Mortality Risk and PM_{10} Air Pollution in Thailand: an Epidemiological and Economic Benefit Analysis

Samuel J. Goldstein[1,2], James P. Bottomley[1,2], Cameron A. Champion[1,2], Nikole Toms[1,2], Sebastien Bonnet[2], Savitri Garivait[2], Pham Thi Bich Thao[2], Sitthipong Pengjan[2]

[1]Institute for the Environment, University of North Carolina at Chapel Hill, Chapel Hill, NC 27599, USA

[2]The Joint Graduate School of Energy and Environment (JGSEE), King Mongkut's University of Technology Thonburi, 126 Pracha Uthit Road, Bangmod, Tungkru, Bangkok 10140, Thailand

Abstract

Background: Ambient particulate matter pollution is one of the world's highest risk factors for mortality, especially in Southeast Asian countries that are experiencing rapid development.

Objectives: To determine the relative risk of PM_{10} concentration variation for non-accidental, cardiovascular, and respiratory mortality in 12 provinces within central and northern Thailand. We pooled these relative risks into two regions and assessed the annual health and economic benefits of incremental PM_{10} reductions.

Methods: Our study is a time series analysis based off of 2007-2016 data that examines the effects of PM_{10} on mortality while controlling for confounding factors. We used distributed lag nonlinear modelling to compare the delayed effects of exposure for several lag structures and multivariate meta-analysis to pool provincial estimates into two main regions. Based on our pooled estimates, we employed BenMAP-CE to calculate annual health and economic benefits for 2012-2016 from incremental PM_{10} rollbacks of 10 and 20 $\mu g/m^3$.

Results: The excess risks associated with a 10 $\mu g/m^3$ increase in PM_{10} for the pooled central region were 0.34% (95% CI 0.04, 0.65), 1.30% (-1.70, 5.76), and 0.78% (-0.57, 2.50) for non-accidental, cardiovascular, and respiratory mortality, respectively. The equivalent excess risks pooled for northern Thailand were 0.34% (0.03, 0.70), 1.35% (-0.78, 4.14), and 0.68% (-0.23, 1.82). The BenMAP-CE analysis showed that the annual average of total mortality cases avoided and the resulting valuation from 10 and 20 $\mu g/m^3$ incremental rollbacks were 285 cases for a savings of $425.2 million USD and 559 cases for a savings of $835.4 million USD, respectively.

Conclusions: The mitigation of particulate matter in Thailand would result in large public health and economic benefits in terms of reduced mortality.

Keywords:

Particulate Matter (PM_{10}), Air Pollution, Thailand, Time-series study, Mortality Valuation

Introduction

As Thailand continues to develop and strengthen its economy, particularly through urbanization, increased concentrations of air pollution have become a rising public health concern.[1] Respiratory and cardiovascular diseases are among the top five leading causes of death and disability in Thailand, and evidence from numerous studies indicates a correlation between these diseases and ambient particulate matter (PM).[2-5] The Global Burden of Disease (GBD) report from 2015 ranks ambient particulate matter pollution as the world's fifth leading risk factor for mortality.[6] The type of particulate matter considered in our study consists of molecules and compounds with an average aerodynamic diameter equal to or less than 10 μm, abbreviated as PM_{10}. Previous studies conducted in Thailand, including one that solely analyzes Bangkok, provide effect estimates relating PM_{10} concentration to mortality.[1,7,8] These relationships tend to be stronger than those reported in Western regions of the world, which likely stems from the region's warmer climate, different weather patterns and other factors such as higher population density next to congested roadways.[9,10] Many regions of Thailand have particulate matter concentrations that exceed both the WHO and National Air Quality standards. Notable sources of this pollution include biomass burning, which includes agricultural burning and forest fires, and automotive emissions.[9,11] Reductions in PM_{10} have been shown to significantly decrease ecosystem impacts by lowering levels of acid rain, marine acidification, and vegetation nutrient absorption.[12-14] With this information in mind, our study seeks to quantify the health and economic benefits of mitigating particulate matter air pollution for two regions of Thailand. These regions are comprised of 8 provinces in northern Thailand, and 4 provinces within the Bangkok Metropolitan Region (BMR). By reporting mortality reductions and monetary valuations, our study hopes to give policymakers an understanding of the public health and

economic benefits of air pollution reduction. In order to conduct these evaluations, we performed an epidemiological time-series analysis to determine health effect estimates that are specific to Thailand using data from 2007-2016. In addition to reporting the economic benefits from mortality reductions, which has never been undertaken in Thailand, our study uses updated epidemiology techniques not used in previous Thailand studies.

Methods

EPIDEMIOLOGY

Daily time-series data were collected for mortality, weather variables, and air pollution from 38 monitoring stations within 12 provinces of central and northern Thailand from 2007 to 2016. Mortality counts were provided by the Thailand Ministry of Public Health and were categorized as either non-accidental, cardiovascular, or respiratory according to the *International Classification of Diseases*, Tenth Revision (ICD-10). Hourly monitoring station data were collected from the Pollution Control Department of Thailand (PCD) and were reduced to daily averages of pollutants and other environmental variables using the *timeaverage* function of the openair R software package (version 3.5.0) with a specified threshold of 75 percent. A summary of the time series data can be found in *S1* of the *Supplementary Materials*.

Distributed lag nonlinear models, DLNMs, were used during the first stage of the analysis to determine provincial health effect estimates, which were reported as relative risk (RR). In this study, RR describes the probability of mortality at a given concentration of PM_{10} based off of a *centering* value of 10 $\mu g/m^3$, where the baseline RR is assumed to be 1.00. This reference value was chosen because it is below the mean of every province's lowest daily average concentration and is close to the assumed non-anthropogenic ambient concentration of 5.8 $\mu g/m^3$.[15]

DLNMs are capable of describing complex non-linear and lagged dependencies by using two functions to separately define exposure-response associations and lag-response associations.[16] The DLNM framework has been considerably described for the effects of temperature on mortality, but it can also be used to understand pollution-mortality relationships.[17] In this analysis, the exposure-response relationship was modeled through a polynomial B-spline with three internal knots placed using the function *equalknots* within a predefined range of PM_{10} concentration (10-160μg/m^3). Although this range excludes average daily concentrations that are nearly double its maximum value, the infrequency of these high concentration days leads to uncertainty in health effect estimations. The effects of varying this range, as well as the centering value, are discussed as part of a sensitivity analysis in the discussion.

The lag-response relationship was defined using a natural cubic B-spline with three internal knots placed at equally spaced values in the log scale. The lag period was set at 10 days to account for short-term delayed effects of air pollution exposure. This study investigates three types of lag structures in order to assess the relationship between RR and PM_{10} concentration. The first type is referred to as discrete lag, which compares mortality of a given day to the environmental conditions of the previous day (lag 1), or days (lag 2 or lag 3). By summing these discrete lag contributions, the second type of lag structure, known as overall cumulative association, can be attained.[15] Overall cumulative associations were determined for lag periods 0-1, 0-2, and 0-3. The last type of lag structure is known as moving average, which essentially averages the environmental conditions of the day whose mortality is being examined with the conditions of a certain number of days that precede it.[1] Moving averages of lags 0-1, 0-2 and 0-3 were considered in this study.

The models used to generate predictions with the *crosspred* function of the *dlnm* package accounted for overdispersion in daily deaths by using a generalized linear model (GLM) of the quasi-Poisson family. Additionally, these models employed a natural cubic B-spline of time with 10 degrees of freedom per year and a day of the week indicator to account for seasonality and autocorrelation, respectively. Co-pollutants and other environmental variables such as ozone (O_3), nitrogen oxide (NO_X), sulfur dioxide (SO_2), temperature, and relative humidity were controlled for using natural cubic B-splines with 4 degrees of freedom, as these variables are potential confounders of the association between particulate matter and mortality.[1]

The R package *mvmeta* was used to pool provincial health effect estimates into pooled exposure-response relationships for central and northern Thailand. This meta-analysis is explained in detail in Gasparrini 2013, which is the source of much of the original R code used in this study.[17] Based on the strength of the pooled RR-PM_{10} relationship, different types of lag structures were chosen for different endpoints. Assigning each mortality endpoint a lag-specific relationship in this way is justified because PM_{10} effects each endpoint via a distinct biological mechanism.[17]

In order to determine health effect estimates that are compatible with BenMAP-CE[18], RR must be reported as the change in RR corresponding to a 10μg/m^3 increase in PM_{10}. As the exposure-response relationship in this study is specified as non-linear, the average change in RR was calculated over the range of PM_{10} concentration that comprised the majority of the data (20-80μg/m^3). Once these values were determined, **Equation (1)** was used to calculate the health effect estimate values used in BenMAP:

$$\beta = \frac{ln(RR(x))}{x} \qquad \textbf{(1)}$$

Where x represents the change in pollutant concentration, 10μg/m^3, and β is the health effect estimate that can be entered into BenMAP, as discussed below. This method was also repeated for a 95% confidence interval. The R code in *S1* of the Supplementary Materials provides a more detailed look into the epidemiological framework used to determine ß values.

BENMAP-CE

BenMAP-CE is an open-sourced computer program that estimates the health benefits of air pollution reductions by calculating the change in incidence for specific health outcomes based off of health effect estimates.[18] The software (version 1.1) requires 6 separate data inputs in order to complete an economic benefit analysis: grid definition, monitored air pollution, incidence, population, health impact functions, and a valuation function. Below are detailed breakdowns of how each input contributes to the results. The benefit assessment of this study analyzes individual province and regional benefits.

Administrative GIS shapefiles of Thailand's border and provinces were uploaded to BenMAP from GISTA (Geo-Informatics and Space Technology Development Agency).[19] Using QGIS, these files were formatted to become the two regions analyzed in this study. Specific column-row coordinates specified within the GIS files allow for the overlaying of population and incidence onto the map.

There are currently 61 fixed site air monitoring stations dispersed across 31 provinces in Thailand. Each station records hourly measurements of PM_{10}, other pollutants such as O_3, NO_x, and SO_2, and weather factors such as temperature and relative humidity. Relatively few stations measure $PM_{2.5}$, which has been linked to more severe risks in mortality than PM_{10}.[20] Air pollution monitoring data for years 2012-2016 was obtained from the PCD. In order for daily

mean PM_{10} concentrations to be considered, each day required more than 17 hourly measurements. Additionally, each station needed to have more than 70% of its daily values per year in order to be used. Based off of these criteria, each year had a different number of monitoring stations included in the rollback analysis; whether this is a limitation in comparing the economic benefits across different years is uncertain. The PM_{10} monitoring dataset uploaded to BenMAP can be found at the bottom of *S2* in the *Supplementary Materials*.

BenMAP analyzes the impacts of reducing air pollution by performing a *rollback* on the daily mean pollution concentrations of a given year. There are three types of rollback: percentage, incremental, and standard. Percentage rollback involves reducing the daily means by a specified percentage, incremental rollback reduces each daily mean by a specified amount, and rolling back to a standard reduces daily mean concentrations to meet a specified value. The rollbacks undertaken in this study are incremental, assessing how mortality cases may be avoided if daily PM_{10} concentrations are reduced by 10 or 20 $\mu g/m^3$.

It is also important to note that these rollbacks only consider anthropogenic contributions to PM_{10} concentrations and do not take into account a predetermined background level of ambient air pollution. For this study, a value of $5.8\mu g/m^3$ was selected as the ambient, non-anthropogenic PM_{10} concentration based on a previous study.[21] Therefore, the control value is never set to less than $5.8\mu g/m^3$. A rollback generates two population exposure surfaces, the *baseline* surface, which contains the original concentrations, and the *control* exposure surface, which displays PM_{10} concentrations after the rollback has been applied. The two surfaces are compared via a *delta* surface which illustrates the difference between the baseline and control.

The next input required for BenMAP are incidence rates, which, in any given province, is the number of deaths due to a certain disease over the total population of that province. Incidence

is a key factor in the health impact analysis, which determines how many deaths of a given type of mortality are attributable to air pollution. Additionally, population data is necessary to perform a spatial and temporal health impact analysis. The mortality and population data by province for 2012-2016 were obtained from the Thailand Ministry of Public Health. The population data only specifies gender, not taking into account age, race, or ethnicity. Therefore, the health impact functions of this study do not incorporate these demographic factors. Each province analyzed had annual incidence rates for non-accidental, cardiovascular, and respiratory mortality. The BenMAP coordinates used for incidence rates and population counts were aligned with the Thailand province grid definition.

Table 1 is a descriptive summary of important BenMAP inputs for 2014, including the population, average daily mortality by endpoint (which determines incidence), and average daily PM_{10} concentration.

Table 1. 2014 population count, average daily mortality count, and average daily PM_{10} concentration by province.

		Average Daily Mortality			Pollutant (μg/m^3)
Province	**Population**	**Non-Accidental**	**Cardiovascular**	**Respiratory**	**PM_{10}**
Chiang Mai	1,672,586	34.44	4.51	3.50	44.80
Chiang Rai	1,206,179	21.89	3.25	3.15	45.58
Mae Hong Son	247,364	2.96	0.35	0.35	42.00
Lampang	753,937	17.65	2.47	1.91	46.86
Lamphun	405,368	9.53	1.26	0.64	43.93
Nan	478,088	7.90	1.22	1.25	45.22
Phayao	485,599	10.00	1.43	1.21	40.92
Phrae	455,079	10.78	1.37	1.06	54.73
Northern Total	**5,704,200**	**115.10**	**15.86**	**13.07**	**45.505**
Bangkok	5,689,268	104.25	17.22	11.28	44.88
Nonthaburi	1,165,070	17.19	3.04	1.98	45.50

Samut Prakan	1,251,570	18.18	3.24	1.86	47.64
Samut Sakhon	525,672	9.08	1.46	0.84	54.55
BMR Total	**8,631,580**	**148.68**	**24.96**	**15.96**	**48.14**
Total	**14,335,780**	**263.78**	**40.82**	**29.03**	**46.38**

The health impact function of this study relates the number of health outcomes to the concentration PM_{10} via the EPA-recommended formula shown in **Equation (2)**,

$$\Delta Y = Yo\ (1-e^{\beta*\Delta PM10})*Pop \quad (2)$$

Where *Yo* is the incidence, *ß* is the log-linear coefficient from a dose-response epidemiological study (or health effect estimate), and *Pop* is the population. The key factor here is *ß*, which determines the excess risk related to changes in PM_{10} concentration.

Lastly, the valuation function allows the health impacts of air pollution changes to be translated into economic values. The Value of Reduction in Mortality Risk (VMR), previously defined as the Value of a Statistical Life (VSL), was the method of choice for this study. A VMR is the sum of currency every individual in a population would pay to reduce his or her mortality risk by a certain percentage. An example calculation of Thailand's VMR for 2015 as used in BenMAP is shown in **Equation (3).**

$$VMR_{Thailand,\ 2015} = VMR_{US,\ 2010} * \left(\frac{\gamma\ Thailand,\ 2015}{\gamma\ US,\ 2010}\right)^{elasticity} * PPP_{Thailand,\ 2010} * \frac{CPI\ Thailand,\ 2015}{CPI\ Thailand,\ 2010} \quad (3)$$

The key variables of **Equation (3)** include GDP per capita, purchasing power parity (PPP), and the Consumer Price Index (CPI). The U.S EPA recommends a VMR of $7.4 million (in 2006 $USD), or roughly $8 million when adjusted for inflation (2010 $USD).[22] In this study, a ratio of the GDP per capita of the year analyzed (i.e Thailand 2015) to the base year (2010 U.S

GDP per capita) was raised to an income elasticity, which was assumed to be the U.S EPA's recommended value of 0.7.[23] Purchasing power parity is a comparison of how much a specified amount of money can buy in terms of goods and services in one country versus another. The 2010 value was found to be 12.17, indicating that ฿12 THB spent in Thailand is equivalent to $1 USD spent in the United States.[24] CPI accounts for inflation from the base year to the year analyzed. Every year had its own valuation function due to annual fluctuations in CPI and the Thailand GDP per capita. Both these metrics were obtained from the World Bank.[25]

On average, each mortality case is worth roughly ฿52 million THB, or $1.59 million USD, based on the annual valuation functions. The conversion rate between THB and USD was ฿32.7 THB per $1 USD for the entire study period.[26] A detailed run-through of a BenMAP analysis can be found in *S2* of *Supplementary Materials*.

Results

EPIDEMIOLOGY

Figure 1. RR estimates by province for non-accidental (discrete lag 1), cardiovascular (overall cumulative association 0-1), and respiratory (discrete lag 0) endpoints. The figures also include pooled estimates for the northern and central (BMR) regions.

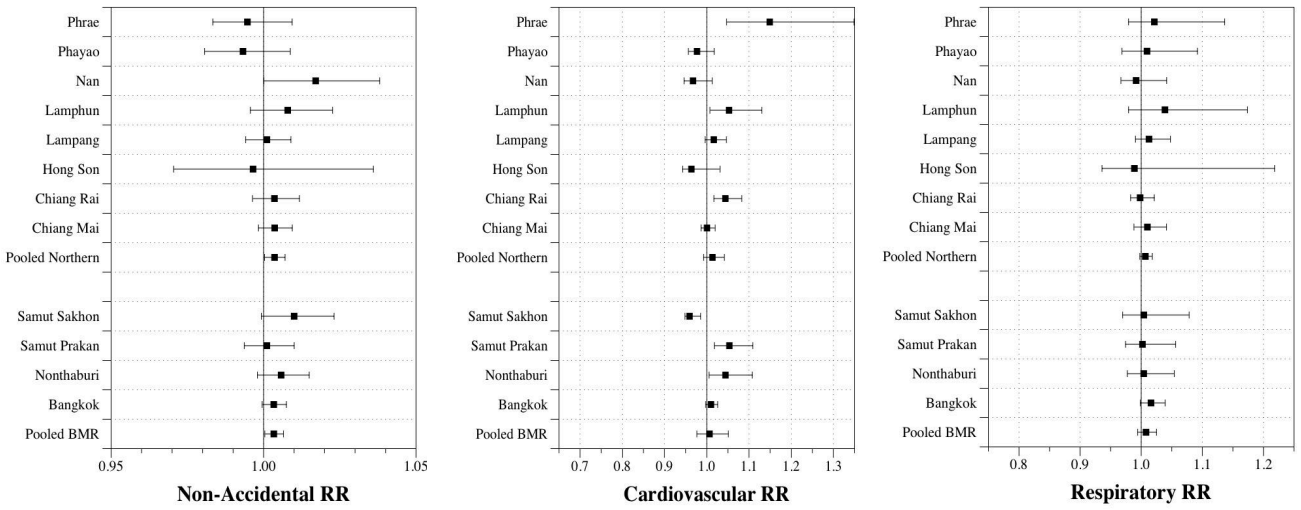


Figure 1 shows the provincial and pooled RR values by mortality endpoint. The range of the x-axis varies between endpoints because of the large confidence intervals of Phrae and Mae Hong Son for cardiovascular and respiratory mortality. Thus, while the non-accidental mortality confidence intervals appear larger than those of cardiovascular mortality, they are actually smaller due to the scale adjustment. Different lag-specific predictions yielded varying results across the provinces, with some responding more significantly to overall cumulative associations and others to discrete lags. For consistency, it was decided that each endpoint would have the same lag structure for both regions. Non-accidental mortality was determined to have the strongest relationship with PM_{10} at a discrete lag of 1 day. Cardiovascular had the most significance with an overall cumulative lag structure of 0-1 days, while respiratory experienced the strongest relationship at a lag of 0 days.

For each endpoint, provincial estimates followed similar trends with few exceptions. Both Samut Sakhon and Nan have a very weak cardiovascular estimates, 0.959 (95% CI: 0.948, 0.986) and 0.967 (95% CI: 0.946, 1.01), despite having significant non-accidental RR values: 1.01 (95% CI: 0.999, 1.02) and 1.02 (95% CI: 1.00, 1.04) , respectively. Mae Hong Son had especially poor RR significance for all three endpoints: 0.971 (95% CI: 0.997, 1.04) for non-accidental, 0.943 (95% CI: 0.964, 1.03) for cardiovascular, and 0.936 (95% CI: 0.989, 1.22) for respiratory. This could be due to Mae Hong Son's relatively small mortality counts and the large standard deviation of its daily mean PM_{10} concentrations, which reduce the power and accuracy of the province's models. Certain provinces in **Figure 1** demonstrate little variation in RR between endpoints. The standard deviations between the RR estimates per endpoint in Bangkok, Nonthaburi, and Lampang are a mere 0.021, 0.023, and 0.008, respectively.

Table 2. Pooled % excess risk (ER) values and 95% CIs for a 10μg/m^3 increase in PM_{10} determined by mortality endpoint per region for single and multi adjusted pollutant models.

Model	Non-accidental ER (%)		Cardiovascular ER (%)		Respiratory ER (%)	
	BMR	Northern Thailand	BMR	Northern Thailand	BMR	Northern Thailand
PM_{10}	0.35 (-0.047, 0.77)	0.41 (0.11, 0.72)	2.4 (-0.13, 5.8)	0.83 (-1.2, 3.4)	0.36 (-1.3, 2.5)	0.93 (0.091, 2.0)
Adjust for O3	0.36 (-0.0098, 0.75)	0.37 (0.063, 0.70)	2.2 (-0.71, 6.2)	1.04 (-1.0, 3.8)	0.22 (-1.3, 2.3)	0.93 (0.062, 2.0)
Adjust for NOX	0.33 (0.011, 0.68)	0.43 (0.13, 0.75)	1.9 (-0.61, 5.5)	1.3 (-0.88, 4.2)	0.57 (-0.77, 2.3)	1.1 (0.17, 2.2)
Adjust for SO2	0.38 (-0.014, 0.79)	0.32 (0.029, 0.63)	2.0 (-0.55, 5.3)	0.78 (-1.2, 3.4)	0.66 (-1.0, 2.8)	0.92 (0.017, 2.0)
Adjust for all Co-pollutants	0.34 (0.040, 0.65)	0.36 (0.032, 0.71)	1.3 (-1.7, 5.8)	1.3 (-0.78, 4.1)	0.78 (-0.57, 2.5)	0.68 (-0.23, 1.8)

The changes in excess risk (ER) shown in **Table 2** that result from adjusting regional models for different co-pollutants cannot be easily generalized. Excluding the cardiovascular models for northern Thailand and the respiratory models for the BMR, the model adjustments that included all co-pollutants had lower ER than those of the single pollutant models. This is reassuring because co-pollutants are normally found to be positive confounds in the relationship between PM_{10} and mortality, so adjusting for them should lead to weaker associations.[1] Although the regional ER of the all inclusive co-pollutant models are fairly similar by endpoint, northern Thailand's single and multi pollutant models generally yielded higher ER than the BMR for non-accidental and cardiovascular mortality. With the exception of respiratory mortality in the BMR, the greatest reductions in ER per region and endpoint that result from including one additional co-pollutant in the single pollutant model occur when adjusting for either SO_2, or NO_X.

Figure 2. The BMR provincial and pooled relationships between PM_{10} concentration and RR for non-accidental mortality and at a discrete lag of 1.

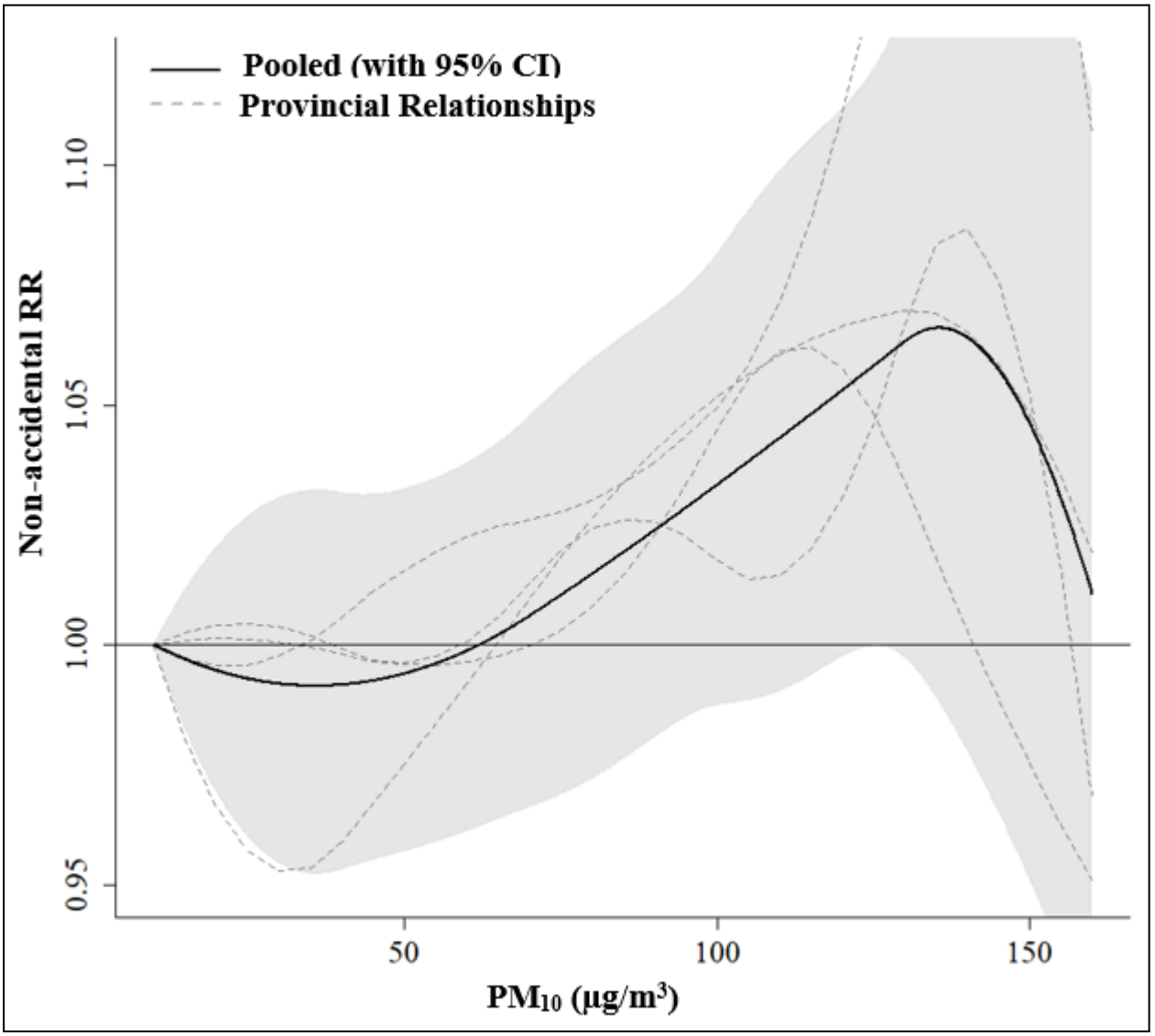


Figure 2 is an example of the graph type that was used to calculate regional health effect estimates by mortality endpoint. Like **Figure 2**, most of these graphs exhibited confidence interval expansion beyond a concentration of approximately 130µg/m^3. This is most likely due to the fact that only a small fraction of daily average concentrations surpassed this value, and when they did, there wasn't necessarily increased mortality. Although the exposure response-relationship was specified as nonlinear, there is still a very strong linear range in the

data, a motif which strengthens the notion that certain ranges of PM_{10} concentration are directly related to RR for certain endpoints.

The pooled BMR and northern estimates are presented in **Table 3** as ß values with corresponding 95% confidence intervals. In the case of non-accidental mortality, both pooled regions were found to have statistical significance with a discrete 1-day lag.

Table 3. Pooled ß values with 95% CI by mortality endpoint for the two regions examined.

	Pooled ß values	
Mortality endpoint	**BMR**	**Northern Thailand**
Non-accidental (discrete lag 1)	0.000335 (3.98E-05, 0.000650)	0.000359 (3.19E-05, 0.000707)
Cardiovascular (cumulative lag 0-1)	0.001289 (-0.00172, 0.00560)	0.001338 (-7.85E-04, 0.00405)
Respiratory (discrete lag 0)	0.000781 (-0.000575, 0.00247)	0.000674 (-0.000229, 0.00180)

BENMAP VALUATION

Figure 3. Average number of annual avoided mortality cases per province for each endpoint during the **(a)** 10μg/m^3 PM_{10} rollback, and **(b)** 20 μg/m^3 PM_{10} rollback scenarios.

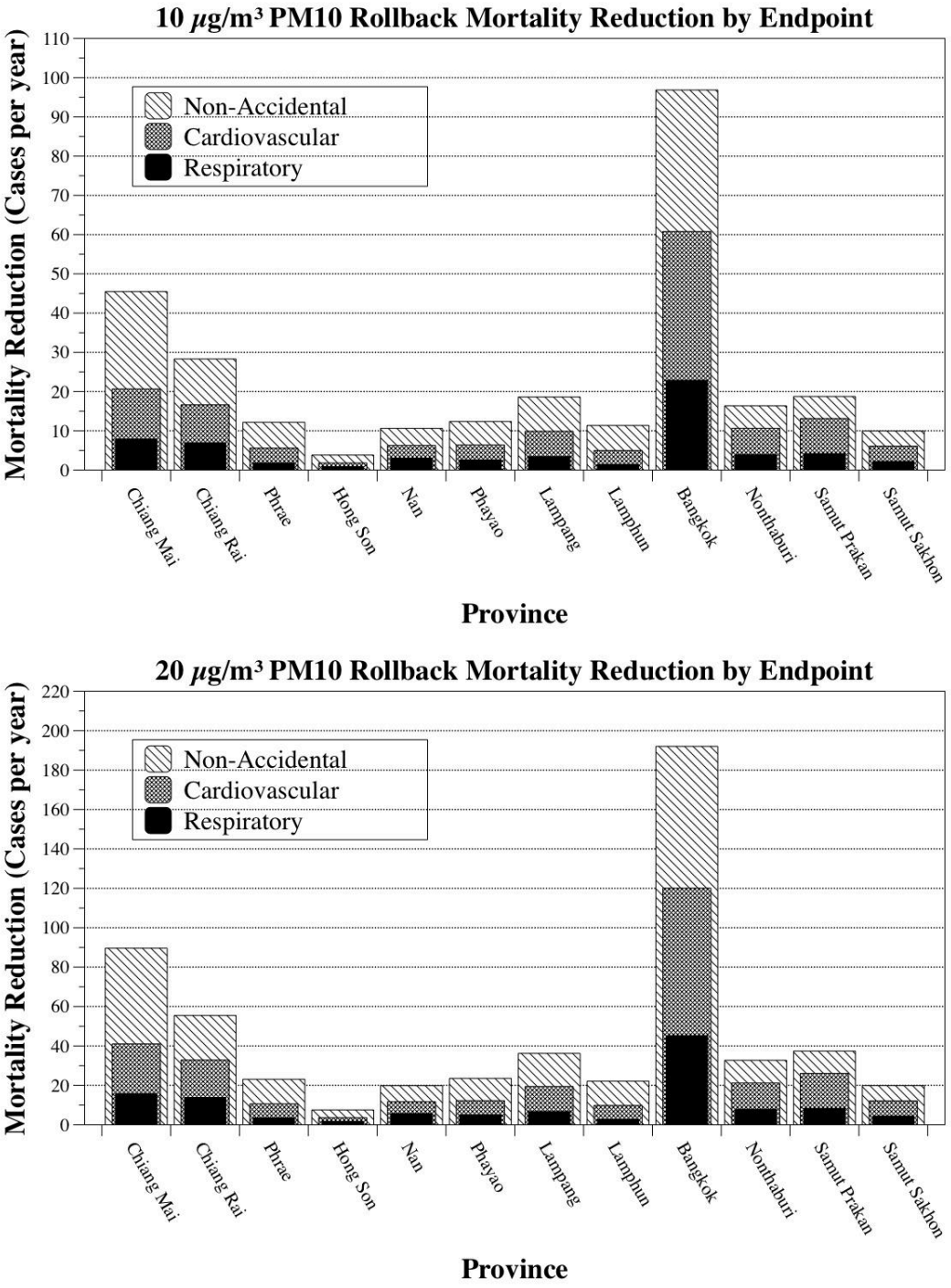


Figure 3 is a representation of the average number of mortality cases avoided by province per year from 2012-2016 for each endpoint. In general, the 10 µg/m^3 rollback results are slightly more than half that of the 20 µg/m^3 rollback. This is due to the fact that more days are reduced to the background concentration of 5.8 µg/m^3 during the larger rollback. When a specific day's

concentration is reduced, it cannot be reduced past the background concentration. Therefore, with more days reaching the background, less days are fully reduced by 20 μg/m^3, so the annual delta value is slightly less than 20 μg/m^3 (usually around 17-19 μg/m^3), causing the rollback to be less than would be expected in a linear case.

Bangkok is evidently the province which would reap the most total health benefit from pollution reductions. This is primarily due to its population size. The total number of avoided mortality cases for the 10 μg/m^3 rollback in Bangkok is roughly 97, of which 61 are due to cardiovascular and 23 to respiratory causes. For the 20 μg/m^3 rollback, the respective benefits are 192, 120, and 45 avoided cases per year. Normalized results are discussed below to assess the benefit per capita.

While the trends of mortality composition are similar across the provinces in **Figure 3** there are slight differences due to relative variations in incidence rates. For example, in the case of respiratory mortality, Chiang Rai has a mortality reduction comparable with that of Chiang Mai. This seemingly disproportionate benefit from pollution reduction in Chiang Rai is due to a higher respiratory incidence rate. The average respiratory incidence rate in Chiang Mai is 7.2e-4, or about 7 cases for every 10,000 people, while the average in Chiang Rai is 8.7e-4, or 8.7 for every 10,000. This is reflected in the respiratory baseline incidence, which for Chiang Mai averages out to roughly 1,180 cases per year, compared to 1,038 cases in Chiang Rai. Conversely, the average baseline incidence for cardiovascular mortality in Chiang Mai is 1,555 while the Chiang Rai baseline is 1,251. These incidence rates explain why the respiratory reductions for Chiang Rai and Chiang Mai are nearly equivalent, with only a 14% difference, while Chiang Mai has noticeably higher estimates for cardiovascular (26% greater), and non-accidental (60% greater). See *S2* of *Supplementary Materials* for the incidence data.

Figure 4. Normalized results by province for **(a)** the 10μg/m^3 incremental rollback and **(b)** the 20μg/m^3 incremental rollback to show avoided mortality cases per 100,000 people for all three endpoints.

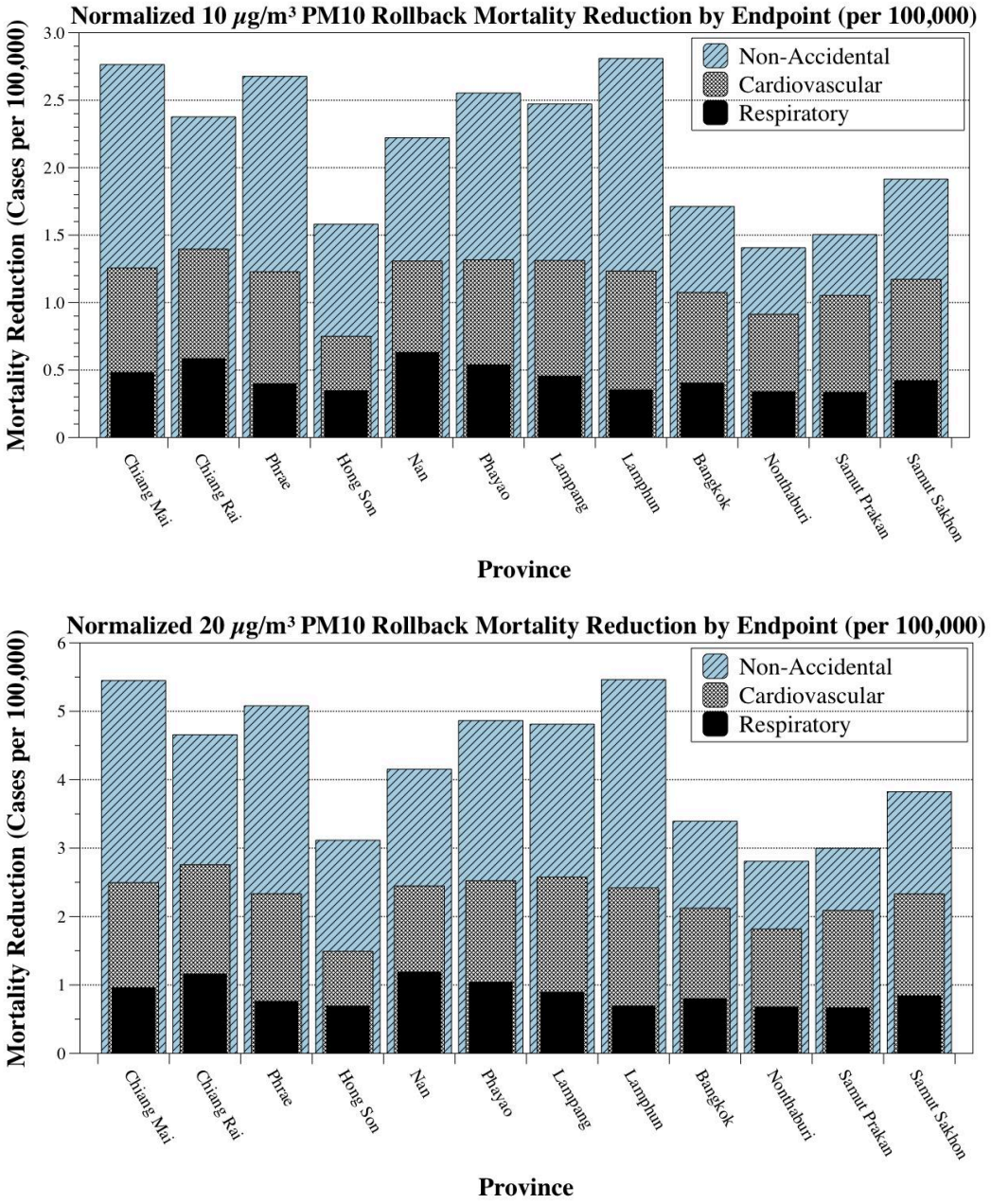


Figure 4 shows the normalized results for each province, which indicate the health benefit per capita of the PM_{10} rollback. The figure compares the number of avoided mortality outcomes per 100,000 people. As with the total benefit in **Figure 3**, the 20 μg/m^3 normalized results follow the same trend as the 10 μg/m^3 rollback results with values slightly less than twice that of the smaller reduction. The results indicate that Lamphun and Chiang Mai would receive

the most normalized benefit from non-accidental mortality, while the northern province of Mae Hong Son receives the least in the region. In Chiang Mai, the initial rollback results in an annual average of 2.7 avoided non-accidental deaths per 100,000, while the Mae Hong Son average is 1.6 avoided cases per 100,000. Overall, the variation is fairly minimal until applied to the total populations, which creates the disparity seen in **Figure 3**. The normalized trends vary slightly across the endpoints, with Chiang Rai receiving the most cardiovascular benefit per capita, and Nan experiencing higher than average savings for respiratory disease. Cardiovascular avoidance averages 1.16 cases a year per 100,000 across the 12 provinces. On average, the BMR provinces receive slightly less normalized benefit for non-accidental and cardiovascular endpoints due to the differences in health effect estimates as shown in **Table 3**.

Table 4. Mean and Standard Deviation of the provincial economic valuations (in millions of Thai baht) for a 10 $\mu g/m^3$ PM_{10} incremental rollback from 2012-2016.

	10 $\mu g/m^3$ - Increment Rollback			**20 $\mu g/m^3$ - Increment Rollback**		
Province	**NAD[a]**	**CD[b]**	**RD[c]**	**NAD**	**CD**	**RD**
Chiang Mai	2,222 (168)	1,017 (275)	390 (89)	4,386 (420)	2,022 (544)	777 (177)
Chiang Rai	1,382 (90)	816 (141)	341 (35)	2,710 (207)	1,608 (261)	676 (65)
Phrae	592 (155)	274 (90)	89 (33)	1,122 (410)	518 (213)	169 (77)
Mae Hong Son	187 (25)	88 (13)	41 (8)	368 (52)	176 (26)	82 (16)
Nan	519 (46)	307 (63)	147 (20)	970 (96)	572 (77)	277 (26)
Phayao	604 (53)	312 (42)	128 (14)	1,149 (162)	597 (89)	245 (39)
Lampang	914 (312)	487 (189)	168 (69)	1,779 (620)	955 (366)	332 (135)
Lamphun	556 (94)	246 (80)	70 (21)	1,080 (184)	482 (153)	138 (40)
Northern Total	**6,976 (653)**	**3,547 (762)**	**1,374 (248)**	**13,564 (1,430)**	**6,930 (1,387)**	**2,697 (464)**
Bangkok	4,714 (1,377)	2,962 (815)	1,114 (366)	9,336 (2,746)	5,858 (1,626)	2,204 (734)
Nonthaburi	806 (468)	525 (315)	195 (110)	1,609 (933)	1,046 (626)	388 (218)
Samut Prakan	921 (232)	646 (196)	206 (53)	1,836 (464)	1,280 (387)	409 (105)
Samut Sakhon	487 (96)	299 (82)	107 (20)	972 (191)	595 (162)	213 (39)
BMR Total	**6,928 (1,391)**	**4,432 (832)**	**1,622 (385)**	**13,753 (2,830)**	**8,779 (1,699)**	**3,214 (784)**

Total	**13,904**	**7,979**	**2,996**	**27,317**	**15,709**	**5,911**
million $USD	*425.2*	*244.0*	*91.6*	*835.4*	*480.4*	*180.8*

[a]NAD stands for non-accidental mortality, [b]CD for cardiovascular mortality, and [c]RD for respiratory mortality. These follow the International Classification of Diseases version 10 (ICD10) of A00-R99, I00-I99, and J00-99 respectively.

Table 4 shows the mean economic valuations (EVs) for three mortality endpoints by province from the five years analyzed (2012-2016). These estimates are based on incremental rollbacks of 10 and 20 μg/m^3, as mentioned above. The trends present in **Table 4** are the same as those depicted in **Figure 3,** since the valuation is linear with respect to avoided mortality outcomes. Therefore, Bangkok is once again the most significant beneficiary of the PM_{10} concentration reductions.

The northern region had very consistent valuation results over the years, as illustrated by the relatively small standard deviations shown in **Table 4**. In contrast, the BMR provinces generally had higher variation. For example, Nan, a northern province, had an average annual savings of ฿519 million THB from reduced non-accidental mortality with a standard deviation of ฿46 million THB, while Samut Sakhon in the BMR had a lower average of ฿487 million THB with a greater standard deviation of ฿96 million THB. Nonthaburi had the largest standard deviations of the 12 provinces, particularly for the respiratory endpoint.

Both regions have similar total valuation outcomes for each endpoint. For the initial rollback of 10 μg/m^3, the northern region received an annual average of ฿6.98 billion THB in reduced non-accidental mortality benefits, while the BMR saves ฿6.93 billion THB. The provinces with the largest share of the northern total included Chiang Mai (฿2.2 billion THB), Chiang Rai (฿1.4 billion THB), and Lampang (฿914 million THB). Bangkok constitutes 66-68% of the summed valuations for the BMR provinces. These northern and central provinces received the largest economic benefits due to their comparatively large population sizes and higher

mortality counts. Total savings across the 12 provinces for the initial rollback equaled $425.2 million USD per year. The additional rollback of 20 μg/m^3 would generate savings of $835.4 million USD, with cardiovascular accounting for $480.4 million USD and respiratory for $180.8 million USD. Over the course of five years, the savings would equal $2.13 billion USD for the smaller PM_{10} reduction and $4.18 billion USD for the larger rollback.

Discussion

To our knowledge, an economic benefits analysis of PM_{10} reductions in terms of mortality is unprecedented in Thailand. Using distributed lag non-linear models and a multivariate pooling method, excess risks for a 10μg/m^3 increase in PM_{10} were determined to be 0.34% (95% CI 0.04, 0.65), 1.30% (-1.70, 5.76), and 0.78% (-0.57, 2.50) for non-accidental, cardiovascular, and respiratory mortality, respectively, in the BMR region. The corresponding excess risks of northern Thailand were 0.34% (0.03, 0.70), 1.35% (-0.78, 4.14), and 0.68% (-0.23, 1.82). The benefit analysis from an incremental PM_{10} rollback of 10μg/m^3 resulted in average annual mortality reductions of 285, 163, and 61, for the three endpoints across both regions. Furthermore, non-accidental economic valuations equated to ฿13.9 and 27.3 billion THB, respectively, for the 10 and 20μg/m^3 rollbacks.

Numerous time-series studies have assessed the short-term health effects of fine particle pollution using poisson regression models at a multi-city or multi-provincial level. Some focus on mortality,[27-30] while others on morbidity.[3,31] While many studies focus solely on a single region or city, we decided to select multi-city studies that employed uni or multivariate meta-analysis or bayesian hierarchical analysis as a basis of comparison for our own values. One such study examined the 90 largest cities in the United States to determine a 0.2% increase in non-accidental

mortality associated with a corresponding 10μg/m^3 increase of PM_{10} (95% CI, 0.1-0.4%).[5] While another study of 29 European cities yielded an estimate of 0.6% (95% CI, 0.4-0.7%).[27] With regards to Asian specific studies, our RR estimates were comparatively higher, albeit by a small margin. For instance, a meta-analysis of Chinese single city studies found significant associations of 0.3% for non-accidental, 0.4% for cardiovascular, and 0.6% for respiratory mortality.[32] The Public Health and Air Pollution Project in Asia (PAPA) assessed 4 asian cities, including Bangkok, and yielded excess risks of 0.55%, 0.58%, and 0.62% for PM_{10} under similar modeling conditions to those of the aforementioned Chinese study.[7]

One particular project published by Guo et al. (2014) titled *The Association Between Air Pollution and Mortality in Thailand* uses general linearized models containing the same co-pollutants considered in this study for 18 provinces in Thailand to examine our same three endpoints.[1] Guo et al. used Bayesian hierarchical meta-analysis to pool the different regions of Thailand and arrive at overall health effect estimates. Results for percent increase in non-accidental, cardiovascular, and respiratory mortality for a corresponding 10μg/m^3 increase of PM_{10} were 0.4%, 0.13% and 0.4%. While the non-accidental estimate is similar to the one derived from this study, the cardiovascular and respiratory estimates for Guo et al. are lower than those of this study. However, a 2008 study from Wong et al. that focused only on Bangkok determined excess risks of 1.3%, 1.9%, and 1.0% for the three endpoints, which are much higher than every pooled estimate in Guo et al.[8] The cardiovascular and respiratory estimates of Wong et al. are more consistent with those determined in this study. Some qualitative explanations as to why the estimates of Wong et al. are larger include that people stay outdoors more during the day, live closer in proximity to roads and automotive emissions, and have less ventilation in their homes.[8]

There are only a small number of sources that serve as basis for comparison with the valuation results of this study. Most BenMAP studies analyze the effects of ozone or $PM_{2.5}$ and report more specific health outcomes and sources of economic benefits such as lung cancer and reductions in the loss of school-days.[33-35] By virtue of being a product of the U.S EPA, BenMAP has been most frequently used for analyses in the United States, with few assessments taking place in Asia. Those that do focus on Asian locations primarily target urbanized areas and pollutants other than PM_{10}.[36,37] Consequently, valuations in other countries besides Thailand are inherently different. For these reasons, it is difficult to compare the health benefit and valuation results with previous studies.

For the epidemiology methodology, a linear exposure-response relationship was initially considered, but ultimately yielded less statistically significant results. Once the non-linear model was selected, pooled results were analyzed for all lag-specific structures. The lag for each endpoint was chosen in order to maximize the strength of the association between PM_{10} and that mortality. It is important to note that while both non-accidental pooled regions achieved statistically significant values, most provinces (and the other pooled mortality endpoints) did not present significant RR values for their respective lower confidence intervals. Although there really is no end to amount a model can be refined, several factors that could've increased the significance of this epidemiological study include accounting for the confounding effects of influenza seasons or other well documented public health crises and correctly categorizing deaths labeled as senility-induced with their underlying causes.[7]

Sensitivity analysis was conducted for several parameters of the DLNM analysis to assess their impact the resulting RR and ß values. One such parameter was the size of the PM_{10} range used to place internal knots for the *argvar* function, which describes the exposure-response

relationship. By changing the range from 10-160 μg/m^3 to 0-170 μg/m^3, the maximum percent difference in RR fit for both regions and all endpoints was 0.76%. Due to the relationship between RR and β as described in **Equation (1)**, it takes very little variation in RR values to drastically change the corresponding ß values. Accordingly, the average percent difference in the health effect estimates across all endpoints in the BMR and northern Thailand were 25.2% and 9.8%, respectively. Interestingly, the lower confidence interval fluctuated the most from these changes, with an average percent difference of 121% for both regions and across all endpoints. When a range of 20-80 μg/m^3 is used, as would be expected, there were greater percent differences in the RR and ß values than when the range was adjusted to 0-170 μg/m^3. The main motivation for restricting the range to such a large extent was to observe what would happen if the knots were placed within the range of PM_{10} values that makes up the majority of average daily means. It was found that the northern region's ß values had larger percent differences than the BMR region.

Variation of the centering value used in the *crosspred* function of the DLNM package was also considered. This value, which serves as the reference from which all other predictions are calculated, was changed from 10 μg/m^3 to 0, 5.8, and 20 μg/m^3 to investigate how the RR predictions adjusted. Once again, the lower confidence interval differed the most between each proposed centering value and the centering value used in this study. For the centering values of 0 and 5.8 μg/m^3, the lower confidence intervals per endpoint were consistent with the centering values of 10 in terms of statistical significance (in fact they were slightly more significant). However, for the centering value of 20, there were no significant lower confidence intervals for any of the endpoints, suggesting that the PM_{10} concentration of no excess risk lies below 20 μg/m^3.

The most volatile aspect of the epidemiology methodology analyzed was the range over which the change in RR was sampled in order to determine the average increase in RR per 10 $\mu g/m^3$ increase in PM_{10}. This instability arises from the fact that the exposure-response relationship was defined as nonlinear in this study, but the aforementioned statistic is usually derived from linear relationships. To reiterate, the sampling range of 20-80 $\mu g/m^3$ was selected for this study because it comprises the majority of the daily averaged PM_{10} concentration values. The ranges of 10-70, 30-90, and 40-100 $\mu g/m^3$ were assessed. The results of this sensitivity analysis show that the average percent difference in the health effect estimates for both regions across all endpoints is 154% for the range of 30-90$\mu g/m^3$, 99.8% for the range of 10-70$\mu g/m^3$, and 58.7% for the range of 40-100$\mu g/m^3$. It is important to note, however, that the percent difference for the health effect estimates of the BMR were generally larger than those of the northern region. Regardless, these percent differences are substantially higher than any other average percent difference encountered in the previous sensitivity adjustments.

By assessing the influence of individual co-pollutants on the regression models, it was found that in general, NO_x and SO_2 have the strongest confounding effects on the relationship between PM_{10} and mortality. The models that included all co-pollutants were chosen for this study because they had the lowest effect estimates, a decision and trend that is not unique to this study.[38] It is very difficult to distinguish the individual contributions each pollutant makes to these all inclusive models.[1] One reason being that SO_2 and O_3 are precursors of secondary particles, so the ability of the models to precisely interpret the independent effects of co-pollutants on RR is restricted. When temperature and relative humidity were removed from the models, the resulting health effect estimates of the all inclusive co-pollutant models were

larger. This increase demonstrates the need to control for temperature and relative humidity when examining air pollution and mortality relationships.

Several recommendations that could further advance the understanding of the relationship between particulate matter and mortality in Thailand are as follows. A key limiting factor that ultimately controlled the accuracy of this study's results was the consistency with which monitoring stations measure ambient PM_{10} concentrations. The PCD of Thailand should prioritize installing more stations and providing more complete hourly data. Large gaps in the data, ranging from days to months to years, introduces uncertainty and prevents a larger, more comprehensive study of other areas in the country. Additionally, it could also be beneficial if a future study were to focus on more specific mortality endpoints such as stroke, ischemic heart disease, COPD, and lung cancer, which have all been shown to be significantly affected by higher PM_{10} concentrations.[3,5] For an epidemiology study for these endpoints, it is important to have longer periods of data due to fewer daily mortality counts of these diseases in most Thai provinces. Furthermore, a project assessing the impacts of $PM_{2.5}$, which causes greater adverse health effects on human health than PM_{10} due to the fact that smaller particles can penetrate deeper into the lungs, tissues, and bloodstream, should be considered for these endpoints as well.[20,39,40] Unfortunately, the PCD does not monitor $PM_{2.5}$ concentrations at most stations, so it is highly recommended that more of these monitors are installed.

Finally, a study assessing the costs of potential strategies to reduce particulate matter should be undertaken. Potential mitigation methods could include better waste management, regulation of roadside cooking and agricultural burning, enforced vehicle emissions standards, and investment in improved forest fire management. The costs associated with each strategy, as well as their effectiveness at improving public health, should be critically assessed in order to

determine which method provides the most benefit at the least expense. These potential studies would raise awareness in the Thai government, amongst other researchers, and in the general public, advancing the ultimate goal of preserving lives through informed policy making.

Summary

The results of this study indicate that reductions in PM_{10} concentrations would likely reduce mortality risk–especially cardiovascular and respiratory–and provide economic benefits. Thailand is one of many countries experiencing higher levels of concentrated air pollution, and as more Southeast Asian countries develop, urbanize, and industrialize, minimizing pollutant exposure should become a high priority. This notion is supported by the Global Burden of Disease report of 2015, which lists ambient air pollution among the top risk factors for mortality. While this study only quantifies mortality reduction benefits, there are other economic incentives to reducing PM_{10} as well, such as less school or work days lost, or less time spent in the hospital.[31] It is our hope that this paper encourages further benefit analyses to be conducted in the field of epidemiological studies as a way for governments, policymakers, and the general public to better comprehend the effects of air pollution on human health, especially in Thailand.

Acknowledgements

We are incredibly grateful for the guidance and support of our research advisors, from fellow researcher and friend Sitthipong Pengjan, and to Dr. Antonio Gasparrini for his detailed responses to our questions via e-mail correspondence. This paper would also not have been possible without the implementation of the UNC Institute for the Environment's Thailand Field

Site under the coordination of Professor Richard Kamens and the JGSEE staff at KMUTT Thonburi.

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