, R.S., Hajat, S., Wilkinson, P., 2004. Contrasting patterns of mortality and hospital admissions during hot weather and heat waves in Greater London, UK. Occup. Environ. Med. 61, 893–898.

Le, A., Lefranc, A., Eilstein, D., Declercq, C., Medina, S., Blanchard, M., Chardon, B., Fabre, P., Filleul, L., Jusot, J., Pascal, L., Prouvost, H., Cassadou, S., Ledrans, M., Tertre, A. Le, Lefranc, A., Chardon, B., Jusot, J., Prouvost, H., 2014. Impact of the 2003 Heatwave on All-Cause Mortality in 9 French Cities * Volume Epidemiology Number. Source Epidemiol. 17, 75–79. https://doi.org/10.1097/01.ede.0000187650.36636.lf

Leonardi, G.S., Hajat, S., Kovats, R.S., Smith, G.E., Cooper, D., Gerard, E., 2006. Syndromic surveillance use to detect the early effects of heat-waves: an analysis of NHS direct data in England. Sozial-und Präventivmedizin 51, 194–201.

Lin, H., Tao, J., Du, Y., Liu, T., Qian, Z., Tian, L., Di, Q., Rutherford, S., Guo, L., Zeng, W., Xiao, J., Li, X., He, Z., Xu, Y., Ma, W., 2016. Particle size and chemical constituents of ambient particulate pollution associated with cardiovascular mortality in Guangzhou, China. Environ. Pollut. 208, 758–766. https://doi.org/10.1016/J.ENVPOL.2015.10.056

Office for National Statistics, 2019. Overview of the UK population - Office for National Statistics [WWW Document]. URL https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/articles/overviewoftheukpopulation/august2019 (accessed 1.17.20).

Onozuka, D., Hagihara, A., 2015. All-Cause and cause-specific risk of emergency transport attributable to temperature: A nationwide study. Med. (United States) 94. https://doi.org/10.1097/MD.0000000000002259

Qiao, L., Cai, J., Wang, H., Wang, W., Zhou, M., Lou, S., Chen, R., Dai, H., Chen, C., Kan, H., 2014. PM 2.5 Constituents and Hospital Emergency-Room Visits in Shanghai, China. Environ. Sci. Technol. 48, 10406–10414. https://doi.org/10.1021/es501305k

Shahmohamadi, P., Che-Ani, A.I., Etessam, I., Maulud, K.N.A., Tawil, N.M., 2011. Healthy environment: The need to mitigate urban heat island effects on human health, in: Procedia Engineering. pp. 61–70. https://doi.org/10.1016/j.proeng.2011.11.139

Stafoggia, M., Forastiere, F., Agostini, D., Biggeri, A., Bisanti, L., Cadum, E., Caranci, N., De'Donato, F., De Lisio, S., De Maria, M., Michelozzi, P., Miglio, R., Pandolfi, P., Picciotto, S., Rognoni, M., Russo, A., Scarnato, C., Perucci, C.A., 2006. Vulnerability to heat-related mortality: A multicity, population-based, case-crossover analysis. Epidemiology 17, 315–323. https://doi.org/10.1097/01.ede.0000208477.36665.34

United Nations, 2015. Sustainable Development Goals [WWW Document]. URL https://sustainabledevelopment.un.org/?menu=1300 (accessed 1.10.20).

Watts, N., Adger, W.N., Agnolucci, P., 2015. Health and climate change: Policy responses to protect public health. Environnement, Risques et Sante. https://doi.org/10.1016/S0140-6736(15)60854-6

WHO, 2018. Climate change and health [WWW Document]. URL https://www.who.int/news-room/fact-sheets/detail/climate-change-and-health (accessed 1.17.20).

Yang, J., Yin, P., Zhou, M., Ou, C.Q., Guo, Y., Gasparrini, A., Liu, Y., Yue, Y., Gu, S., Sang, S., Luan, G., Sun, Q., Liu, Q., 2015. Cardiovascular mortality risk attributable to ambient temperature in China. Heart 101, 1966–1972. https://doi.org/10.1136/heartjnl-2015-308062

Yin, Q., Wang, J., Ren, Z., Li, J., Guo, Y., 2019. Mapping the increased minimum mortality temperatures in the context of global climate change. Nat. Commun. 10. https://doi.org/10.1038/s41467-019-12663-y

Zeng, Q., Ni, Y., Jiang, G., Li, G., Pan, X., 2017. The short term burden of ambient particulate matters on non-accidental mortality and years of life lost: A ten-year multi-district study in Tianjin, China. Environ. Pollut. 220, 713–719. https://doi.org/10.1016/j.envpol.2016.10.036

Zhan, Z.-Y., Yu, Y.-M., Qian, J., Song, Y.-F., Chen, P.-Y., Ouid, C.-Q., 2018. Effects of ambient temperature on ambulance emergency call-outs in the subtropical city of Shenzhen, China. https://doi.org/10.1371/journal.pone.0207187

CHAPTER 8 : APPENDICES

8.1 Manuscript accepted for publication

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The impact of air pollutants on ambulance dispatches: A systematic review and meta-analysis of acute effects☆

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ABSTRACT

A number of systematic reviews have investigated the association between air pollutants and health impacts, these mostly focus on morbidity and mortality from hospital data. Previously, no reviews focused solely on ambulance dispatch data. These data sets have excellent potential for environmental health research. For this review, publications up to April 2019 were identified using three main search categories covering: ambulance services including dispatches; air pollutants; and health outcomes. From 308 studies initially identified, 275 were excluded as they did not relate to ambulance service dispatches, did not report the air pollutant association, and/or did not study ambient air pollution. The main health outcomes in the remaining 33 studies were cardiac arrest (n = 14), cardiovascular (n = 11) and respiratory (n = 10) dispatches. Meta-analyses were performed to summarise pooled relative risk (RR) of pollutants: particulate matter less than 2.5 and 10 µm ($PM_{2.5}$, PM_{10}), the fraction between PM_{10} and $PM_{2.5}$ (coarse) and suspended particulate matter (SPM) per 10 µg/m^3 increase, carbon monoxide (CO) per 1 ppm increase and of sulphur dioxide (SO_2), nitrogen dioxide (NO_2), and ozone (O_3) per 10 ppb increment and ambulance dispatches. Statistically significant associations were found for ambulance dispatch data for all-respiratory and $PM_{2.5}$ at 1.03 (95% CI: 1.02–1.04) and at 1.10 (95% CI: 1.00–1.21) for asthma and NO_2 associations. For dispatches with subsequent paramedic assessment for cardiac arrest with $PM_{2.5}$, CO and coarse dispatches at 1.05 (95% CI: 1.03–1.08), 1.10 (95% CI: 1.02–1.18) and 1.04 (95% CI: 1.01–1.06) respectively. For dispatches with subsequent physician diagnosis for all-respiratory and $PM_{2.5}$ at 1.02 (95% CI: 1.01–1.03). In conclusion, air pollution was significantly associated with an increase in ambulance dispatch data, including those for cardiac arrest, all-respiratory, and asthma dispatches. Ambulance services should plan accordingly during pollution events. Furthermore, efforts to improve air quality should lead to decreases in ambulance dispatches.

1. Introduction

The World Health Organization (WHO), states that ambient air pollution increases the incidence of stroke, heart disease, lung cancer and respiratory disease, and it is one of the leading causes of death and disability worldwide. Air pollutants reported to adversely impact on health include: particulate matter with aerodynamic diameters less than 2.5 ($PM_{2.5}$) and 10 µm (PM_{10}); carbon monoxide (CO); ozone (O_3); nitrogen dioxide (NO_2); and sulphur dioxide (SO_2) (WHO, 2018).

Emission of most pollutants in Europe have decreased substantially over the last twenty years, but continue to cause significant mortality and morbidity (European Energy Agency, 2015). Estimates vary, but the WHO has stated over 4.2 million premature deaths from cardiovascular and respiratory diseases (WHO, 2018) and the Lancet Commission reported nine million premature deaths due to ambient air pollution globally (Landrigan et al., 2017). These relationships have been summarised in previous systematic reviews, examining the association between health impacts and short-term exposure to $PM_{2.5}$, PM_{10}, SO_2, NO_2 and O_3 (Aunan and Pan, 2004; Kan et al., 2005; Lai et al., 2013; Shang et al., 2013),

☆ This paper has been recommended for acceptance by Dr. Payam Dadvand.

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Impact of extreme temperatures on ambulance dispatches in London, UK

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ABSTRACT

Background: Associations between extreme temperatures and health outcomes, such as mortality and morbidity, are often observed. However, relatively little research has investigated the role of extreme temperatures upon ambulance dispatches.

Methods: A time series analysis using London Ambulance Service (LAS) incident data (2010–2014), consisting of 5,252,375 dispatches was conducted. A generalized linear model (GLM) with a quasi-likelihood Poisson regression was applied to analyse the associations between ambulance dispatches and temperature. The 99th (22.8°C) and 1st (0.0°C) percentiles of temperature were defined as extreme high and low temperature. Fourteen categories of ambulance dispatches were investigated, grouped into 'respiratory' (asthma, dyspnoea, respiratory chest infection, respiratory arrest and chronic obstructive pulmonary disease), 'cardiovascular' (cardiac arrest, chest pain, cardiac chest pain RCI, cardiac arrhythmia and other cardiac problems) and 'other' non-cardiorespiratory (dizzy, alcohol related, vomiting and 'generally unwell') categories. The effects of long-term trends, seasonality, day of the week, public holidays and air pollution were controlled for in the GLM. The lag effect of temperature was also investigated. The threshold temperatures for each category were identified and a distributed lag non-linear model (DLNM) was reported using relative risk (RR) values at 95% confidence intervals.

Results: Many dispatch categories show significant associations with extreme temperature. Total calls from 999 dispatches and 'generally unwell' dispatch category show significant RRs at both low and high temperatures. Most respiratory categories (asthma, dyspnoea and RCI) have significant RRs at low temperatures represented by with estimated RRs ranging from 1.392 (95%CI: 1.161–1.699) for asthma to 2.075 (95%CI: 1.673–2.574) for RCI. The RRs for all other non-cardiorespiratory dispatches were often significant for high temperatures ranging from 1.280 (95% CI: 1.128–1.454) for 'generally unwell' to 1.985 (95%CI: 1.422–2.773) for alcohol-related. For the cardiovascular group, only chest pain dispatches reported a significant RR at high temperatures.

Conclusions: Ambulance dispatches can be associated with extreme temperatures, dependent on the dispatch category. It is recommended that meteorological factors are factored into ambulance forecast models and warning systems, allowing for improvements in ambulance and general health service efficiency.

1. Introduction

Previous research has shown significant associations between meteorological variables and health. Typically, this research has focused on mortality and hospital admission data to examine the impact of meteorology on health, especially with respect to respiratory and cardiovascular diseases (Elliot et al., 2016; Hajat et al., 2007; Medina-Ramón et al., 2006; Wichmann, 2004). The World Health Organization (WHO) has highlighted that rising temperatures, due to climate change, can increase mortality and morbidity due to increased heat stress (World Health Organization, 2017). However, rising temperatures could also diminish the effect of cold weather upon health.

Previous research has shown the relationship between temperature and health outcomes exhibits a U-, V- or J-shaped curve. U and V relationships show both hot and cold effects, whereas J relationships only show effects at one temperature extreme. A landmark study by (Gasparrini et al., 2015a) investigated a large mortality dataset from 14 countries. A greater percentage of temperature-attributable mortality were found in cold conditions (7.29%; 95% CI: 7.02–7.49) compared to hot conditions (0.42%; 95% CI: 0.39–0.44). Systematic reviews have

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8.2 Conference presentations

- **Oral presentation**

- I presented initial results with oral presentation at Thai Student Association Community (TSAC 2016) between 11-14th May 2016, Alghero, Italy.
- I presented "The Impact of Temperature and Seasons on London Ambulance Respiratory and Cardiovascular call outs 2010-2014" with oral presentation at the 6th Health Challenge Thailand on the 20th May 2017 at Office of Educational affairs, the Royal Thai Embassy
- I presented " The effect of temperature (low and high) on ambulance incidents in Social sensing of health and wellbeing impacts of pollen and air pollution: Workshop #3" on the 27th March 2018 at University of Exeter with oral presentation
- I am going to present "WHAT IS THE EFFECT OF RAINFALL ON ROAD ACCIDENTS IN NORTHERN AND SOUTHERN THAILAND?" with oral presentation at the 12th Samaggi Academic Conference and Careers Fair (SACC) 2020 between the 15th and 16th February 2020 in London

- **Poster presentation**

- I presented "TIME SERIES ANALYSIS OF THE EFFECT OF CLIMATE, METEOROLOGY AND AIR POLLUTION ON LONDON AMBULANCE CALL-OUT RATES" with poster at 6th Asia-Pacific Conference on Public Health (APCPH) between 23-25th of August 2016.
- I presented "The Impact of Temperature and Seasons on London Ambulance Respiratory and Cardiovascular call out 2010-2014" with poster at the *29th Annual*

Scientific Conference of the International Society of Environmental Epidemiology will be held in Sydney, Australia, from 24-28 September 2017.

- I presented “The impact of particulate matter on ambulance dispatches: A systematic review and meta-analysis” with poster at Annual Aerosol Science Conference 2018 on the 8th November 2018 at University of Birmingham
- I am presenting “The impact of air pollutants on ambulance dispatches: A systematic review and meta-analysis of acute effects” with poster at ISEE 2019 at Utrecht, the Netherlands between 25-28 August 2019