Peat and vegetation fires in Indonesia: Emissions, impacts and prevention

Laura Kiely

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Declaration of Authorship

The candidate confirms that the work submitted is her own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

This thesis is submitted in a University of Leeds alternative thesis-by-publication format, with two thirds of the research peer reviewed and published, and one third submitted to a suitable journal. This has allowed the research to be available and accessible during the PhD. This thesis is comprised of an introductory chapter, three manuscripts, a concluding chapter and appendices.

Chapter 2 is the following publication:

Kiely, L., Spracklen, D. V, Wiedinmyer, C., Conibear, L., Reddington, C.L., Archer-Nicholls, S., Lowe, D., Arnold, S.R., Knote, C., Khan, F., Latif, M.T., Kuwata, M., Budisulistiorini, S.H. and Syaufina, L. 2019. New estimate of particulate emissions from Indonesian peat fires in 2015. *Atmospheric Chemistry and Physics*. **19**, pp.11105–11121.

Conceptualization of the work was done by the candidate and DVS, with support from SRA and LS. The candidate carried out modelling work and analysis, with supervision from DVS and SRA. CK provided WRFotron modelling scripts, and SAN and DL provided model code and technical support with modelling. LC and CLR provided technical support with modelling. The candidate and CW provided fire emissions, and MK, SHB, MFK and MTL all provided observations. The candidate prepared the manuscript with help from all authors.

Chapter 3 is the following publication:

Kiely, L., Spracklen, D. V, Wiedinmyer, C., Conibear, L.A., Reddington, C.L., Arnold, S.R., Knote, C., Khan, M.F., Latif, M.T., Syaufina, L. and Adrianto, H.A. 2020. Air quality and health impacts of vegetation and peat fires in Equatorial Asia during 2004 – 2015. *Environmental Research Letters*.

This study was designed by the candidate and DVS, with support from SRA. Modelling work and analysis was completed by the candidate, with supervision from DVS and SRA. Health impact calculations were performed by LC and the candidate, using model output provided by the candidate. CK provided WRFotron modelling scripts, and LC and CLR provided technical support with modelling. The candidate and CW provided fire emissions. Observations were provided by MFK, MTL and HAA. The candidate prepared the manuscript, with feedback from all authors.

Chapter 4 is the following manuscript, prepared for submission to Nature Communications:

Kiely, L., Spracklen, D. V, Arnold, S.R., Papargyropoulou. E, Conibear, L, Wiedinmyer, C, Knote, C., and Adrianto, H.A. 2020. Economic cost of Indonesian fires and the benefits of restoring peatland. *In prep.*

Conceptualization of this study was done by the candidate, DVS and SRA. Modelling work and analysis was completed by the candidate, advised by DVS, SRA and EP. Health impact calculations were done by LC and the candidate, using model output provided by the candidate. CK provided WRFotron modelling scripts. The candidate provided fire emissions with help from CW. The candidate prepared the manuscript, assisted by all authors.

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Abstract

Vegetation and peat fires occur regularly in Indonesia following a history of land-use change, deforestation, and peatland drainage, which has resulted in an environment prone to fire. Fires occur in the dry season (August – October), and are greatest during periods of drought, resulting in strong inter-annual variability in emissions. Fires destroy agricultural crops and forest, and emit considerable amounts of carbon dioxide, particulate matter (PM) and other trace gases. These emissions have local, regional and international impacts, affecting human health, and resulting in economic losses. Emissions from peat fires are uncertain, however, due to uncertainties in the burn dynamics. Policy efforts to prevent fire in Indonesia include recently announced plans for restoration of degraded peatlands. The effect of peatland restoration on fire is not well known.

This thesis gives the first consistent estimate of emissions and the public health and economic impacts of Indonesian fires during 2004-2015, and is also the first to estimate the potential economic benefits of peatland restoration. The largest dry season fire emissions were in 2015, with 9.4 Tg of $PM_{2.5}$ emitted, over three times the average for the period. Peat fires contributed 68% of PM emissions in this year. In total for 2004-2015, dry season fires emitted 32 Tg of $PM_{2.5}$, around half of which came from peat burning. It has been shown that a better representation of peat fire emissions improves model simulations of PM concentrations. In particular, soil moisture has been shown to be an important controlling factor of burn depth.

The Weather Research and Forecasting model with chemistry has been used to simulate dry season PM concentrations for the 6 largest fire events during 2004-2015, showing that Indonesian fires regularly expose millions of people to poor air quality for long periods. Estimating the health impacts of long-term exposure to PM, it has been shown that fire emissions from dry season fires resulted in an estimated 131 700 excess deaths during the 2004-2015 period. Fires result in substantial economic losses, with the largest six Indonesian fire events costing US$93.7 billion through damages to land cover, long term health impacts, and CO_2 emissions. It has been shown that the cost of fires outweighs the financial benefit.

The benefit of peatland restoration has been evaluated, and it has been found that restoring 2.49 Mha of peatland could have resulted in CO_2 and $PM_{2.5}$ fire emissions being reduced by 18% and 24% respectively, the latter preventing 12,000 premature mortalities across the 6 fire events. Restoration would have prevented US$8.6 billion of fire costs over the 6 events, and has been shown to be a cost effective policy for reducing the impacts of fires.

The emissions inventory created during this work will enable a better upstanding of Indonesian peat fires, continuing beyond the work presented in this thesis. The findings of this thesis will contribute to the ongoing discussion of Indonesian fires, with relevance for both research and policy.

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List of Abbreviations

ACSM: Aerosol Chemical Speciation Monitor

AERONET: Aerosol Robotic Network

AFWA: Air Force Weather Agency

AOD: Aerosol Optical Depth

ARCTAS: Arctic Research of the Composition of the Troposphere from Aircraft and Satellites

ARW: Advanced Research WRF

ASEAN: Association of South East Asian Nations

BC: Black Carbon

BL: Boundary layer

CH4: Methane

CO: Carbon monoxide

CO2: Carbon dioxide

DALY: Disability affected life years

ECMWF: European Centre for Medium-Range Weather Forecasts

HTAP: Hemispheric Transport of Air Pollution Inventory

EDGAR: Emissions Database for Global Atmospheric Research

EF: Emissions factor

ESA: European soil moisture

ETS: Emissions Trading System

EU: European Union

FB: Fractional Bias

FEER: Fire Energetics and Emissions Research

FINN: Fire Inventory from NCAR

FLAMBE: Fire Locating and Modeling of Burning *Emissions*

FNL: Final Operational Global Analysis data

FRP: Fire radiative power

F-TUV: fast Tropospheric Ultraviolet-Visible

GBD: Global Burden of Disease

GEMM: Global Exposure Mortality Model

GEOS: Goddard Earth Observing System

GFAS: Global Fire Assimilation System

GFED: Global Fire Emissions Inventory

GFED4s: Global Fire Emissions Database v4 with small fires

GFS: Global Forecast System

GPW: Gridded Population of the World

IASI: Infrared Atmospheric Sounding Interferometer

IOD: Indian Ocean Dipole

IPCC: International Panel on Climate Change

ISPO: Indonesian Sustainable Palm Oil

MEGAN: Model of Emissions of Gases and Aerosols from Nature

MJO: Madden-Julian oscillation

MODIS: Moderate Resolution Imaging Spectroradiometer

MOPPITT: Measurements of Pollution in the Troposphere

MOSAIC: Model for Simulating Aerosol Interactions and *Chemistry*

MOZART: Model for ozone and related chemical tracers

NASA: National Aeronautics and Space Administration

GMAO: Global Modelling Assimilation Office

NCAR: National Center for Atmospheric Research

NCD: Non-communicable Disease

NCEP: National Centers for Environmental Prediction

NEA: National Environment Agency

NH3: Ammonia

NMAEF: Normalised Mean Absolute Error Factor

NMBF: Normalised Mena Bias Factor

NMVOC: Non-methane Volatile Organic Compounds

NO: Nitrogen oxide

NPV: Net Product Value

O3: Ozone

OA: Organic Aerosol

OC: Organic Carbon

OIN: Other Inorganics

PBL: Planetary Boundary Layer

PM: Particulate Matter

PM1: Particulate matter with a radius less than 1 μm

PM10: Particulate matter with a radius less than 10 μm

PM2.5: Particulate matter with a radius less than 2.5 μm

POA: Primary Organic Aerosol

QFED: Quick Fire Emissions Dataset

REAS: Regional Emissions inventory in Asia

REDD+: Reducing emissions from deforestation and forest degradation

RRTMG: Radiative transfer model

SM: Soil Moisture

SMAP: Soil moisture active passive

SOA: Secondary Organic Aerosol

UNESCO: United Nations Educational, Scientific and Cultural Organization

US: United States

VOC: Volatile Organic Compound

WHO: World Health Organisation

WPS: WRF Prepossessing System

WRF: Weather Research and Forecasting model

WRF-chem: Weather Research and Forecasting model with chemistry

WRI: World Research Institute

YLD: Years lived with a disability

YLL: Years life lost

Chapter 1 Introduction

Large fire events have occurred in Indonesia over past decades, as tropical forests have been removed to make way for plantations (Field et al., 2009). The dynamic of these fires is complex; controlled by both meteorological and anthropogenic conditions (Page and Hooijer, 2016). Many fires occur on large areas of tropical peat swamp which have been poorly studied until recently (Page et al., 2007). A lack of data means fire emissions from Indonesian peat fires can be poorly constrained in global emissions inventories (Reddington et al., 2016). Fire emissions from this region regularly cause poor air quality across Equatorial Asia, reaching several million people in multiple countries (Marlier et al., 2012). As more becomes known about the detrimental effects of air pollution on human health, there is increasing national and international concern about the impacts of these fires. This concern has led to increasing pressure to prevent future fire events (Herawati and Santoso, 2011). In this thesis, the emissions and impacts of Indonesian fires have been investigated.

This chapter provides a background to the research I have done, and a discussion of current literature. I have set this out in five sections. Section 1.1 describes the drivers of fires in Indonesia, and highlights recent findings on the dynamics of peat fires. Section 1.2 evaluates current fire emissions inventories, and introduces the social and environmental impacts of emissions. The impacts of fires on air quality and health are further discussed in section 1.3, and the economic impact of fires is considered in section 1.4. In section 1.5 current fire mitigation efforts and policy are reviewed. Section 1.6 provides a summary of the background knowledge and highlights the knowledge gaps which are addressed by this thesis. The objectives of this work are given in section 1.7.

In Chapter 2, Chapter 3 and Chapter 4, I include three manuscripts investigating Indonesian fires, from emissions to impact. In the first, a fire emissions inventory has been extended to include peat fire emissions, created specifically for Indonesian peat. In the second, this inventory has been used to estimate the effects fires have had on human health in the region. The third paper considers the economic cost of fires and the potential benefits of peatland restoration. In Chapter 5, I discuss the key findings and limitations of my work.

1.1 Indonesian fires

Indonesia is an archipelago in Equatorial Asia and makes up a substantial part of the region known as the Maritime Continent, along with the Philippines, Malaysia, Singapore, Brunei, East Timor and Papua New Guinea. Two of the biggest regions in Indonesia are Sumatra and Kalimantan, the latter being the Indonesian part of Borneo, a large island shared with Malaysia and Brunei. Fires are a transboundary issue and smoke from fires regularly effects Malaysia, Singapore, Brunei and the Philippines. Indonesia contains several different land types, including mangroves, tropical forest and peatland swamps. The two main fuel types for fires in Indonesia are tropical forest and peat (Figure 1.1).

The causes of fires in Indonesia are complex with a mixture of natural and anthropogenic influences (Reid et al., 2013). The largest fire events occur in El Niño years with strong drought, but are also dependent on land-use change, and evidence suggests that fires would rarely ignite naturally (Gellert, 1998; Field et al., 2016). Fire is used in Indonesia as an agricultural tool to clear land. Commonly referred to as ‘slash and burn’ fires, the left-over material from crops and cut vegetation are piled on the ground and allowed to dry, then set alight (Roulston et al., 2018). Fire is often

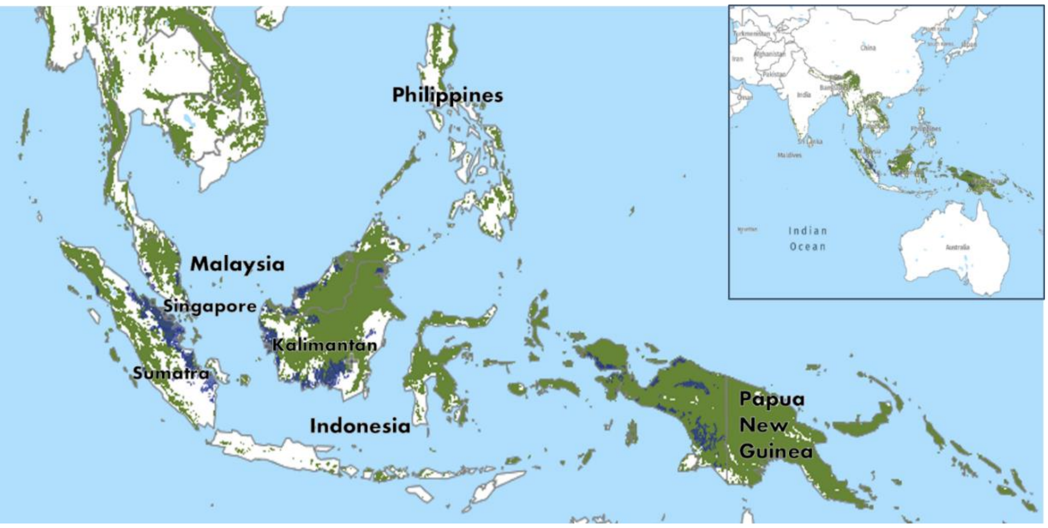

Figure 1.1: Primary forest cover in 2001 (green) and location of peatlands (blue) in Equatorial Asia. Accessed from Global Forest Watch on 30/10/2020.

considered the most cost efficient way of clearing land (Simorangkir, 2007; Varkkey, 2013), and is also thought to reduce pests (Ooi and Heriansyah, 2005) and fertilize the soil (Varma, 2003). Fire is therefore a popular tool for land owners. Fires can also be used during disputes over land ownership and some fires may be accidental, although there is some doubt over the latter (Harrison et al., 2009). Profits from converting land to plantations can be great, providing a strong incentive for starting fires (World Bank, 2016b; Purnomo et al., 2017).

Fires occur across the globe, but emissions from fires are particularly high in the tropics, with tropical fires contributing around 84% of global carbon emissions between 1997 and 2016 (van der Werf et al., 2017). The regions with the largest emissions in this period are Southern and Northern hemisphere Africa, South America, and Equatorial Asia (Figure 1.2; van der Werf et al., 2017). For Equatorial Asia, the majority of emissions come from Indonesian fires. Outside the tropics, fires also frequently occur in North America, Australia and Europe (Verdon et al., 2004; Marlon et al., 2012; Ganteaume et al., 2013). Fires in Equatorial Asia were responsible for 8% of global fire carbon emissions between 1997 and 2016, a similar amount to that emitted from all boreal forest fires (van der Werf et al., 2017).

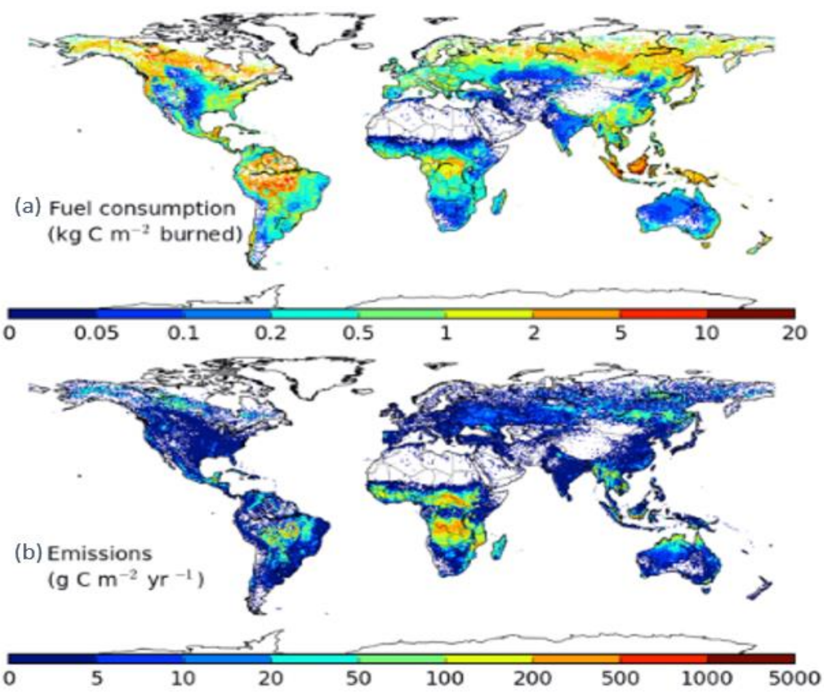

Figure 1.2: Fuel consumption (a) and carbon emissions (b) from fires globally from GFED4s, averaged over 1997-2016. Adapted from van der Werf et al. (2017).

1.1.1 Land Use Change

Since the 1970s large scale deforestation started in Indonesia to make way for plantations (Gaveau et al., 2014; Gaveau et al., 2016). Before the 1970s forest loss had only occurred in heavily populated regions such as Java and Bali, and forest cover for Indonesia in 1950 is thought to have been 83.5%, covering 159 Mha (Tsujino et al., 2016). In the 1970s and 1980s transmigration projects moved people from populated areas to settle in the less populated areas of Sumatra and Kalimantan (Fearnside, 1997). This move led to forest loss, as land was converted to cropland and logging began (Fearnside, 1997; Tsujino et al., 2016). Before the 1980s only state owned oil palm plantations were allowed; however, this was lifted in the 1980s to allow private and smallholder plantations (Yusuf et al., 2018). Foreign investment led to commercial logging and crops being the main driver of forest loss, and oil palm and timber plantations expanded up to 2015 (Tsujino et al., 2016). In 1995-98 the Mega Rice Project, an aim to increase food production, encouraged the conversion of unproductive peat swamp in Kalimantan (Ritzema et al., 2014). The project failed and was terminated in 1999, but the cleared and drained peatland has since had recurrent fires (Dohong et al., 2017). 59 Mha of forest had been lost between 1950 and 1997 (Tsujino et al., 2016).

By early 2000 there was an estimated 94.2 – 98.4 Mha of primary forest in Indonesia (Margono et al., 2014; Turubanova et al., 2018). Over the next 12-14 years annual forest loss increased steadily, and 6.02 – 7.7 Mha of primary forest was lost (Figure 1.3; Margono et al., 2014; Turubanova et al., 2018). 86% of this loss was from Sumatra and Kalimantan (Margono et al., 2014). Almost half of the forest loss between 2000 and 2014 occurred within industrial concessions during this period (Abood et al., 2015), areas assigned for a particular land use by the government. Wood fibre and logging concessions resulted in the greatest forest loss, followed by oil palm. The area of land being used for oil palm in Indonesia increased almost threefold between 1960 and 1980 (from 70,000 ha to 0.2 Mha), but then by 2014 had increased by 37 times to 7.4 Mha (Yusuf et al., 2018). By 2015 forest cover in Indonesia was at 49.8%, covering 91 Mha, with 46-90 Mha of this being primary forest (FAO, 2015; Tsujino et al., 2016; Turubanova et al., 2018).

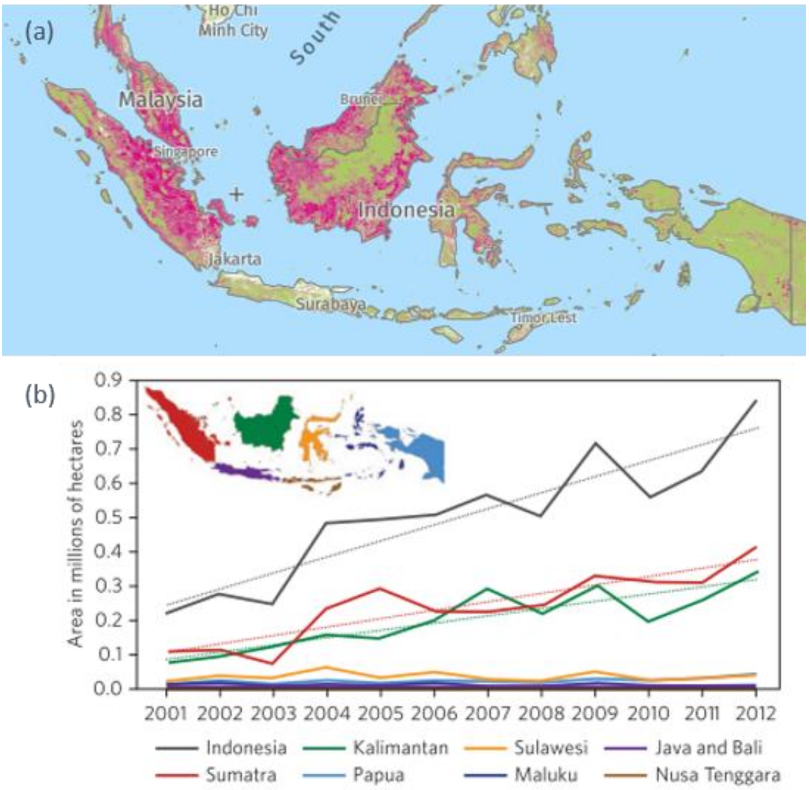

Figure 1.3: (a) Forest cover loss between 2001 and 2019 (pink) and forest cover in 2010 (green), taken from Global Forest Watch on 28/08/20 at https://gfw.global/3hJ4U1e. (b) Annual primary forest loss for all of Indonesia and for each Island group between 2000 and 2012, showing that deforestation is increasing. Dotted lines show linear fit. Adapted from Margono et al. (2014).

Fires began occurring frequently in Kalimantan in the 1980s (Field et al., 2009), just as transmigration was occurring, suggesting the fires were linked to the increased population. Adrianto et al. (2020) show that the majority of fires in Riau, Sumatra, are associated with land-use change, and Adrianto et al. (2019) find that the number of fires increases locally with forest loss. Fire density in non-forest between 2000 and 2010 has been shown to be ten times greater than in forest (Cattau et al., 2016). Lilleskov et al. (2019), however, found that, for peatlands in Peru and Indonesia, while forest loss on peatlands is positively related to increasing population density, burned area is not. They suggest that climate drivers are also important for fire occurrence.

Fires are used as a tool to clear land and prepare it for planting, both in the initial conversion from forest, and between crop cycles. Atwood et al. (2016) found that for a study area in Kalimantan the largest fire occurrence was on concessions (land allocated for a particular use) which were not yet converted, followed by plantations. Land use type is important, as fire frequency has been shown to be increased close to existing oil palm plantations, while the influence of logging on fires is negligible (Sloan et al., 2017). By 2015, oil palm made up the majority of plantations in Sumatra and Kalimantan (73%), with wood pulp a close second (26%; Miettinen et al., 2016). Although logging is often not directly related to fires, it causes forest degradation. It has been shown that logging often precedes conversion of forest to plantation (Miettinen et al., 2012; Margono et al., 2014).

Between 1990 and 2010, Wijedasa et al. (2018) suggest that 70% of peatland conversion occurred outside of known concessions. Determining the cause of fire outside of known concessions and land uses is difficult as it involves confirming satellite imagery on the ground, which can be expensive to do on a large scale (Tacconi, 2016).

1.1.2 Meteorology and climate dynamics

Fires will only spread when the fuel is dry, and natural influences on fire mostly pertain to rainfall. Due to its location and topography, Indonesia's meteorology is controlled by many different weather patterns, and is a complex region for rainfall (Mori et al., 2004). Chang et al. (2011) summarises the influence of monsoons on Indonesia's weather patterns. The Asian winter monsoon causes the large scale movement of rainfall across the region, with the Asian Summer monsoon and Australian summer monsoon also influencing some areas. Aldrian and Dwi Susanto (2003) found that Indonesia has three climate regions, with the southern parts of Sumatra and Kalimantan having different patterns of rainfall to the Northern parts, as well as to the Eastern Indonesian Islands (Figure 1.4). Turk and Xian (2012) suggest that Indonesia's topography also drives weather patterns; in central Sumatra the mountain range shelters the drier East side of the Island from the wetter West side. Diurnal cycles of rain are caused by the convection over the land and sea, with precipitation over the islands in the afternoon (Qian, 2008; Turk and Xian, 2012).

Rainfall occurs across Indonesia year round; however, there is an annual cycle with the period of lowest rainfall starting around July for Sumatra and Kalimantan; the beginning of the dry season (Chang et al., 2005). The onset of rain occurs around August for North Sumatra and moves south-eastward, reaching south Sumatra around

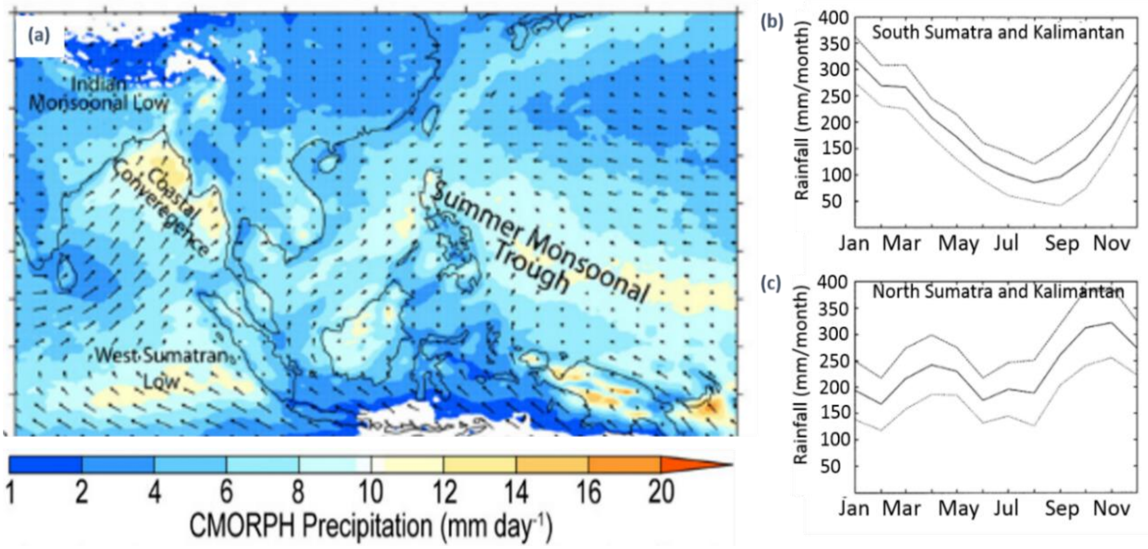

Figure 1.4: (a) Average June – November wind direction and rainfall for 2003 – 2009. 30m wind data is from Navy Global Atmospheric Prediction System and precipitation rate is from Climate Prediction Center MORPHing technique. Adapted from Reid et al. (2013).

(b) and (c) Seasonal variation in rainfall for Sumatra and Kalimantan, separated into (b) the southern part of the region and (c) the northern part. Bold lines show the 1961-1993 average, with one standard deviation indicated by the fine lines. Adapted from Aldrian and Dwi Susanto (2003).

September and Kalimantan around October, marking the end of the dry season (Moron et al., 2009). The beginning and end dates of the seasons can vary between studies, but for western Indonesia the dry season is around May-October and the wet season is October-March (Aldrian and Dwi Susanto, 2003; Chang et al., 2005; Moron et al., 2009; Turk and Xian, 2012; Reid et al., 2013). These seasons are reversed for some islands in the eastern part of Indonesia (Turk and Xian, 2012), and some areas of Indonesia also experience a semi-annual cycle; for North Sumatra rainfall peaks also occur in July (Chang et al., 2005). The burning season moves in time with the monsoon, and the peak season for fires in Sumatra and Kalimantan matches the dry season (Reid et al., 2013; Miettinen et al., 2017). The Madden-Julian oscillation (MJO) also effects Indonesia, causing wet and dry phases every 30-90 days during boreal summer (Reid et al., 2013).

At longer time scales, Indonesia is strongly affected by the Indian Ocean dipole (IOD) and El Niño, when anomalies in sea surface temperature cause the meteorology over Indonesia to change. A positive IOD means that the Western part of the Indian Ocean is warmer than the Eastern part, resulting in reduced moisture being carried to Indonesia, and reduced rainfall. The El Niño is the warm phase of the El Niño-Southern

Oscillation, when warm water develops in the central Pacific, and Easterly trade winds are reduced. Rain which normally reaches land falls in the Pacific Ocean (Wooster et al., 2012), resulting in increased drought in Indonesia (Lyon, 2004), particularly in southern Sumatra and Borneo during the dry season (Chang et al., 2011; Miettinen et al., 2017). El Niño can cause reduced rainfall for 1-2 years. The largest reduction in rainfall is seen when El Nino and a positive IOD occur together (Figure 1.5). Fire events are very sensitive to drought, and the largest fire events occur in years when meteorological events cause reduced rainfall over Indonesia (Field et al., 2009; Tosca et al., 2011). Strong El Niño years occurred in 2015, 1982, and 1997, years when the largest fire events of the past 40 years were recorded (Wooster et al., 2012; Koplitz et al., 2016; Pan et al., 2018). Although 2006 did not have a strong El Niño, there was a strong IOD in this year (Figure 1.5), leading to a high fire year (Koplitz et al., 2016). In years without a regional rainfall deficit, localised fire events can still occur. In July 2013, Riau in Sumatra experienced low rainfall and large fires burned; however, this event did not spread to other areas (Betha et al., 2014).

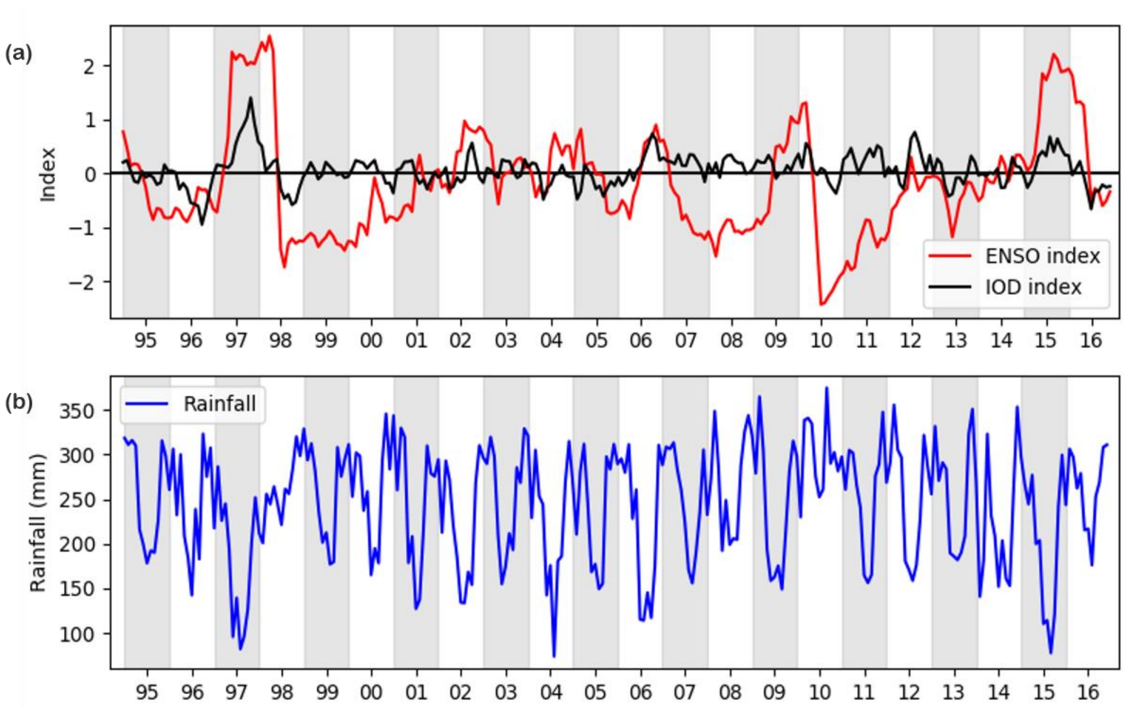

Figure 1.5: (a) Multivariate ENSO Index from NOAA (2020) showing the intensity of the warm (positive index) and cold (negative index) phases of the ENSO in red, and Dipole Mode Index from NOAA (2020a) showing the positive IOD (positive index) and negative IOD (negative index) in black, for 1995 - 2016. (b) Monthly rainfall for Indonesia from the World Bank (2020) for 1995-2016. Shading shows individual years.

Globally, temperatures are predicted to increase in the future, with the amount dependent on emissions scenarios (IPCC, 2014). Future predictions show the climate of Indonesia getting hotter and drier, with less rainfall during the dry season in Southern parts of the country (Herawati and Santoso, 2011; Qalbi et al., 2017). The temperature increase for Sumatra and Kalimantan predicted over the next century under a high emission scenario (3.94 – 3.97°C) is greater than the increase under a low emissions scenario (3.06 – 3.22°C), while the decrease in rainfall is similar for both emissions scenarios (11.8% and 11.9% decrease respectively) (Herawati and Santoso, 2011). It has been predicted that El Niño will be more common in the future due to climate change (Cai et al., 2014), and that El Niño events will be drier (Qalbi et al., 2017). Towards the end of the 21st century there is expected to be increased drought in Indonesia with a risk of fire on more days (Herawati and Santoso, 2011). Large fire events are therefore likely to occur more frequently.

Meteorology also drives the transport of smoke around the region. There is a prevailing south-westerly wind during the dry season which carries smoke from fires in Sumatra and Kalimantan across to Malaysia and Singapore (Figure 1.4; Reid et al., 2013; P.S. Kim et al., 2015). Interactions between trade winds and sea breezes throughout the day lead to changing inshore and offshore winds, which can hold smoke in an area until it is scavenged by local precipitation (Wang et al., 2013). Transport of smoke out of Kalimantan can also be effected by the mountains in the centre of Borneo (Reid et al., 2013).

1.1.3 Peatland fires

Peat is a soil type formed of partly decomposed plants over thousands of years, and accumulation of new peat is slow (Sorensen, 1993). Wiggins et al., (2018) found that peat burnt in fires in Indonesia in 2015 was up to 1200 years old, and some peatlands may be much older (Sorensen, 1993). Peatlands can store huge amounts of carbon, making them an important carbon store (Sorensen, 1993; Page et al., 2011). However, when disturbed, either through exposure or fire, they become a large source of carbon emissions (Miettinen et al., 2012).

Indonesia is thought to have the largest tropical peat reserves in the world (Page et al., 2011; Dargie et al., 2017), with other tropical peatlands being found in Central and South America and Africa, most recently in the Congo (Dargie et al., 2017). Until recently little was known about tropical peat (Page et al., 2007), and there are still uncertainties about the extent of peat and the carbon stored in it. Warren et al. (2017) found that government estimates of Indonesian peatland (15 Mha storing 13.6 Gt carbon) are lower than Wetlands International estimates (21 Mha storing 40.5 Gt carbon). Page et al. (2007) reviewed literature and found estimates of between 17 and 27 Mha peatland in Indonesia, storing 10-32 Gt carbon, assuming the peatland has a 1-2 m depth. Peat thickness data is sparse, as it comes from the field and is time consuming to measure (Page et al., 2011). Jaenicke et al. (2008) use 3D modelling of peat domes with radar data and peat core samples to estimate the 55 Gt carbon stored in Indonesian peatlands, larger than other estimates.

Peatlands in Indonesia are naturally wet, with the water level above the surface for most of the year (Taufik et al., 2018), making them resilient to fire. However, anthropogenic influences can dry out and degrade the peat, leaving it susceptible to burning. When peatlands are converted from natural to managed land, they are drained to make the soil arable (Hooijer et al., 2010). This is done by digging drainage canals around plantations, causing increased run-off and resulting in a drop in the level of the water table (Figure 1.6). Since the 1990s there has been a large scale conversion of peatland; managed land went from making up 11% of peatlands in 1990 to 50% in 2015 (Miettinen et al., 2016). Logging and conversion to plantations are two of the main drivers of peatland degradation (Dohong et al., 2017).

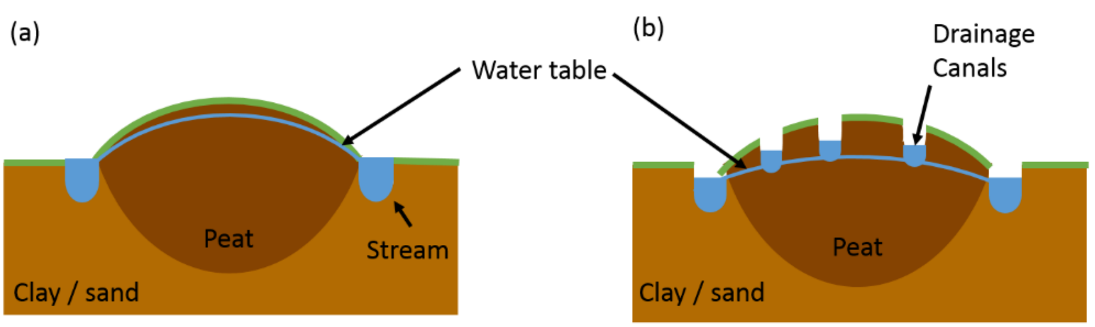

Figure 1.6: The change in water table level between an (a) intact and (b) drained peat dome. Peat above the water table is susceptible to burning. A peat dome might be 10,000-40,000 m across with a centre point 4-10 m higher than the dome edge (Jaenicke et al., 2008).

With drainage canals, the ground water level of peatlands is below the surface year round, and can drop further during periods of drought (Putra et al., 2018). Soil moisture and water levels are an important dynamic of peat fires (Huang and Rein, 2015). Fires can burn down into the peat with the depth of burning controlled by water levels and soil moisture (Rein et al., 2008). High soil moisture slows or stops peat smouldering (Prat-guitart et al., 2016a), although the exact value of this limit varies across studies (Frandsen, 1997; Prat-guitart et al., 2016b). Canals make fires 4.5 times more likely, and without them the groundwater would rarely be low enough for ignition to occur (Taufik et al., 2018). The probability of recurrent fires is also increased close to drainage canals (Konecny et al., 2016). There is little reliable data on the spatial extent of drainage canals, however (Dohong et al., 2017).

Peatland fire characteristics differ to vegetation fires. Vegetation fires are mostly flaming while peat fires burn into the ground and smoulder, often burning for days and even weeks (Yin et al., 2016; Hu et al., 2018). Smouldering fire moves through peat at a slower rate than a flaming fire through vegetation, and the speed of propagation of a peat fire is also dependent on soil moisture (Prat-guitart et al., 2016b). The average spread of fire through peat has been found to be 24-120 cm/day, with a max of 155-216 cm/day, while the speed of a vegetation fire above the surface can often be over 500 m/day, with a minimum of 4 m/day (Usup et al., 2004; Prat-guitart et al., 2016b; Atwood et al., 2016). The speed of surface fires depend on the wind speed and fuel loads.

Fires have a diurnal cycle of burning driven by winds and temperature. The diurnal pattern is slightly different for the two fire types, with the peak burning for peat fires occurring later in the day than for vegetation fires. This may be due to underground fires being less effected by wind and temperature (Wooster et al., 2018).

Fires do not occur randomly, and there is often a high fire density in specific areas of Kalimantan and Sumatra, where peat swamp forest is being converted to plantations (Margono et al., 2014). Miettinen et al. (2017) found that for Borneo and Sumatra 52% of fire detections occurred on peatlands which only made up 12% of the study area. South Sumatra and Central Kalimantan contained 29% of the peatland in the study, yet had 71% of the peatland fires, and deforested peatland had 25 times as many fires detected as on undrained peat swamp.

1.1.4 Notable fire events

The earliest Indonesian fire event which has been well studied was the 1982 dry season event, when a severe fire episode occurred in Central Kalimantan during a strong El Niño (Wooster et al., 2012). This event was unprecedented in size and is the earliest report of regional haze (Sastry, 2002; Aiken, 2004). Two of the largest fire events on record were in the dry seasons of 1997 and 2015 (Wooster et al., 2012; Huijnen et al., 2016). Both were during severe El Niño drought. It is estimated that emissions from the 1997 event may have been over double those of the 2015 event, although lack of satellite products covering both events make them difficult to compare (Huijnen et al., 2016; Yin et al., 2016). Being the largest recent fire event, the 2015 fire event is one of the most studied, both in the field at the time, and in the years after (Crippa et al., 2016; Stockwell et al., 2016; Lohberger et al., 2017; Wooster et al., 2018; Eck et al., 2019; Shi et al., 2019 and others).

Other fire events frequently studied were in 2006 and 2013. Fires in the 2006 dry season were severe, but less so than those in 1997 or 2015 (Varkkey, 2013; Field et al., 2016). Fires in 2013 differed from the other fire events mentioned because they were localised to Riau in Northern Sumatra, and occurred in June (Kusumaningtyas and Aldrian, 2016). Fire in Riau contributed little to emissions in other years (Koplitz et al., 2016). The 2013 fires followed a two month localised dry period during an otherwise wet year (Gaveau et al., 2014). Although the emissions were not large compared to other years, the location meant that the fires caused severe haze for Singapore (Betha et al., 2014).

Differences between studies, such as the area or months included in the study, can make it difficult to compare fire events across studies. There are some studies, however, which focus on multiple years. Wooster et al. (2012) compares fire years in El Niño years of the 1980s and 1990s, and shows that the 1982 and 1997 events stand out amongst these. Varkkey (2013) looks at haze events between 1982 -2012, finding 1997 the worst followed by 2006. Yin et al. (2016) compare carbon emissions from fires from 1997 – 2015, with a focus on the 1997 and 2015 events (also noting emissions in 2006 and 2009 are higher than average). Chang and Song (2010) and van der Werf et al. (2008) both analyse emissions from fires from 2000 – 2006, finding the 2006 fire emissions to be the greatest. The 2006 fire event is also found to have the largest emissions of all fires between 2005 and 2009 (Marlier et al., 2014). Field et al. (2016) and Koplitz et al. (2016) both compare the 2006 and 2015 fire events.

The literature reviewed in this section shows the history of Indonesian fires events and why they occur. Fires are driven by land-use change which has been occurring rapidly over the past few decades. Deforestation and drainage on peatland have resulted in peat being an important fuel source for fires. Peat fires smoulder below the ground, moving at a slower rate and burning for longer than vegetation fires. This behaviour also effects the emissions from the fires, described in section 1.2. When peatland drainage is combined with drought, caused by the dry season and enhanced by anomalous weather events, large fire events occur. Identifying the drivers of fires is critical for modelling them, and important when considering fire prevention, and is therefore meaningful for the work done in Chapter 2 and Chapter 4. Also of key significance is the ‘where’ and ‘when’ of Indonesian fires. Sumatra and Kalimantan have experienced the majority of land-use change, and contain large areas of peatland, and are therefore regions with a high number of fires. Dry season winds transport emissions from these fires to heavily populated regions, including Singapore and Malaysia, which increases the human impacts of fires, relevant to the work done in Chapter 3. The dry season leads to reduced rain in these regions during August to October, while weather events typically occur every few years, leading to an interannual variability in fires. This information has informed the area studied, and the year-to-year approach taken throughout this thesis. Drought conditions are likely to be increasingly common in future years, indicating the importance of understanding fires and their impacts, which has in part motivated this study. The importance of these fires is largely due to the emissions and impacts, discussed in sections 1.2 - 1.4.

1.2 Emissions

When fires burn they emit a multitude of gases and aerosols (Akagi et al., 2011; Stockwell et al., 2016; Jayarathne et al., 2018). Carbon is a major component of emissions, mostly in the form of carbon monoxide (CO), carbon dioxide (CO_2) and methane (CH_4), the three gasses which have the greatest emissions per kg of fuel burnt (Akagi et al., 2011). Carbon is also emitted as an aerosol in organic carbon (OC) (Jayarathne et al., 2018).

Particulate emissions describes all aerosols emitted from fires, containing over 70 different species (Jayarathne et al., 2018). Particulate matter (PM) is commonly grouped by size into PM_{10} (particulate matter less than 10 µm in diameter), $PM_{2.5}$ (particulate matter less than 2.5 µm in diameter) and PM_1 (particulate matter less than 1 µm in diameter). The impacts of particles on the climate and health changes, dependent on the size of the particles. Smaller particles can penetrate further into the body, causing greater health problems, with $PM_{2.5}$ able to enter the lungs and PM_1 able to enter the blood stream (K.H. Kim et al., 2015). Particle size also effects the scattering and absorption properties of particles, important for the climate impacts (Boucher et al., 2013). A subset of PM is OC, which makes up around 72% of the $PM_{2.5}$ emissions of Indonesian fires (Jayarathne et al., 2018). OC from Indonesian peat fires includes Brown Carbon, the absorbing component of the OC (Stockwell et al., 2016). Black carbon (BC) makes up a small mass of total $PM_{2.5}$, but is important due to its optical properties (see section 1.2.2).

Emissions of species depend on the amount of biomass being burnt and on the amounts of each species emitted per kg of biomass, known as the emissions factor (EF). The EFs vary from fire to fire, dependent on the fuel and type of burning. Peat fire emissions can differ from vegetation fire emissions, with a higher EF of PM and lower EF of BC (Iinuma et al., 2007; Stockwell et al., 2016; Wooster et al., 2018). Tropical peat has a higher carbon content than boreal peat, resulting in different EFs (Akagi et al., 2011). Studies have found high levels of sulfur in Indonesian fire smoke, as sulfur from volcanoes in the region is deposited into the peat soils over time (Reid et al., 2013). Sulfur is emitted either as gaseous sulfur dioxide (SO2) or as particulate sulfate within PM. The high PM emissions from peat fires are one reason the impacts of Indonesian fires are so high, and what makes the emissions from the region so large (Van Der Werf et al., 2010). Indonesia contributed 41% of fire emissions in Equatorial Asia in 2000-2009, with only 2% of the burned area (Song et al., 2010). Wooster et al. (2018) suggest that 95% of $PM_{2.5}$ from the Indonesian fires in 2015 was from peatland.

Emissions from peat fires can vary over time and for fires in different locations. Roulston et al. (2018) found that when peat fires burn ash can build up which will reduce the $PM_{2.5}$ emissions over time. The emission are therefore highest on the first day of burning. Wooster et al. (2018) found that for several smoke plumes across five sites in Kalimantan in 2015, emissions factors for CO_2 varied by about 10% and emissions factors for $PM_{2.5}$ varied by about 50%.

Heat from fires causes convection which lofts smoke into the air creating a smoke plume. Smoke plume dynamics, such as the top height of the plume, can depend on the heat produced by a fire and the atmospheric stability, which depend on fire type and location. Smouldering fires tend to have lower plumes, with emissions remaining close to the surface. Tosca et al. (2011) estimated the height of smoke plumes in 2001-2009, finding an average height of 709 m for Borneo and 749 m for Sumatra. Between dry and wet years average plume heights varied by around 100m. Tosca et al. (2011) found the majority of plumes were confined to within 500m of the boundary layer top height. Smoke clouds, however, have been observed up to 2000m (Tosca et al., 2011).

Emissions estimates can vary significantly between studies. For example, studies calculating emissions of CO from Indonesian fires have estimated the 1997 fires emitted between 124 and 345 Tg CO and the 2015 fires between 84 and 138 Tg CO (Table 1.1). Differences can be due to slightly different areas or periods of study, or due to uncertainties in emissions inventories. These make it difficult to compare estimates of fire emissions in different years between studies.

Table 1.1: Emissions of CO estimated by different studies. Variations in estimates due to different study areas or periods and uncertainties in emissions, make it difficult to compare between years.

	Tg CO	Study	Parameters of study
1997	345	Heil et al. (2007)	Indonesia; June-December 1997
	124	Duncan et al. (2003)	Borneo, Sumatra, New Guinea; September – Nov 1997
2015	122	Yin et al. (2016)	Indonesia, Malaysia and Papau New Guinea; June 2015-October 2015
	84	Huijnen et al. (2016)	Indonesia, Malaysia and Papau New Guinea; September 2015 – October 2015
	113-138	Nechita-banda et al. (2018)	Indonesia and Papau; mid-August – mid-November

1.2.1 Emissions Inventories

Emissions inventories combine the amount of fuel burnt with the EF of different species to create emissions estimates for fires. The amount of a fuel burnt is determined by the burned area and the fuel loading in that area. Difference fire emission inventories estimate burned area and fuel loading in different ways. The Fire Inventory from NCAR (FINN; Wiedinmyer et al., 2011), the Global Fire Emissions Database (GFED; van der Werf et al., 2017) and the Global Fire Assimilation System (GFAS; Kaiser et al., 2012) are three global fire emissions inventories which are commonly used, and there are slight differences in the methods used. There are also uncertainties associated with these methods.

For the burned area, GFED uses a satellite burned area product and FINN uses active fire detection with a burned area of 1 km^2 assigned to each fire detected. GFAS uses satellite fire radiative power which is converted to the amount of fuel burnt using a conversion factor. Even during the dry season Indonesia has a lot of cloud cover, and this can be a problem for satellite detection of fires in the region (Kaiser et al., 2012; Yin et al., 2016; Lohberger et al., 2017), particularly for measuring burned area. Sometimes smoke from fires can also obscure satellite imagery (Shi et al., 2019). If the burned area is only visible at a later date, then the timing of the fire detection may be wrong (Giglio et al., 2013; Nechita-banda et al., 2018), and if the burn scars are not visible within two to three weeks then vegetation regrowth may have already covered them. Repeat fires over an area within the same season may also be missed when using satellite burned area (van der Werf et al., 2017).

Fire radiative power and active fire detection also have uncertainties associated with them (Freeborn et al., 2014). Active fire hotspots from the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the Terra and Aqua satellites can be underestimated due to the timing of the satellite, if fires occur outside of the overpass window (Hyer et al., 2013; Liu et al., 2020). Tansey et al. (2008) suggest that MODIS hotspots can have omission errors of up to 60%, due to satellite coverage, saturation or cloud cover. They suggest that false hotspots only happen 8% of the time, although Syaufina and Sitanggang (2018) suggest that only hotspots lasting two or more days in Indonesia are likely to be real fires. There is also uncertainty in the burned area that should be applied to each hotspot, as it is likely to depend on the location and fire type

(Tansey et al., 2008). For fires in Indonesia 1 km^2 per hotspot (as used in the FINN inventory) is likely to overestimate the area burned (Atwood et al., 2016). Liu et al. (2020) suggest that MODIS hotspots may be better to use in Indonesia than burned area. The conversion of fire radiative power to fuel consumed used in GFAS is from GFED, which could lead to underestimation of small fires (Liu et al., 2020).

Emissions from small fires can increase total Indonesian fire emissions by 157% (Randerson et al., 2012), but small fires can be difficult to detect using burned area (Liu et al., 2020). To account for this the most recent version of GFED (GFED4s) uses fire radiative power (FRP) alongside burned area to detect small fires. Wiedinmyer et al. (2011) suggest that small fires may also be missed by the hotspot detection used in FINN, although Hoelzemann et al. (2004) suggests hotspot detection is the better method for detecting small fires. Alternately, FINN may overestimate small fire emissions by assuming that at least 75% of a pixel areas is burned when a fire is detected (Liu et al., 2020).

All three global fire emissions inventories use EFs to convert biomass consumption into emissions and these also have uncertainty (Hu et al., 2018). Natural variations in external factors such as relative humidity, temperature and winds can cause EFs to vary over time, and variations in the fuel dynamic, such as water content, or previous burn history can change EFs (Iinuma et al., 2007; Kuwata et al., 2018).

EFs can be measured in the field by passing air samples through a spectrometer close to the fire to measure the species (Stockwell et al., 2016). Measurements taken upwind from fires are used to determine background levels, and the ratio of each emissions species to CO or CO_2 is found. This ratio can be combined with the mass fraction of carbon in the fuel type, to get the EF. For particulate matter EFs, the ratio of PM collected on a filter to CO in the same air mass is used to scale the CO EF (Jayarathne et al., 2018; Wooster et al., 2018). It can be difficult to distinguish between flaming and smouldering emissions in the field (Andreae and Merlet, 2001), or between multiple fuel types, such as peat and the overlying vegetation (Stockwell et al., 2016). Emissions factors are applied based on the fuel type a fire is detected on, which comes from land cover maps. There can be errors in these however, particularly for Indonesia where rapid land cover change is occurring (Hyer and Chew, 2010).

Calculating peat fire emissions has additional difficulties than for vegetation fires. Until recently, there were very few measurements of tropical peat fire emissions (Kuwata et al., 2018), and emissions factors for tropical peat can be larger than those for boreal peat (Hu et al., 2018). The peat EFs used in GFED and GFAS came from a single laboratory study of Indonesian peat burning by Christian et al. (2003), and as this study does not give a value for $PM_{2.5}$ EF, both inventories use the EF for tropical forest instead (van der Werf et al., 2008). This could be underestimated by a factor of three (Wooster et al., 2018; Roulston et al., 2018). The FINN inventory does not include peat burning, and any emissions on peatland are from the surface vegetation only.

As peat fires burn below the surface, a burn depth is needed to calculate emissions. This cannot be easily detected by satellite, so is estimated. GFED uses soil moisture to estimate burn depth, between an upper and lower limit. In GFED4s soil moisture from the European Centre for Medium-Range Weather Forecasts (ECMWF) is used, while in earlier versions the soil moisture was calculated using rainfall data (van der Werf et al., 2017). Soil moisture is likely the controlling factor of the depth a peat fire burns to (Frandsen, 1997; Huang and Rein, 2015), but the relationship is complex. There may be a lag between rainfall and groundwater level (Putra et al., 2018), and burn depth can also depend on nearby drainage canals (Konecny et al., 2016; Page and Hooijer, 2016). It is unclear how repeated burning may affect the available peat, but Konecny et al. (2016) suggests that the burn depth decreases for repeat fires. The upper and lower limit of burn depth come from studies in the field, but there are few of these (Page and Hooijer, 2016), and there is a large variation in burn depth between fires (Wooster et al., 2012). Moreover, studies are likely to choose large fires as they are also often measuring emissions, and so burn depths may be higher than average (Stockwell et al., 2016). Lidar and radar have been used to detect burn depth (Jaenicke et al., 2008; Ballhorn et al., 2009), but this data is not available on a large scale.

Finally there is a lot of variation in the peat itself. Peatland in Indonesia can also include other soil types, with layers of sand or clay which have different properties when burnt

(Shimada et al., 2001; Smith et al., 2018). The density and carbon content of peat can also change across locations and with depth (Warren et al., 2012; Stockwell et al., 2016). Sinclair et al. (2020) found that peat density increased close to drainage canals, with forest degradation, and after repeated fires. Over time emissions from a peat fire vary, and Roulston et al. (2018) suggest the EF should reduce by 9% each day.

Generally these global emissions inventories underestimate PM emissions in Equatorial Asia. FINN underestimates PM emissions the most of the three datasets, due to not including peat fires (Reddington et al., 2016). GFEDv1 did not include peat combustion, and also had a large underestimation in Equatorial Asia (van der Werf et al., 2006). Kaiser et al. (2012) find that using GFAS emissions causes the Monitoring Atmospheric Composition and Change aerosol model to underestimate aerosol optical depth (AOD). For species other than PM, however, emissions inventories may be overestimating. Heymann et al. (2017) find top down estimates of CO emissions are less than those given by GFED and GFAS. Whitburn et al. (2016) also use top down estimates to suggest that GFED overestimates NH_3. Shi et al. (2015) suggest that FINN could be overestimating CO_2 emissions from savannah and crop fires.

Often fire emissions inventories, or simulated PM concentrations, are scaled for Equatorial Asia, to account for the underestimation in PM. Koplitz et al. (2016) scaled GFAS by 50% to use for simulating air pollution from the 2015 fires, and Marlier et al. (2012) scaled simulated AOD and $PM_{2.5}$ by a factor of 1.36-2.26 when studying air quality from fires in South East Asia. Hyer and Chew (2010) found that simulated PM_{10} in 2006 was underestimated by a factor of 2.5-10, which they suggest is partially due to the fire emissions used not including the correct fuel types for Indonesia. Reddington et al. (2016) found that globally FINN, GFAS and FINN all required scaling in various studies.

Other emissions inventories for Indonesian fires are the Fire Energetics and Emissions Research (FEER) inventory and the Quick Fire Emission Dataset (QFED) (Ichoku and Ellison, 2014). These inventories apply a top down method to calculate aerosol emissions, which may negate some of the previously discussed problems around fuel types. In Indonesia, these top-down emissions inventories better match the increased smoke in high fire years than FINNv1.5, although not as well as GFAS (Liu et al., 2020). Fire Locating And Modelling of Burning Emissions (FLAMBE) provide a global emissions product which uses MODIS active fire detection combined with EFs (Reid et al., 2009) and has been used previously to study Indonesian fires. It has also been found to underestimate Indonesian fire emissions, likely due to the lack of peat and plantation fuel types (Hyer and Chew, 2010).

1.2.2 Impacts of fire emissions

When emissions are dispersed, increased concentrations of chemical species and particles occur in the surrounding atmosphere. High concentrations of PM in Singapore have been repeatedly traced back to peat fires in Indonesia (Hyer and Chew, 2010; Engling et al., 2014; Aouizerats et al., 2015; Kusumaningtyas and Aldrian, 2016; Budisulistiorini et al., 2018; Eck et al., 2019). High concentrations of $PM_{2.5}$ cause poor air quality, and the World Health Organization (WHO) suggests that daily $PM_{2.5}$ concentrations should be below 25 μg m^{-3} (World Health Organization, 2005). This limit is frequently exceeded in Indonesia, Singapore and Malaysia, as a result of emissions from fires (Figure 1.7). The impacts of air quality on human health are presented in section 1.3.1. High $PM_{2.5}$ concentrations have also been found to cause signs of stress in Orangutans (Erb et al., 2018).

High concentrations of pollutants can result in reduced visibility, commonly referred to as haze events. Lee et al. (2017) found that fire emissions caused 34% of the haze days in Singapore between 2003 and 2014, with half of these caused by fires in Sumatra.

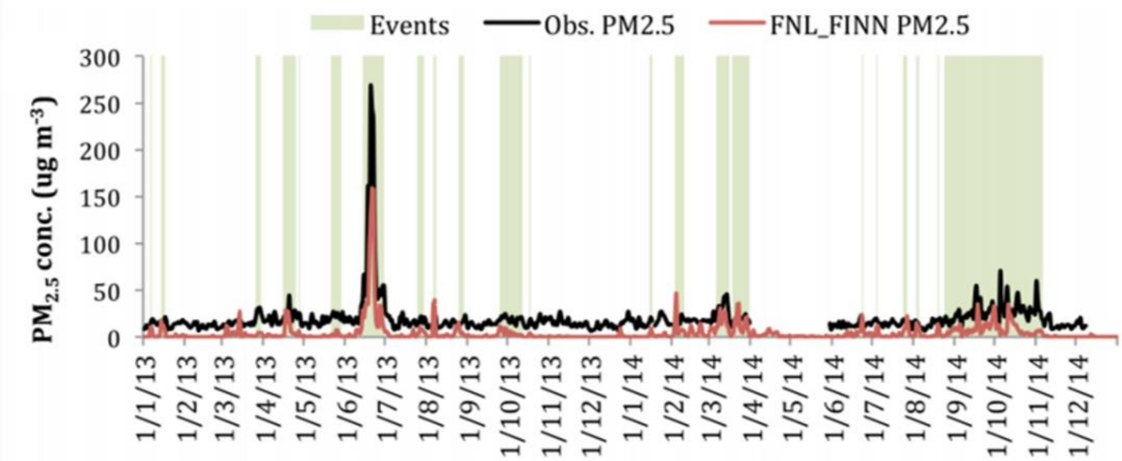

Figure 1.7: Observed and simulated $PM_{2.5}$ concentrations frequently exceed 25 μg m^{-3} during fire related haze events (green) in Singapore in 2013 – 2014. Adapted from Lee et al. 2017.

Haze events are commonly portrayed in local and global media and on social media, particularly with regards to the health impact of the haze, widening awareness of the fires (Figure 1.8; Ekayani et al., 2016; Lin, 2019).

Fires in Indonesia emit large amounts of CO_2 and CH_4 (van der Werf et al., 2017). The CO_2 emissions from the 2015 Indonesian fires have been estimated at 547-692 Tg (Huijnen et al., 2016; Jayarathne et al., 2018), with a daily CO_2 emissions rate (11.3 Tg day^{-1}) greater than the daily fossil fuel CO_2 rate for the European Union (8.9 Tg day^{-1}; Huijnen et al., 2016). Fires are an important source of atmospheric CH_4, particularly smouldering peat fires (Hatano et al., 2016). Emissions of CH_4 can vary substantially between fires, with greater emissions for denser peat, suggesting that degraded peatland, which has a higher density, will have greater emissions when burnt (Smith et al., 2018). The CO_2 and CH_4 emitted from fires contribute to greenhouse gases and warming in the atmosphere. Pribadi and Kurata (2016) suggest that the greenhouse gas emissions from Indonesian fires between 2000 and 2012 make the largest contribution to Indonesia's total greenhouse gas emissions, almost twice that of all other sectors, including energy, industry and agriculture.

Emissions from fires can also effect levels of ozone in the atmosphere, a species which, in the troposphere, can be detrimental to human health, damaging to plants, and

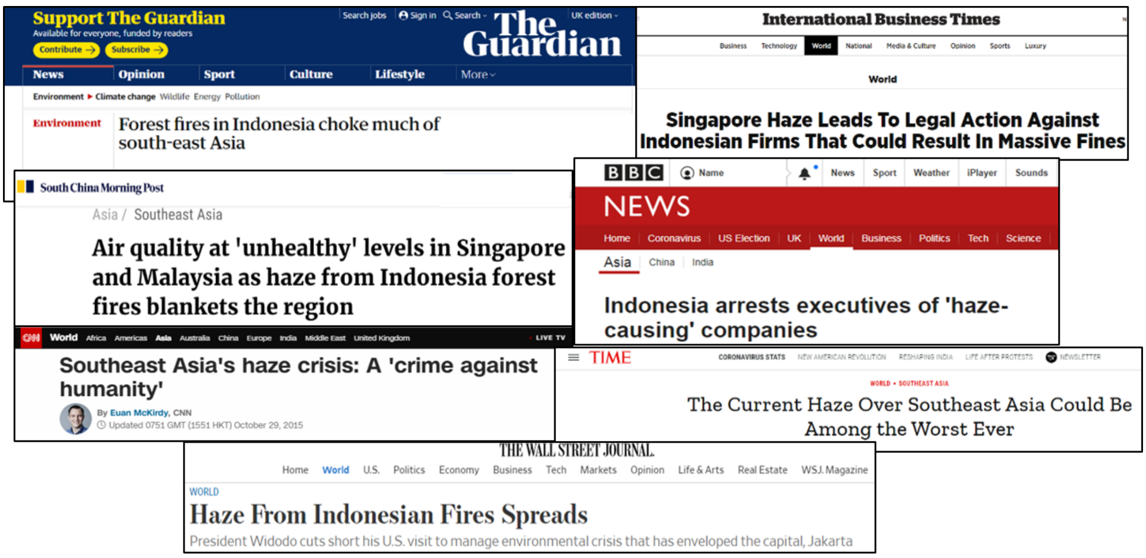

Figure 1.8: Global news headlines during and after the 2015 fire event showing the concern over haze caused by fires. Accessed from various news websites on 29/08/2020.

contributes to greenhouse gasses and to haze (Monks et al., 2015). Fires in the United States (US) have been linked to increased ozone levels, particularly over cities (Brey and Fischer, 2016). Ozone in the troposphere is produced through photochemical oxidation of volatile organic compounds (VOCs) and CO in the presence of NO_x (Brasseur and Jacob, 2017). Peatland fires emit VOCs, CO, NO and NO_2 (Hu et al., 2018), and can contribute to the production of tropospheric ozone. Indeed, high concentrations of CO_2, NO_x and ozone have all been measured in Indonesian fire plumes (Tsutsumi et al., 1999).

Aerosols in the atmosphere can interact with radiation through the scattering and absorption of solar radiation (Boucher et al., 2013). Overall this scattering is likely to have a net cooling effect, although for BC the solar radiation absorption can lead to warming (Boucher et al., 2013). The increased vertical stability from the particle heating can also reduce convection and clouds. When absorbing aerosols, such as BC, are found in the cloud layer, cloud cover has been found to decrease. When found above the cloud layer, however, absorbing particles may increase clouds (Boucher et al., 2013). Indeed, Hodzic and Duvel (2017) found fire aerosols over Borneo can increase or decrease convection, depending on the aerosol type, and Kolusu et al. (2015) found that fires in the Amazon can change the boundary layer height and effect winds, through heating and cooling of different levels of the atmosphere. Aerosol scattering of solar radiation can also increases the radiation available at the surface, by redirecting radiation to previously shaded areas. This effects the productivity of forests. A study over the Amazon found that aerosols from fires resulted in enhanced net primary production, and increased the carbon sink of forests, mitigating some of the carbon emissions from the fires (Rap et al., 2015).

Within clouds, aerosol-cloud interactions can affect the height, lifetime and water content of clouds, which will cause changes to rainfall (Boucher et al., 2013). Aerosols can also effect the albedo of clouds, increasing the reflectiveness (Boucher et al., 2013). Aerosols from fires have been shown to reduce or delay rainfall (Rosenfeld, 1999; Andreae et al., 2004; Grant and van den Heever, 2014; Lee et al., 2018). Tosca et al. (2013) find that smoke aerosols cause a reduction of rainfall in the tropics, and Tosca et al. (2010) suggest that black carbon from fires reduces precipitation in Indonesia and increases drought during El Niño. Reduced rainfall can then lead to less removal of pollutants from the atmosphere, further increasing poor air quality (Ramanathan et al., 2001). But links between aerosols and meteorology in Southeast Asia are uncertain (Boucher et al., 2013; Reid et al., 2013). Rosenfeld et al. (2008) suggests that competing effects of aerosols confuse the impact of fires on rainfall. Takahashi et al. (2017) finds that the contribution of land cover change after fires can have an effect, and rainfall can increase due to increased convection.

Two key findings from the literature reviewed in this section are the many impacts fire emissions can have, and the uncertainty around peat fire emissions. The impacts on air quality, meteorology and the climate illustrate the importance of understanding Indonesian fire emissions, but global emissions inventories often underestimate them. This gives a significant motivation for studying Indonesian fires.

The complex dynamics of peat fires described in this section is central to the work done in Chapter 2. Many of the findings from recent field studies are yet to be included in global emissions inventories, although they have previously been used to estimate emissions from individual fire events. These estimates are not easily comparable between events, and it is uncertain how fire emissions and subsequent impacts vary over a period of time.

1.3 PM in the atmosphere

Concentrations of particulate matter in the atmosphere are dependent on primary emission, secondary formation, and removal through dry and wet deposition (Figure 1.9).

Primary PM emissions come from fires, anthropogenic, and natural sources, and include mineral dust, sea salt, BC, and organic aerosol (OA) (Boucher et al., 2013). Secondary formation of PM occurs through reactions of gaseous precursors, such as SO_2, ammonia, NO_x and VOCs, creating sulfate, nitrate and ammonium particles, and also OA (Boucher et al., 2013). Particles are nucleated from gasses to form ultrafine PM (<0.01 µm). These particles grow in size through condensation and coagulation to form fine PM (0.01-1 µm). Particles are also emitted as course PM, greater than 1µm in

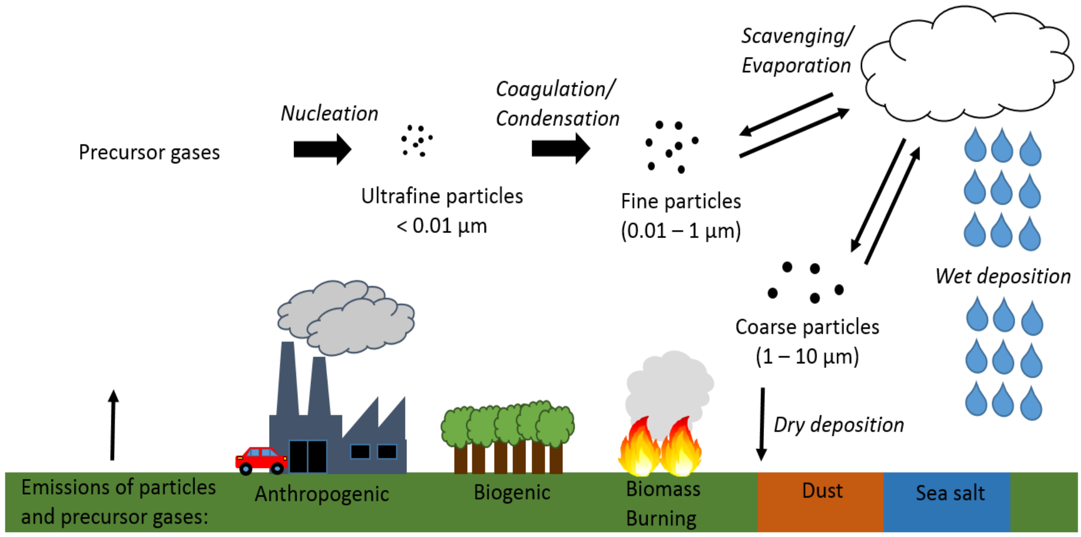

Figure 1.9: The life cycle of particulate matter in the atmosphere.

diameter. Secondary organic aerosols (SOA) rely on the oxidation of VOCs, which are emitted from peatland fires (Hu et al., 2018), although there is uncertainty as to the magnitude of SOA produced in fire smoke (Ortega et al., 2013; Aouizerats et al., 2015). Of the PM_1 reaching Singapore in October 2015, Budisulistiorini et al. (2018) found that 80% was organic aerosol, and of this 30% was primary fire emissions while up to 50% was SOA, although it is difficult to determine exact amounts. SOA is important for water uptake and aerosol-cloud interactions (Chen et al., 2018).

Concentrations are also effected through the removal of PM. Particles are removed from the atmosphere through in-cloud and below cloud scavenging, and also through dry deposition at the surface. For coarse particles, removal can also occur through sedimentation. The lifetime of PM in the atmosphere depends on the size of the particles. Coarse particles have a lifetime of around 1 day, while fine and ultrafine particles can remain in the atmosphere for around 7-10 days (Boucher et al., 2013). $PM_{2.5}$ can travel 100s to 1000s of kilometres before being removed (K.H. Kim et al., 2015).

1.3.1 Air quality problems & dangers

Fires in Indonesia cause increased PM concentrations in densely populated regions across South East Asia (Reddington et al., 2014). When $PM_{2.5}$ is inhaled it can get into the body and cause many health problems (P.S. Kim et al., 2015). High concentrations of $PM_{2.5}$ can cause respiratory problems, heart attacks and stroke (Reid et al., 2016). In 2016, exposure to $PM_{2.5}$ reduced global life expectancy by 1-2 years (Apte et al., 2018). While any exposure to $PM_{2.5}$ is thought to be detrimental to health, the WHO has set air quality standards, with PM limits which result in an acceptable level of risk (World Health Organization, 2005). For $PM_{2.5}$ the WHO recommendation is that annual average $PM_{2.5}$ concentrations should not be above 10 µg m^{-3}, and 24 hour averaged $PM_{2.5}$ concentrations should not be above 25 µg m^{-3}. Reducing $PM_{2.5}$ concentrations to within these guidelines can drastically reduce mortality (Apte et al., 2015).

Globally, fire events have been linked with increased hospital visits for respiratory and cardiovascular illnesses (Delfino et al., 2009; Ignotti et al., 2010; Henderson et al., 2011; Rappold et al., 2011; Liu et al., 2017; Reid et al., 2019), and with increased mortality (Analitis et al., 2012; Sahani et al., 2014; Faustini et al., 2015; Tinling et al., 2016). Haze from the Indonesian fire events has been shown to have caused increased respiratory illness, cardiac problems and mortalities in Singapore, Malaysia and Indonesia (Emmanuel, 2000; Jayachandran, 2013; Sahani et al., 2014; Kim et al., 2018). Sastry (2002) found that increased mortalities in Malaysia as a result of the 1997 fire event effected all age groups, although the greatest increase was seen for people aged over 65. These studies look at the immediate effects of fires on health, but the effects can also go on for years. Tan-Soo and Pattanayak (2019) found that pre-natal exposure to smoke from the 1997 fires caused a decrease in height in adulthood, something which is also linked to income.

Many of these studies are showing the effects of short term exposure, during a fire event lasting days. Indonesian fire events, however, often last for months, and there is therefore long-term exposure to high $PM_{2.5}$ concentrations, which has a larger effect that short-term exposure (World Health Organization, 2005). Johnston et al. (2012) use long term exposure functions when estimating mortality from fires in South East Asia, due to the chronic exposure to smoke. The health effects from long-term exposure are estimated using cohort studies, and risk functions for different diseases are made by plotting the risk from multiple cohort studies against the concentration exposed to. Cohort studies use $PM_{2.5}$ exposure from several sources and often include studies on smoking at the top end of the risk function (Burnett et al., 2014; GBD 2017 Risk Factor

Collaborators, 2018; Burnett et al., 2018). Risk functions have seen large improvements in the last decade, although further studies are still needed (Ostro et al., 2018). Cohort studies are commonly done in Western countries, where ambient $PM_{2.5}$ concentrations are often much lower. The Global Exposure Mortality Model (GEMM) risk functions from Burnett et al. (2018), include a study from China, meaning that it may be more realistic for use in Asia.

The use of all-source $PM_{2.5}$ could also be unrealistic when calculating health impacts, as the toxicity from fire smoke may differ from other types of PM (Naeher et al., 2007; Lelieveld et al., 2015). Even across different fuel sources of fires, and types of burning the health impacts can vary. Kim et al. (2018) found that out of Oak Pine, Eucalyptus and peat burning, PM from peat had the highest toxicity for smouldering fires and the second highest for flaming. Per kg of fuel burnt, peat toxicity was similar to oak and pine, although eucalyptus was higher. The high toxicity of peat PM is possibly due to having coarser $PM_{2.5}$, which in mice effects the lungs more and the heart less than fine $PM_{2.5}$ (Kim et al., 2014).

Using risk functions to estimate the mortality from fire smoke, Johnston et al. (2012) find global mortality between 1997 and 2006 was 339,000 deaths per year, with around a third of these in South-East Asia. They find that global mortality in El Niño years is over double that of La Niña years.

Crippa et al. (2016) estimated exposure to $PM_{2.5}$ from fires in Equatorial Asia in 2015, and the resulting health impacts. They find that 69 million people were exposed to high concentrations of $PM_{2.5}$ for at least half of September – November 2015. They provide two estimates for mortality resulting from fires, 11,880 premature deaths from short-term exposure over the three months, or 75,600 deaths from long term exposure, looking over the entire year. Koplitz et al. (2016) estimated 100,300 excess deaths from long-term exposure to smoke from the 2015 fires, higher than the estimate from Crippa et al. (2016) . This is due to the risk response function used being more sensitive in the Koplitz et al. (2016) study. Koplitz et al. (2016) estimate that the 2006 fire event resulted in 37,600 excess deaths, 2.7 times lower than for 2015. Marlier et al. (2012) found that during El Niño years between 1997 and 2006, fires resulted in an estimated

10,800 excess adult cardiovascular mortalities. Comparing between studies is difficult due to the different methods used, and the multi-year impact of fires on health is unclear.

As well as the premature mortality caused by fires, years of life lost (YLL) and years of life disabled (YLD) can be estimated using similar calculations. YLL combine life expectancy and the age of death with the number of mortalities, and YLD combines the number of cases with the number of years they last for. Combining these gives disability adjusted life years (DALY), a metric used to evaluate the total health impacts of fires (Devleesschauwer et al., 2014).

The base of estimating health impacts of fires comes from simulated $PM_{2.5}$ concentrations caused by fires. Areas effected by smoke can depend on wind direction (Kuwata et al., 2018), and Hansen et al. (2018) shows that small-scale meteorology can be important for modelling the haze in Singapore. Health impacts also depend on the population exposed, and the location of fires is important. Koplitz et al. (2016) found that although fire emissions are greater in Kalimantan, Sumatran fires contribute more to population exposure and mortality, due to the proximity to heavily populated regions. Marlier et al. (2015) find the same, as do Reddington et al. (2014).

This section has described the strong link between increased PM concentrations due to fires and adverse health impacts, which is the rationale behind the work done in Chapter 3. Methods for estimating the health impacts, and the applicability to Indonesian fire haze, have also been discussed. Of particular significance is the benefit of using the GEMM relative risk function, which informs the methodology used in Chapter 3. Previous estimates of the mortality caused by exposure to fire haze suggest that the health impacts are substantial; however they also vary considerably, and there are few studies to compare between. This points to a need for further work to better quantify the health impacts of Indonesian fires. Another key message in this section is the importance of atmospheric transport and chemistry on simulating health impacts. These dynamics are controlled by the model used, and are considered in Appendix A.

1.4 Economics of Fire

The clearing of land in Indonesia is primarily for economic benefit. Since the 1960's forest resources have been used for export and profit, and in the 1980's, when laws restricting foreign investment were removed, oil palm and logging started to be financed by foreign companies (Tsujino et al., 2016). There are large profits in oil palm; The World Bank (2016) suggests that if all the area burned in 2015 was converted to oil palm it would be worth US$8.8 billion. Purnomo et al. (2017) found that cleared land in Riau could be sold for US$665 per hectare, while cleared and burnt land is worth US$856 per hectare. The benefits are felt at multiple levels, with community organisers getting up to US$468 of this amount, while those clearing and burning the land receive US$188.

Fire is often thought to be the most cost effective method of clearing land and the financial benefit for land owners is clear. Clearing land mechanically requires equipment, and the land may require fertilization before planting. Varma (2003) suggests that in 1997 the cost of preparing land for planting in Indonesia without using fire would have been US$1.01 billion. Simorangkir (2007) finds that in some cases mechanically clearing land can be cost effective if the removed timber is sold, but it depends on the land type and forest density. Mechanical equipment is also often not an option for small-scale farmers.

Alongside the economic benefit of fires, there is also a cost. The economic cost of fires can be estimated by summarising the economic losses resulting from the different impacts of fires. Losses can come from direct damage by fires, such as to crops, forest resources, equipment and infrastructure. The financial losses from damages to forests can include lost products such as timber, rattan, honey and nuts, lost services such as clean water and pollinators, and lost recreational and tourism activities (Varma, 2003; World Bank, 2016b). The loss of crops and forest can impact across several years, if the crop takes time to mature (World Bank, 2016b). Economic costs also come from the disruption caused by haze, such as health impacts and reduced productivity. In Equatorial Asia haze has been known to impact transport, oil production and mining, cause school closures, and it has been suggested that crops may even be impacted by the reduction in sunlight (Tacconi, 2016). The health impacts of fire haze can relate to economic losses through associated medical costs and loss of income, or can be estimated by finding the value people are willing to pay to prevent becoming ill (World Bank, 2016a). De Mendonça et al. (2004) finds that costs resulting from the latter method are greater than hospital costs and suggests that willingness to pay evaluates the total losses experienced by a person. Environmental damages, such as increased greenhouse gas emissions and reduced biodiversity also have associated costs. Reduced tourism during periods of haze, or due to biodiversity losses, can have large financial losses (Glover and Jessup, 2006; Doerr and Santin, 2013; World Bank, 2016b; Tacconi, 2016). Finally, additional costs come from fire suppression. Costs without a direct market value, such as health and social impacts, are difficult to measure and subject to approximations (Tacconi, 2002).

Different studies focus on different costs. For the 1997 fire event, costs for Singapore have been estimated by two studies. Glover and Jessup (2006) used data on hotel occupancy and the losses registered by airlines to estimate the costs of the fires to the tourist sector, and used hospital costs and data on hospital visits to estimate the cost for the short-term health impacts of the fires. They found the total cost to be US$69-79 million. Quah (2002) estimated a much larger cost of US$164-286 million in total damages. Quah (2002) also considered the loss of tourism and the short term health impacts, the latter including loss of earnings from illness as well as hospital costs. These totals are likely underestimated, as many fire impacts are not accounted for (Quah, 2002).

Varma (2003) estimated that the 1997 fires cost US$19.7 billion for Indonesia. This cost includes losses caused by damage to forest, including timber, rattan, genetic resources, water control, pollinators, recreational spaces and tourism. However they do not include health related costs, firefighting costs or loss of trade. Varma (2003) shows that the expected benefits of using fire to clear land (US$1.04 billion) are far smaller than the costs. In 2013, Kusumaningtyas and Aldrian (2016) found that fires slowed economic performance in Sumatra. An increase in inflation was caused by the disruption and delay of transporting goods due to haze, and cancelled flights also led to an economic loss for airlines.

The most comprehensive cost evaluation of Indonesian fires has been done by The World Bank (2016) for the 2015 fire season. They include damage to agriculture and forestry, impacts on trade, transportation and tourism, the costs of short-term health effects, and of the fire suppression, environmental costs such as CO_2 emissions and biodiversity loss, and also loss of productivity from schools closing and impacts on manufacturing and mining. They estimate a total cost across all these sectors of US$ 16.1 billion. Calculated in a similar way, the costs of the 2019 fire episode have been estimated as US$ 5.2 billion. For both these estimates, over half of the costs come from the CO_2 emissions of the fires and the damage to agriculture.

The current global view of fires in Indonesia may also result in future financial losses. The World Bank (2019) Indonesian Economy report suggests that fires give a negative connotation to palm oil exports, and results in declining demand from Europe. The European Union is considering banning palm oil as a biodiesel from 2030, which could result in losses of US$467 million (Purnomo et al., 2020).

In a study looking at the cost of fires in the Amazon, De Mendonça et al. (2004) suggests that only accidental fires should be considered to have caused unwanted damage, since the intentional use of fire obeys an economic rationale. This has not been considered by studies looking at Indonesian fires, however. One reason could be that it is difficult to determine accidental fires in Indonesia, where fire is used within established land uses as well as during land conversion. Tacconi (2002) suggests that costs associated with fire damage to crops and plantations could be overestimated, as the area may not have been planted before the fire. Tacconi (2002) also suggests that the economic cost from forest loss may be too high, as many factors such as soil erosion and biodiversity loss may not result in direct economic losses.

While it is clear who is benefitting from these fires, it is less obvious who should be paying for the costs. Simorangkir (2007) found the companies which are profiting are often not responsible for the cost. Lin et al. (2017) surveyed the public to estimate Singaporeans ‘willingness to pay’ for a haze reduction, and found that on average people were willing to pay 1% of their income for clean air, the equivalent of US$643 million.

Globally the cost of Indonesian fire events is of a similar scale to other fires. González-Cabán (2013) find that Californian wildfires in 2003 had an estimated economic impact of over US$10 billion, while financial losses of South American fires were up to US$1.6 billion annually. For 1993-1996 De Mendonça et al. (2004) estimates average costs of fires in the Amazon to be up to US$5 billion. A series of fires in San Diego in 2003 cost US$2.45 billion (Diaz, 2012). Australian bushfires between 1982 and 2009 cost up to US$2.9 billion per event (Stephenson et al., 2013).

This section highlights the importance of economics on the use of fire. Fires have been shown to have an economic benefit, and also a cost. This cost comes from the many impacts of fires on the environment and health, and estimates vary in what impacts they include. Current estimates of the economic cost of fires do not include the long-term health impacts, meaning that the total costs are likely underestimated. Costs associated with CO_2 emissions and damage to land cover have been shown to be significant, a finding which informs the approach taken in Chapter 4. Understanding the economic impact of fires is important, particularly as a motive for fire mitigation, discussed in the next section. However, costs have previously been estimated for only three Indonesian fire events, meaning the total economic impact of fires in recent years is uncertain.

1.5 Fire prevention

Since the large fire event in 1983 there have been national and international efforts to prevent fires in Indonesia (Dennis, 1999). The detrimental impact to human health and the substantial greenhouse gas emissions make them a pressing issue for the region, particularly as fire events are predicted to be more common in the future. Fires have been increasing in recent years (Yin et al., 2016) and have been more severe than during previous years with similar levels of drought (Field et al., 2016). Climate change is predicted to cause southern parts of Indonesia to be drier, and to cause lower water levels in peatlands during the dry season (Herawati and Santoso, 2011; Dohong et al., 2017). Business as usual scenarios see increasing land-use change and increasing use of fires in the future (Marlier et al., 2014), and high emissions could occur unless peatlands are conserved (Marlier et al., 2015).

Fires in Indonesia are closely linked to land-use change (Adrianto et al., 2019) and land management is key to future emissions (van der Werf et al., 2008). Since fires are anthropogenic in origin, an enforced ban on the use of fire should be enough to prevent them. However, as land is cleared and drained it becomes susceptible to fire, and so fire prevention and reduced land-use change must be considered together. Restoring peatland swamps and protecting forests from land clearing are therefore fire prevention methods, alongside fire bans. Atwood et al. (2016) found that some fire boundaries in 2015 matched where canal blocking and peatland restoration had occurred.

1.5.1 Policy on fire and land-use change

Indonesia's history of fire prevention is complex, as deforestation and land-use change are rooted in Indonesia's political structure (Tsujino et al., 2016). Herawati and Santoso (2011) and Ekawati et al. (2019) give an overview of relevant government policies on fire. The first government response to fires in the 1980's was to establish the National Centre for Forrest Control and the National Co-ordinating team for Land Fire. In 1999 an act was passed forbidding the burning of forest, with a penalty of US$500,000 and 15 years imprisonment, followed by a pollution regulation in 2001 prohibiting the burning of all land. In 2004 an act named plantation companies responsible for controlling and supressing all fires on land they manage. The Forest Climate Alliance was established in 2007, with the purpose of developing the national framework for REDD+ (Reducing Emissions from Deforestation and Degradation). Between 1997 and 2007 over US$30 million was spent across 40 fire prevention projects in Indonesia, but fires were still occurring. Tacconi et al. (2007) suggest that a complete end to fires is impossible, and fires need to be viewed as a land use tool to be managed, rather than a problem to be eradicated.

In 2010 Indonesia pledged to reduce greenhouse emissions by 26% by 2020, and reducing land-use emissions was a large part of this (Republic of Indonesia, 2016). Also in 2010 a Letter of Intent was signed by the Governments of Indonesia and Norway, stating that Norway would provide US$1 billion for REDD+. This preceded a moratorium on new concessions, established in 2011 and extended until 2016. Until this act, the government responses to fires emphasised fire suppression rather than prevention (Herawati and Santoso, 2011). In 2016 the government of Indonesia announced plans to restore 2.49 million hectares of peatland, blocking drainage canals to rewet land (Peatland Restoration Agency, 2016) and revegetating 670,000 hectares of peatland not already on any concessions (Hansson and Dargusch, 2018).

Studies have found that a mixture of incentives and deterrents are most effective for preventing fires (Carmenta et al., 2020; Jefferson et al., 2020), although the incentives need to resonate with local communities. One deterrent which had positive outcomes was the use of air quality monitoring in villages, alongside information on how air quality effects health (Carmenta et al., 2020). Incentive schemes at village levels have been found to improve compliance with existing regulations, resulting in reduced fires even during strong El Niño years (Watts et al., 2019). Morello et al. (2019) found that in the Amazon fire prevention policies which included a financial incentive were most likely to be accepted by farmers. A pilot of the Forest Carbon Partnership Facility carbon fund in Kalimantan, where payments can be received for forest carbon services (Ekawati et al., 2019), may help to cover the loss of income that would occur through not converting land (Koh and Ghazoul, 2010), and could be effective in reducing emissions (Busch et al., 2012). Yusuf et al. (2018) found that economic losses caused by the moratorium on new oil palm plantations could be compensated by a one off payment for reduced CO_2 emissions.

There are multiple issues surrounding fire prevention policies and fire management initiatives. Jefferson et al. (2020) found that only 12% of initiatives targeted periods when fires were high-risk. REDD+ initiatives are conflicted by laws around accelerating economic development (Ekawati et al., 2019). A lack of clarity over land ownership may also cause challenges to fire prevention (Harrison et al., 2019). Luca Tacconi et al. (2007) suggest that a zero burning strategy is not realistic, and will negatively affect small-scale farmers. They suggest the focus should instead be on preventing and controlling peat fires.

Part of the problem is the strong networks between policy makers and those profiting from fires. Those who gain the largest profit from selling cleared land are also influencing decision making at the policy level (Purnomo et al., 2017). Less than 3% of the area burned in 2019 was within the areas put forward for peatland restoration, suggesting that the areas chosen for restoration may not be the most at risk.

There is also a risk that certain prevention methods may simply encourage illegal activity and make fires worse. In the 2000’s local governments were given management of forest, and confusion around land management resulted in increased illegal logging (Tsujino et al., 2016). Wakker (2014) suggests that illegal clearing of land is considered the norm. Recent assessments have suggested that fires are being started at night, and those responsible are leaving the site quickly to avoid getting caught (World Bank, 2019), meaning there is no attempt to control the fire and it may be more likely to spread.

Since haze is an international issue, fire prevention is important across the Equatorial Asian region. The Transboundary Haze Agreement was started in 2002 and brought together the Association of South-East Asian Nations (ASEAN) with an objective to prevent and monitor transboundary haze from fires (ASEAN, 2002). It states that all member states should ensure activities within their control do not damage the human health of other states, should take measures to prevent fires, and should manage resources in a sustainable manor. Initiatives call for promoting peatland sustainability, enhancing understanding of peatland management, monitoring peatlands, and implementing zero burning strategies (ASEAN, 2003). Luca Tacconi et al. (2007) suggest that one reason for lack of progress with the Transboundary Haze agreement is that the financial resources needed by Indonesia to prevent fires are not provided by ASEAN. There should be financial support both from ASEAN and globally to prevent peat fires.

The Singapore Transboundary Haze Pollution Act allows legal action to be taken against Singaporean companies associated with fires which cause haze in Singapore (Lin et al., 2017). This could target a gap in previous fire management schemes, which can put all the responsibility on farmers rather than investors and other stakeholders (Carmenta et al., 2017). There are also fire prevention measures aimed directly at oil palm plantations. Indonesian Sustainable Palm Oil (ISPO) initiative prohibits the use of fire and the Indonesian Palm Oil Pledge is for companies to pledge they will only trade in deforestation-free palm oil (World Bank, 2016b).

One of the main obstacles in the way of reducing fires is the reliance on fire by farmers. Alternatives to fire, such as mechanical clearing, can require equipment which is expensive and not always suitable for the land. Tacconi (2016) suggest that small-scale farmers could be allowed to burn when fire risk is low, as there is less chance of the fire spreading. Carmenta et al. (2020) suggest that conditional financial rewards for not burning land could mitigate the food insecurity faced by small scale farmers unable to clear land.

1.5.2 Protected areas

Fires are almost non-existent in pristine peat swamps (Page and Hooijer, 2016; Miettinen et al., 2017), and deforestation is reduced inside protected areas (Gaveau et al., 2009). Protecting and increasing these natural habitats can therefore help to prevent fires. In 1980 and 1990 two government decrees made it possible to protect all peatland forest (Wakker, 2014). However with the first decree areas had to meet specific requirements, such as total rainfall, and with the second decree peatlands had to be identified as being more than 3m deep within 2 years of the decree. Many peatland areas were therefore not covered by this protection.

Current protected areas may not be protected enough, and are being encroached upon by smallholders (Wijedasa et al., 2018). Protected areas in Indonesia have been found to be poor at preventing deforestation, which may be due to weak management (Spracklen et al., 2015). Curran et al. (2004) found that between 1995 and 2002 Kalimantan’s lowland protected areas declined by over 56% due to illegal logging. Illegal logging is often accompanied by the digging of canals, used to transport logs, which can then drain the peat (Page et al., 2009). In 1990 around 40% of the log supply to mills in Riau was thought to be from illegal logging (Wakker, 2014). Although companies claim to use only legal wood, the use of third party suppliers makes the supply chain difficult to track. During the 2015 fire event, Atwood et al. (2016) found that 0.2-0.7 Mha has burnt within Sebangua National Park in Kalimantan. Allowing indigenous communities to use protected areas can increase the protection against fire, as well as supporting communities (Nelson and Chomitz, 2011).

There is some uncertainty as to how protected areas effect the surrounding land. There is a concern that protecting an area will simply move the land-use change, with the 10 km buffer around one National Park losing over 70% of forest (Curran et al., 2004). Gaveau et al. (2009), however, found that the area directly outside of protected areas in Sumatra had a lower deforestation rate between 1990 and 2000 than the wider unprotected areas, suggesting that protected areas also benefited the surrounding area.

Protecting land has other benefits than fire reduction. Beukering et al. (2003) found that several benefits came from a National Park, including water supply, flood prevention and increased tourism. Pienkowski et al. (2017) suggest that in Cambodia protected forest are linked to reduced illness. Indonesia has high biodiversity and contains 12% of the world’s mammal species, 16% of reptile species, 17% of bird species and 10% of flowering plant species (CBD, 2020), and protecting forests is critical for preserving biodiversity (Curran et al., 2004).

1.5.3 Peatland restoration

One of the most recent government initiatives is to restore 2.49 Mha of degraded peatland. Restoring peatland can help to make it less susceptible to fire. This involves building dams in drainage canals, which blocks drainage and raises the water level in the peatland (Ritzema et al., 2014). Dams act to slow the flow of water rather than hold water, as water will eventually seep away through the peat. Multiple dams closely spaced is therefore most effective for re-wetting peatland (Page et al., 2009). Restoration cannot return peatlands to how they were pre-drainage, but re-wetting and re-vegetation can bring them close (Giesen and Nirmala, 2018).

Marlier et al. (2019) found that if all fires on restored peatland were prevented, then the peatland restoration announced by the government could reduce future mortality by up to 46%. However there is little data on the effect of restoration on fire. Ritzema et al. (2014) found that although blocking canals raised the average water level, it still fell to 40 cm below the ground level during a drought period, a level which leaves peat susceptible to burning (Wösten et al., 2008). The water level after canal blocking can depend on the type of dam used, and whether gaps have been left for transport purposes (Giesen and Nirmala, 2018). Canal blocking alone is therefore unlikely to prevent dry season fires, although it may reduce them. Jaenicke et al. (2011) used radar imagery to show that while peatland soil moisture increased close to dams in Kalimantan, the dams did not achieve large-scale rewetting, and fires still occurred. This study also shows the possibility of using satellite data to monitor restoration efforts.

It is also uncertain whether re-wetted peat will have the same characteristics as pristine peat. Canals disrupt the topography of peat domes, which can effect water run-off (Ritzema et al., 2014). Peat density changes when peat is drained (Sinclair et al., 2020), and this is an important component for emissions (Smith et al., 2018). There has been little work in the field on fire after restoration.

One obstacle to restoration and revegetation is the cost. The World Bank (2016) suggests that a one-time buy back of peatland would cost US$10,000 per hectare. Canal blocking also has costs, with 2 MHa of restoration costing US$1.9 billion (World Bank, 2016b). Dams can also be damaged by flooding (Ritzema et al., 2014), and continued maintenance is needed. Natural revegetation is unlikely after fires (Page et al., 2009), but manually revegetating peatlands can be expensive, and may be beyond the current funding budget for the restoration announced by the government (Hansson and Dargusch, 2018). As a single fire can wipe out years of restoration work, and reducing fires is essential for revegetation (Harrison et al., 2019). Tacconi (2002) suggests that policy initiatives to reduce fires should have an economic cost-benefit analysis.

Another obstacle is the unpopularity of canal blocking. Canals can be used for transport and fishing as well as drainage (Harrison et al., 2019). Local support of projects are therefore vital.

The literature reviewed in this section shows that quantitative studies on the effectiveness of fire mitigation are limited, and few indicate what fire prevention could mean for the various impacts of fire. They also tend to be done on a small scale. This gap in understanding motivates the study done in Chapter 4. Of particular significance for this work is the uncertainty in the effect of peatland restoration and of protected areas, although both are likely to reduce fire emissions. The combination of large profits and adverse impacts makes the position of fire use politically complex. Both fires and fire prevention schemes effect many people, and any policy needs to be carefully considered and the benefits analysed. Studies have shown that a mixture of initiatives and deterrents is most effective in fire mitigation schemes. One deterrent is the effect of fires on air quality and health, showing that a better understanding of this impact can be used to drive fire prevention.

1.6 Summary and Motivation

Following decades of land-use change which has both made land susceptible to fire and introduced fire as a component, fires are now a recurring problem for Indonesia. Large peatland fire events are a result of both anthropogenic and meteorological drivers, occurring when the water table is low and peat is exposed, often due to a combination of drainage and drought. Peat burning results in large emissions for the area burned and peat fires are difficult to extinguish, continuing to burn and spread for weeks to months. The dynamics of peat fires are complex and differ from vegetation fires, but until recently there were few studies on tropical peat burning. Peat combustion is often not included in emissions inventories, and when it is there is large uncertainty, often underestimating emissions. **Further research is needed to quantify the emissions from Indonesian peat fires.**

The impacts of Indonesian fires are wide. The fires themselves destroy forests and land, while emissions effect rainfall and convection, contribute to climate change, cause poor visibility and adversely affect the health of millions of people across multiple countries. These impacts can also have associated costs. Fires in Indonesia predominantly occur because of the economic benefit of using them to clear land, and while this benefit is known, the economic cost is more uncertain. There are large uncertainties in the economic and health impacts of fires, and few studies quantify these impacts. Moreover, there is no available comparison of impacts across multiple years. **Additional estimates of the economic and health impacts of fires are required to better evaluate the impact of fires.**

The adverse impacts of Indonesian fires across Equatorial Asia and globally have resulted in efforts to reduce emissions from fires. Fires are not a natural aspect of the environment and therefore can be prevented by introducing policy to regulate them. A decision to restore peatland areas effected by drainage could help to prohibit fire, although it is unclear how peatland fires will respond to restoration and rewetting. Despite there having been many fire prevention schemes, there is no clear evidence of the effect. **Research on the effect of restoration is needed.**

The motivation to better understand fire emissions comes from the many social, climatological and economic impacts of fires, and from the large uncertainties causing bias in current emissions inventories. Currently, the full impact of Indonesian peatland fires are difficult to ascertain. Recent data taken in the field during the 2015 fire event means that it may be possible to better constrain Indonesian peat fire emissions in global inventories, and re-evaluate knowledge of fire impacts. Current understanding of how impacts vary between fire events is uncertain, as many studies focus on one or two events and differing methods make it difficult to compare across studies.

The impacts of fires also motivate fire prevention schemes. Analysing the effectiveness of such schemes and quantifying potential benefits can help schemes to succeed. However there are few efforts to do this. The cost of fires is often overlooked as an impact, and rarely investigated alongside an atmospheric study. The economics of fire is important for decision making, particularly as fire prevention can be expensive and a cost benefit analysis may be needed. The cost of fires rely heavily on the emissions and area burned, which amplifies the need to improve emissions data.

The areas which have been identified as needing further research after reviewing the literature are shown in bold in the text above. The aims of this study builds on these points.

1.7 Aims and Objectives

The aim of this research is to analyse the emissions of fire events in Indonesia between 2004 and 2015, and to evaluate the impacts of fire emissions on air quality and health, the economic cost of the fire events, and the potential effectiveness of peatland restoration as a fire mitigation tool. The period considered includes multiple fire events, including one of the largest in recent decades. This work is the first study using consistent methods to evaluate all these events, allowing for a comparison of the effects of fires between years. The following objectives have been considered:

- To evaluate emissions from Indonesian fires and to create an improved emissions inventory, including the complexities of peat burning;
- To determine the contribution of peat burning to Indonesian fire emissions, and evaluate the controlling factors of peat fire emissions;
- To estimate the impact of fire emissions on air quality and human health in South East Asia;
- To estimate the economic cost of Indonesian fire events, and evaluate the implications for fire policy;
- To investigate how the emissions and impacts of fire events vary between years, and provide a comparison of several fire events;
- To determine the effectiveness of peatland restoration on reducing fire emissions and impacts.

This analysis has been split into three papers, addressing the following research questions:

1. Does a new estimate of emissions from Indonesian peat fires in 2015 better constrain emissions than current fire emissions inventories?

2. What are the air quality and health impacts of vegetation and peat fires in Equatorial Asia during 2004–2015?

3. What is the economic cost of Indonesian fires and the benefits of restoring peatland?

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Chapter 2 New estimate of particulate emissions from Indonesian peat fires in 2015

Kiely, Laura[1], Spracklen, Dominick V.[1], Wiedinmyer, Christine[2], Conibear, Luke[1], Reddington, Carly L.[1], Archer-Nicholls, Scott[3], Lowe, Douglas[4], Arnold, Stephen R.[1], Knote, Christoph[5], Khan, Md Firoz[6], Latif, Mohd Talib[7], Kuwata, Mikinori[8, 9, 10], Sri Hapsari Budisulistiorini[8], Syaufina, Lailan[11]

1. School of Earth and Environment, University of Leeds, Leeds, UK

2. CIRES, University of Colorado, Boulder, Colorado, USA

3. Department of Chemistry, University of Cambridge, Cambridge, UK

4. University of Manchester, Manchester, UK

5. Ludwig-Maximilians University, Munich, Germany

6. Department of Chemistry, University of Malaya, Malaysia

7. School of Environmental and Natural Resource Sciences, University Kebangsaan Malaysia, Malaysia

8. Earth Observatory of Singapore and Asian School of the Environment, Nanyang Technological University, Singapore 639798, Singapore

9. Campus for Research Excellence and Technological Enterprise (CREATE) Program, Singapore

10. Center for Southeast Asian Studies, Kyoto University, Kyoto, Japan

11. Faculty of Forestry, Bogor Agricultural University (IPB), Bogor, Indonesia

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Abstract

Indonesia contains large areas of peatland which have been drained and cleared of natural vegetation, making them susceptible to burning. Peat fires emit considerable amounts of carbon dioxide, particulate matter (PM) and other trace gases, contributing to climate change and causing regional air pollution. However emissions from peat fires are uncertain due to uncertainties in emission factors and fuel consumption. We used the Weather Research and Forecasting model with chemistry, and measurements of PM concentrations to constrain PM emissions from Indonesian fires during 2015, one of the largest fire seasons in recent decades. We estimate primary $PM_{2.5}$ (particles with diameters less than 2.5 μm) emissions from fires across Sumatra and Borneo during September to October 2015 were 7.33 Tg, a factor 3.5 greater than those in Fire Inventory from NCAR (FINNv1.5), which does not include peat burning. We estimate similar dry fuel consumption and CO_2 emissions to those in the Global Fire Emissions Database (GFED4s, with small fires), but a factor 1.8 greater $PM_{2.5}$ emissions, due to updated $PM_{2.5}$ emission factors for Indonesian peat. Fires were responsible for an additional 3.12 Tg of secondary organic aerosol formation. Through comparing simulated and measured PM concentrations, our work provides independent support of these updated emission factors. We estimate peat burning contributes 71% of total primary $PM_{2.5}$ emissions from fire in Indonesia during September-October 2015. We show that using satellite-retrieved soil moisture to modify the assumed depth of peat burn improves the simulation of PM, increasing the correlation between simulated and observed PM from 0.48 to 0.56. Overall, our work suggests that peat fires in Indonesia produce substantially greater PM emissions than estimated in current emission inventories, with implications for the predicted air quality impacts of peat burning.

2.1 Introduction

Vegetation and peatland fires across Indonesia and Malaysia result in habitat and biodiversity loss, large emissions of carbon and regional haze episodes. Fire events cause regional reductions in visibility and severe air pollution (Reddington et al., 2014; Gaveau et al., 2014; Kim et al., 2015; Lee et al., 2017) with associated morbidity and mortality (Marlier et al., 2012; Reddington et al., 2015; Crippa et al., 2016).

Indonesia contains 36% of the worlds tropical peatland, the largest of any country in the tropics (Page et al., 2011; Dargie et al., 2017). Undisturbed peatlands typically have high moisture content, making them naturally resilient to fire (Wösten et al., 2008). Indonesian peatlands are experiencing deforestation and conversion to agriculture, oil palm and timber plantations (Hansen et al., 2013; Gaveau et al., 2014; Miettinen et al., 2017). During this conversion, drainage canals are installed, lowering the water table and making the peatland more susceptible to burning (Konecny et al., 2016). Fire is also used as an agricultural tool to clear vegetation (Page et al., 2002; Carlson et al., 2012). These human disturbances can make peatlands particularly prone to fire. In 2015, 53% of fires in Indonesia occurred on peatland, which made up only 12% of the land area (Miettinen et al., 2017).

Peatlands have thick organic soil layers up to 10 m deep (Hu et al., 2018). Fires on peatland can burn into these underground organic layers and smoulder for weeks after the surface fire has gone out (Roulston et al., 2018), resulting in substantially greater emissions compared to surface vegetation fires (Heil et al., 2007). Peat fires are estimated to contribute 3.7% of global fire carbon emissions (van der Werf et al., 2017). In Indonesia, peatland fires are the largest contributor to fire emissions in the region (Van Der Werf et al., 2010; Reddington et al., 2014). For the fires in 2015, Wooster et al. (2018) found that 95% of the particulate matter ($PM_{2.5}$) emissions came from peatland fires, and Wiggins et al. (2018) estimated that 85% of smoke plumes detected in Singapore originated from peat fires.

Whilst it is known that emissions from peatland fires are substantial, current emissions estimates have large uncertainties. Emission estimates are typically based on remote sensed information from satellites on the area burned by the fires. Burned area may be underestimated in SE Asia due to extensive cloud cover (Ge et al., 2014). Furthermore, estimates of burned area are limited to surface fires and may miss fires that burn underground (Kaiser et al., 2012). For peat fires, the amount of biomass consumed by the fire depends on how deep into the peat the fire burns (Hu et al., 2018). Burn depth is variable, with some fires recorded as burning to a depth of 0.85 m, resulting in carbon emissions of 31.5 kg C m^{-2} (Page et al., 2002; Page and Banks, 2007). Burn depth depends on the level of the water table and the water content of the peat, with increased burn depth when the water table is lowered and the peat dries out (Rein et al., 2008;

Ballhorn et al., 2009; Huang and Rein, 2015). Konecny et al. (2016) also suggest that burn depth changes based on the frequency of fire, with reduced burn depth for repeat fires at the same location. Information on the spatial and temporal variability of burn depth is limited and current emission inventories make broad assumptions regarding these parameters. Emission factors (EFs), estimated from field or laboratory measurements, are used to convert mass of fuel consumed by the fire to the emitted mass of gas phase and particulate pollutants (e.g. Andreae and Merlet, 2001; Akagi et al., 2011). Compared to flaming combustion, smouldering peat fires have colder combustion temperatures, and typically higher EFs for products of incomplete combustion including CO, CH_4, CO_2, HCN, NH_3 and PM (Stockwell et al., 2016). Until recently there have been few specific measurements of EFs for tropical peat fires. Roulston et al. (2018) and Wooster et al. (2018) found that EFs for tropical peat fires could be underestimated by a factor of three ($PM_{2.5}$ EF from peat fires is assumed to be 9.1 g kg^{-1} in GFED4, compared to 24 g kg^{-1} suggested by Roulston et al. (2018) and 28 g kg^{-1} suggested by Wooster et al. (2018)) . There are large variations in EFs for peat in Indonesia. In one study measuring emissions from peat fires in Central Kalimantan during 7 days in 2015, $PM_{2.5}$ EFs were found to vary between 6 and 30 g kg^{-1} (Jayarathne et al., 2018). Kuwata et al. (2018) used measurements from Indonesian peatland fires to estimate EFs of PM_{10} of 13±2 g kg^{-1} in 2013 and 19±2 g kg^{-1} in 2014.

These uncertainties cause corresponding uncertainty in estimates of emissions from peat fires, and impacts on the regional air pollution. Previous studies underestimate measured aerosol optical depth (AOD) or PM, and scale particulate fire emissions from global fire emissions inventories, or simulated fire derived aerosol by a factor of 1.36 – 3.00 in order to match observations (Marlier et al., 2012; Ward et al., 2012; Johnston et al., 2012; Tosca et al., 2013; Reddington et al., 2016; Koplitz et al., 2016). This suggests that particulate emissions from tropical peatland regions are underestimated in current fire emission inventories.

Severe fire events in Indonesia occur during periods of drought (van der Werf et al., 2008; Tosca et al., 2011; Gaveau et al., 2014; Field et al., 2016), resulting in strong seasonal and interannual variability. Severe droughts lower the water table, exposing more peat and increasing the susceptibility of burning. Extensive fires and regional haze episodes across Indonesia have occurred in 1982-1983, 1997-1998, 2006, 2009, 2013 and 2015. During September to October 2015, dry conditions caused by a strong El Niño, resulted in large fires across Sumatra and Kalimantan. This fire episode was the largest in Indonesia since 1997 (Huijnen et al., 2016), releasing an estimated 188±67 TgC (Huijnen et al., 2016) as CO_2, and 149±71 TgC from peat fires (Jayarathne et al., 2018). The fires also emitted substantial amounts of $PM_{2.5}$ estimated at 9.1±3.2 Tg (Wooster et al., 2018), with 6.5±5.5 Tg from peat fires (Jayarathne et al., 2018). Particulate air pollution from these fires may have caused between 6,513 and 17,270 excess premature deaths through short term exposure to fire-sourced $PM_{2.5}$ (Crippa et al., 2016) and as many as 100,300 excess premature deaths over the longer term due to exposure to this pollution (Koplitz et al., 2016).

Given the importance of peatland fires as the main contributor to fire emissions in Indonesia, there is a high priority in reducing the large uncertainties in these emissions. In this study we aim to improve understanding of the emissions from peat fires in Indonesia by combining fire emission inventories, a regional air quality model and extensive measurements of PM. We focus on the large fires of September to October 2015. We updated an existing fire emissions inventory to include emissions from peat fires, applying updated information on emission factors from tropical peat combustion and using satellite-retrieved information on soil moisture to control assumed depth of peat burn. We used the existing and new emissions inventories with an air quality model, and evaluate simulated PM concentrations against observations. The new emissions inventory demonstrates a substantial improvement in simulating regional $PM_{2.5}$ concentrations.

2.2 Methodology

We used a regional atmospheric model to simulate PM concentrations during August - October 2015, with different combinations of peat and vegetation fire emissions, described below. Our study region included Borneo, Sumatra and mainland Malaysia (Figure 2.1, 95-120°E and 10°S-10°N), which is at the centre of the model domain. We used surface observations of PM and AOD to assess the performance of the model with the different fire emissions. Atmospheric PM concentrations are impacted by a range of atmospheric processes including atmospheric transport, deposition and secondary production of aerosol. Evaluating the fire emissions is complicated by the treatment of these processes in the model.

2.2.1 WRF-chem Model

We used the Weather Research and Forecasting model with Chemistry (WRF-chem), version 3.7.1. WRF-chem simulates gas-phase chemistry and aerosol processes fully coupled to the meteorology (Grell et al., 2005). The model was run at 30 km horizontal resolution with 33 vertical levels over 140x140 grid points centred at 110°E 0°N (90-130°E and 17°S -18°N), with Mercator projection. Simulations were run over the period of the 18th July until the 1st November. The MOZART (Model for Ozone and Related Chemical Tracers, version 4; Emmons et al., 2010) chemistry scheme was used to calculate gas-phase chemical reactions, with aerosol dynamics and processes represented by MOSAIC (Model for Simulating Aerosol Interactions and Chemistry; Zaveri et al., 2008; Hodzic and Knote, 2014). This includes a secondary organic aerosol (SOA) scheme based on Hodzic and Jimenez (2011). Primary organic aerosols (POA) are considered non-volatile in the model. Within MOSAIC, 4 aerosol bin sizes were used; 0.039-0.156 µm, 0.156 – 0.625 µm, 0.625 – 2.5 µm and 2.5 – 10 µm. Anthropogenic emissions were from EDGAR-HTAP2 (Janssens-Maenhout et al., 2015) for 2010, and biogenic emissions were from MEGAN (Model of Emissions of Gases and Aerosols from Nature; Guenther et al., 2006). A similar model setup has been used for studies in India (Conibear et al., 2018), the United States (Knote et al., 2014) and Indonesia (Crippa et al., 2016). The meteorology was reinitialised each month with NCEP GFS (NCEP, 2007), with a 24 hour spin-up, and was then free-running through the month. More information on the chemistry and physics options used can be found in Table B.1 in Appendix B.

2.2.2 Fire emissions

We applied four different emission inventories in the WRF-chem model, all based on the Fire Inventory from NCAR (FINNv1.5). All emission inventories included emissions from vegetation fires as treated in FINNv1.5, but with different treatment of peat combustion, as described below.

1. *FINN (FINN)*

The Fire Inventory from NCAR (FINNv1.5) combines data on active fires, biomass burned and EFs to give daily fire emissions at 1 km resolution (Wiedinmyer et al., 2011). Vegetation burned is assigned based on the MODIS Land Cover Type and Vegetation Continuous Fields (VCF) products. Fire area burned is assumed to be 1 km^2 (100 ha) per hotspot detected (scaled back by any non-vegetated area assigned by the VCF product). Fuel loading is from Hoelzemann et al. (2004) and EFs are from Akagi et al. (2011), Andreae and Merlet (2001) and McMeeking et al. (2009). FINNv1.5 includes emissions from combustion of above-ground vegetation but does not include emissions from combustion of peat.

2. *FINN with GFED4s peat (FINN+GFEDpeat)*

In this inventory we combined vegetation emissions from FINNv1.5 with emissions from peat fires from the Global Fire Emissions Database (version 4 with small fires) (GFED4s). GFED combines burned area from Giglio et al. (2013), with assumed combustion completeness and EFs. For peat fires the depth burned is dependent on the soil moisture, with a maximum depth of 0.5 m. GFED4s peat EFs come from studies on Indonesian peat fires for CO_2, CO and CH_4, and from deforestation fires for all other species.

GFED4s data is available daily at 0.25° resolution. GFED emissions are available split by fuel type, allowing us to combine GFED4s emissions from peat fires with FINN emissions from other fuel types.

3. *FINN with peat emissions (FINNpeat)*

We created a new emissions inventory (FINNpeat), based on FINNv1.5 emissions with the addition of emissions from combustion of peat. Emissions from vegetation fires in FINNpeat are identical to those in FINN. For those fire detections occurring on peat as identified using a peatland distribution map (WRI), additional emissions from the peat burning were calculated using Eq. (1):

$$E_s = BA\ x\ BD\ x\ \rho\ x\ EF_s \tag{1}$$

where E_s is the emissions of a species, *s*, from a fire, *BA* is the burned area and *BD* is the burn depth for the fire, ρ is the peat density and EF_s is the emissions factor for species, s. The peatland map only includes peatlands in Indonesia, so emissions from Malaysian peat fires are not included. For each fire, the corresponding emissions are released on the day that the fire was detected, with no long-term smouldering effects, which may be important for peat fires.

Tansey et al. (2008) used an analysis of MODIS hotspots and MODIS burned area in a peat swamp in Indonesia, to estimate 15-16 ha of burned area per hotspot. However, 60% of burned areas did not have an identified hotspot, implying an area burned per MODIS hotspot of approximately 40 ha. Over areas defined as peatland we therefore assumed a burned area of 40 ha of peat burnt per hot spot, smaller than the 100 ha assumed for vegetation fires.

The mass of peat burned during peat fires was calculated from an assigned burned area, peat density and burn depth (Table 2.1). We assumed a peat density of 0.11 g cm^{-3} (Driessen and Rochimah, 1976; Neuzil, 1997; Shimada et al., 2001; Warren et al., 2012) and a burn depth of 37 cm for all fires detected (Page et al., 2002; Usup et al., 2004; Ballhorn et al., 2009). We assumed that all peat within the burned area and depth is combusted, as is assumed in GFED3 (van der Werf et al., 2006). This gives a fuel consumption of 40.7 kg dry matter m^{-2}, consistent with Leeuwen et al. (2014) who found the average fuel consumption for Indonesian peatland fire to be 31.4 kg dry matter m^{-2} (from studies by Page et al., 2002; Usup et al., 2004; Ballhorn et al., 2009).

We assigned the average EFs from previous studies (Table 2.2) (Christian et al., 2003; Hatch et al., 2015; Stockwell et al., 2016; Wooster et al., 2018; Jayarathne et al., 2018; Nara et al., 2017; Smith et al., 2018): CO_2 (1670 g kg^{-1}), $PM_{2.5}$ (22.3 g kg^{-1}), organic carbon (OC) (11.5 g kg^{-1}) and black carbon (BC) (0.07 g kg^{-1}). By comparison, GFED4s assumes similar EFs for CO_2 (1703 g kg^{-1}) and BC (0.04 g kg^{-1}), but substantially lower EFs for $PM_{2.5}$ (9.1 g kg^{-1}) and OC (6.02 g kg^{-1}).Some of the EFs used have been calculated from fires on peatland which also contain vegetation burning.

The variation in measured EFs vary widely depending on the emitted pollutant, 20% for CO_2 (1507-1775 g kg^{-1}), a factor 2-3 for $PM_{2.5}$ (17.3-28.0 g kg^{-1}) and OC (6.02 – 16.0 g kg^{-1}), and an order of magnitude for BC (0.006 – 0.134 g kg^{-1}). The EFs used by

Table 2.1: Values for peat burn depth and peat density found in previous studies, and the average value across studies. All studies were based in Kalimantan, Indonesia.

	Burn depth (m)	Peat density (gcm^{-3})
Page et al. (2002)	0.51	
Ballhorn et al. (2009)	0.33	
Centre for international co-operation in measurement of tropical peatlands (From Ballhorn et al., 2009)	0.3	
Usup et al. (2004)	0.35	
Stockwell et al. (2016)	0.34	
Neuzil (1997)		0.093
Driessen and Rochimah (1976)		0.11
Warren et al. (2012)		0.127
Shimada et al. (2001)		0.112
Konecny et al. (2016)		0.121
Average	0.37	0.11

Table 2.2: Emission factors from previous studies, in $g\ kg^{-1}$, and an average value across all studies.

	Christian et al. (2003)	Wooster et al. (2018)	Stockwell et al. (2016)[b]	Stockwell et al. (2015)	Hatch et al. (2015)	Jayarathne et al. (2018)	Smith et al. (2018)	Nara et al. (2017)	Average
Method	Lab	In situ	In situ	Lab	Lab	In situ	In situ	In situ	
CO_2	1703	1775	1564	1507.23			1579	1663	1669
CO	210.3	279	291	224.66			251	205	243.48
CH_4	20.80	7.9	9.51	11.69			11.00	7.6	11.17
C_2H_2	0.06		0.12	0.1644			0.06		0.11
C_2H_4	2.57		0.96	1.09			2.30		1.60
C_5H_8			0.0528	1.1382					0.5823
CH_3OH	8.23		2.14	3.78					4.48
HCHO	1.40		0.867	1.532			0.77		1.220
$C_2H_4O_2$	1.59		0.108						0.849
CH_3CHO	3.27		0.697	1.496					1.740
HCOOH	0.79		0.18	0.53			0.25		0.46
C_3H_6O	1.5		0.69	1.38					1.18
C_2H_6			1.52						1.52
C_3H_8			0.989						0.989
$C_{10}H_{16}$			0.00167	0.1925	0.0068				0.0984
NH_3	19.92		2.86	1.33			7.82		7.09
$PM_{2.5}$		28.0[a]	21.5			17.3			22.3
Black carbon		0.134	0.00552						0.0695
Organic carbon	6.02		16.0			12.4			11.5
Higher alkanes			0 .87						0.87

[a] Contains both peat and vegetation burning. [b] Stockwell et al. (2016) and Jayarathne et al. (2018) are based on the same measurements

Wooster et al. (2018) for $PM_{2.5}$ and CO_2 are at the upper end of the ranges of EFs considered for this study. Substantial uncertainty in BC emissions has implications for the climate impacts of the aerosol, but since BC only makes a minor contribution to overall mass it has less importance for simulation of $PM_{2.5}$.

4. *FINN new peat with soil moisture (FINNpeatSM)*

As peat dries out the burn depth increases (Usup et al., 2004; Rein et al., 2008; Wösten et al., 2008). However, FINNpeat assumes a constant peat burn of 37 cm depth regardless of soil moisture. FINNpeatSM emissions were calculated in the same way as FINNpeat emissions, but with peat burn depth varying dependent on surface soil moisture.

Daily soil moisture from the European Space Agency (ESA CCI SMv04.4) was used to estimate the burn depth of peat (Liu et al., 2012; Dorigo et al., 2017; Gruber et al., 2017). Frequent cloud cover leads to numerous missing values in the daily soil moisture data at 0.25° resolution. To help account for this soil moisture was averaged to 2° resolution. In 2015, average daily soil moisture across peatlands in the study area declined from around 0.24 m^3 m^{-3} in August, to 0.23 m^3 m^{-3} in September to a minimum of around 0.22 m^3 m^{-3} in October 2015, then increasing to 0.25 m^3 m^{-3} in November (Figure B.1). By comparing the temporal change in soil moisture over high fire regions in Sumatra and Kalimantan, we chose upper and lower limits of 0.25 m^3m^{-3} and 0.15 m^3m^{-3}, which reflected the soil moisture in these regions before and during the dry season (Figure B.2).

We scaled burn depth linearly from a minimum of 5 cm for a soil moisture of 0.25 m^3m^{-3} to a maximum of 37 cm for soil moisture of 0.15 m^3m^{-3}. Under these assumptions, mean peat burn depth across peatland areas in Indonesia increased from 15.0 cm in August to 23.6 cm in September and 24.8 cm in October.

The PM2.5 EF used for FINNpeat and FINNpeatSM is at the higher end of the range of values used in other studies. The same emissions combined with a lower EF would require a greater burn depth or area burned per fire hotspot.

2.2.3 Vertical profile of fire emissions

Fires can inject emissions into the air above the surface layer of the model, which in this model set-up is about 70 m. By default in WRF-chem, the vertical distribution of fire emissions uses a plume rise parameterization based on a 1d cloud model (Freitas et al., 2007). However smoke from smouldering peat fires can be emitted close to the ground. Recent work suggests that tropical fires mostly inject emissions into the BL and the WRF-chem scheme may overestimate fire injection heights. Tosca et al. (2011) found that the average plume height for fires in Sumatra and Borneo was 729 m, with 96% of plumes confined to within 500 m of the boundary layer. Martin et al. (2018) found that 90% of fire emissions in South Asia in September to November were injected below 1500 m. Archer-Nicholls et al. (2015) found that the WRF-chem plume rise parameterisation overestimated the injection height for fires in South America. For this reason we chose not to use the plume-injection option and instead tested two alternate approaches to control the vertical profile of fire emissions:

- All of the emissions were added to the surface model layer (surface injection),
- Half of the emissions were added to the surface model layer and 50% of the emissions were spread evenly to model layers throughout the boundary layer (boundary layer injection).

2.2.4 Particulate measurements

Measurements of particulate matter with diameter less than 2.5 µm ($PM_{2.5}$), less than 10 µm (PM_{10}), and less than 1 µm (PM_1), and measurements of AOD (**Table 2.3**) were used to evaluate the model. Figure 2.1 shows the locations of measurements. Hourly measurements of $PM_{2.5}$ concentrations are available from the National Environment Agency of Singapore for five sites in Singapore during October 2015. We averaged concentrations across the five sites to produce mean $PM_{2.5}$ concentrations for Singapore. From Singapore, there are also measurements of non-refractory, composition resolved sub-micron PM from an Aerosol Chemical Speciation Monitor (ACSM) (Budisulistiorini et al., 2018). We summed the chemically-resolved masses to give PM_1. Betha et al. found that for fire-induced haze in Singapore in 2013, 96-99% of the $PM_{2.5}$ was PM_1.

Table 2.3: Observational data for 2015.

Data	Location	Time period	Frequency of observations	Method	Reference/source
$PM_{2.5}$	5 Sites in Singapore: N: 1.41° N, 103.80° E; E: 1.33° N, 103.69° E; C: 1.34° N, 103.82° E; W: 1.33° N, 103.93° E; S: 1.27° N, 103.83° E	28 September–15 November 2015	1h	Thermo Scientific™ 5030 SHARP monitor	National Environment Agency for Singapore
Composition resolved non-refractory PM_1	National Technological University in Singapore 1.35° N, 103.68° E	10–31 October 2015	2–3min	Aerosol chemical speciation monitor (ACSM)	Budisulistiorini et al. (2018)
PM_{10}	Pekanbaru, Indonesia 0.52° N, 101.43° E	1 January 2010 –31 December 2015	30min	Measured using a Met One BAM 1020 real-time portable beta-attenuation mass monitor (BAM-1020)	
PM_{10}	52 locations across Malaysia	August–November 2015	1h	Measured using a Met One BAM 1020 real-time portable beta-attenuation mass monitor (BAM-1020)	Mead et al. (2018)
AOD	8 AERONET sites	August–October 2015	24h average	Ground-based remote-sensing sun photometer instrument, measuring the intensity of solar radiation at 500nm wavelength, from which AOD is derived	AERONET version 2

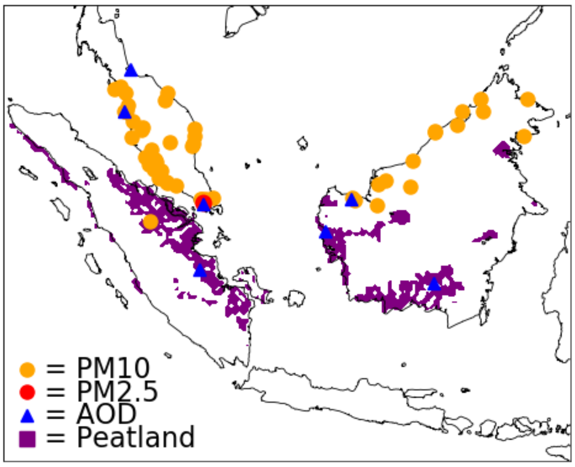

Figure 2.1: The study area showing the locations of PM_{10} measurements in yellow circles, $PM_{2.5}$ in red circles and AOD in blue triangles. Peatland is shown in purple.

In October 2015, measured PM_1 agreed to within 20% of the mean $PM_{2.5}$ concentration from the NEA. Ground-based AOD measurements were available from 7 Aerosol Robotic Network (AERONET) sites for August to October. Measurements of hourly PM_{10} were available from 52 locations across Malaysia (Mead et al., 2018) and one location in Indonesia during August to October 2015. We compared daily mean observations at each site with simulated PM and AOD in section 2.3.2. The fractional bias (defined in Appendix B) and correlation coefficients were used to evaluate the simulations. We did not use AOD data from MODIS retrievals, which significantly underestimated AOD over the region during this period, due to excluding smoke plumes that were mistook for clouds (Shi et al., 2019).

2.3 Results

2.3.1 Fire emissions

Table 2.4 shows total dry matter consumption, $PM_{2.5}$, CO_2, CO and SOA emissions from fires across Sumatra and Borneo in September and October 2015. The dry fuel consumption is lowest for FINN (230 Tg), which does not include peat fires. Dry matter consumption is similar for GFED, FINN+GFEDpeat and FINNpeatSM (455 Tg, 514 Tg, 465 Tg respectively), and is highest for FINNpeat (612 Tg). This is likely due to the peat burn depth being greatest for FINNpeat. Wooster et al. (2018) estimated 358±107 Tg of dry matter consumption for Kalimantan and Sumatra in September and October, using satellite CO emissions (from the MOPITT instrument) and a CO EF. This dry matter estimate is in reasonable agreement with GFED and FINNpeatSM. FINN estimates a smaller dry matter consumption compared to Wooster et al. (2018), whereas FINNpeat estimates greater dry matter consumption. Whitburn et al. (2016), have estimated dry matter fuel consumption of 525 Tg, calculated using satellite CO emissions (from the IASI instrument) from peatlands, and the CO EF for peat from GFAS. This estimate is larger than that found for GFED or FINNpeatSM, and smaller than that found for FINNpeat.

Total September and October 2015 emissions of CO_2 follow a similar pattern to dry matter consumption, with similar values for GFED, FINN+GFEDpeat and FINNpeatSM (773 Tg, 822 Tg and 781 Tg), largest emissions for FINNpeat (1014 Tg) and smallest emissions for FINN (353 Tg). CO_2 EFs, are similar for GFED and FINNpeat (1703 g kg^{-1} and 1669 g kg^{-1}), explaining the similarity between dry matter consumption and emissions for these inventories. The total CO_2 emissions for September to October estimated by Wooster et al., (2018) was 692±213 Tg, matching GFED, FINN+GFEDpeat and FINNpeatSM. Jayarathne et al., (2018) estimated 547±259 Tg of

Table 2.4: Total dry matter fuel consumption, $PM_{2.5}$, CO_2, CO and SOA fire emissions for September and October 2015. Totals are shown for the area shown in Figure 2.1. The percentage contribution from peat fires is indicated.

	FINN	GFED	FINN+GFEDpeat	FINNpeat	FINNpeatSM
Peat fires included	No	Yes	Yes	Yes	Yes
Dry matter fuel consumption (Tg)	230	455	514	612	465
CO_2 emissions (Tg)	353	773	822	1014	781
Contribution from peat fires	*0%*	*63%*	*57%*	*65%*	*55%*
$PM_{2.5}$ emissions (Tg)	2.09	4.14	4.60	10.60	7.33
Contribution from peat fires	*0%*	*62%*	*55%*	*80%*	*71%*
CO emissions (Tg)	20	75	77	109	78
Contribution from peat fires	*0%*	*80%*	*74%*	*82%*	*74%*
SOA from biomass burning (Tg)	0.80	3.00	3.08	4.36	3.12

CO_2 were emitted from peat fires over South Sumatra and Kalimantan, a range which includes the total CO_2 emissions from peat fires for FINN+GFEDpeat (469 Tg), FINNpeat (661 Tg) and FINNpeatSM (428 Tg).

Total emissions of $PM_{2.5}$ vary across simulations due to differences in assumed $PM_{2.5}$ EFs. FINN has the smallest total $PM_{2.5}$ emissions for September to October (2.09 Tg; Table 2.4). GFED and FINN+GFEDpeat have similar total $PM_{2.5}$ emissions (4.14 Tg and 4.60 Tg), smaller than that for FINNpeatSM (7.33 Tg) despite these inventories having similar dry matter consumption and CO_2 emissions. This is due mainly to the difference in the assumed EFs for $PM_{2.5}$ from peat fires, with 9.1 g kg $^{-1}$ used in GFED, and 22.26 g kg $^{-1}$ used in FINNpeatSM. Wooster et al., (2018), assumed a $PM_{2.5}$ EF of 28±6 g kg $^{-1}$ and estimated that 9.1±3.2 Tg of $PM_{2.5}$ was emitted over the whole of Sumatra and Kalimantan for September and October 2015, similar to that found in FINNpeat (10.60 Tg) and FINNpeatSM (7.33 Tg). In contrast, FINN and FINN+GFED, which use the lower EF, produce smaller $PM_{2.5}$ emissions by a factor of 2 and 4 respectively. Jayarathne et al. (2018) found that, for a smaller study area in Sumatra and Kalimantan, the total $PM_{2.5}$ emission from peat fires was 6±5.5 Tg, a range which covers the total $PM_{2.5}$ emissions from peat fires from FINN+GFEDpeat (2.51 Tg), FINNpeat (8.51 Tg) and FINNpeatSM (5.24 Tg).

GFED, FINN+GFED and FINNpeatSM all emit similar total amounts of CO over September and October (75 Tg, 77 Tg and 78 Tg respectively). This is likely due to the similar EFs used for peat fires (243 g kg $^{-1}$ in FINNpeatSM, 210 g kg $^{-1}$ in GFED). The total CO emissions from FINN are smaller (20 Tg) and from FINNpeat are larger (109 Tg). The contribution from peat fires to total CO emissions (74 - 82%) is larger than for CO_2 (55 – 65%) and $PM_{2.5}$ (55% - 80%). For every 1g of CO emitted from fires, 0.04g of SOA is assumed, and the total SOA from each fire emission inventory is shown in Table 2.4. The SOA increases the total PM emitted from fires to 2.89 Tg from FINN, 7.14 Tg from GFED, 7.68 Tg from FINN+GFED, 14.96 Tg from FINNpeat and 10.45 Tg from FINNpeatSM.

Table 2.4 also shows the fraction of emissions that are estimated to come from peat fires. Across the inventories that include peat burning, peat fires contribute 51-62% of dry matter consumption, 55-65% of CO_2 emissions and 55-80% of $PM_{2.5}$ emissions. The emission inventories with updated $PM_{2.5}$ emission factors result in a greater contribution from peat burning (71%-80%) compared to emission inventories with the older EFs (55%-62%). Wooster et al. (2018) found that peatland fires contributed 85% of the dry matter fuel consumption, and 95% of the $PM_{2.5}$ emissions in September and October 2015, greater than our estimates with updated EFs.

Figure 2.2 shows the spatial variations of the total $PM_{2.5}$ emissions during September and October 2015. In all inventories, greatest emissions occur in southern Kalimantan and central and southern Sumatra, matching the locations of peatlands (Figure 2.1). For the FINNpeatSM emissions, Sumatra contributes 42% of the total $PM_{2.5}$ emissions, for FINNpeat, FINN+GFEDpeat and FINN, the contribution is 39%, 40% and 32% respectively. Wooster et al. (2018) found that 33% of the total $PM_{2.5}$ emissions came from Sumatra, while Koplitz et al. (2016) found that that 47% of OC and BC emitted in June to October 2015 came from Sumatra. Our estimates exclude fire emissions from eastern Indonesia. Nechita-banda et al. (2018) estimated that fires in eastern Indonesia and Papua New Guinea contributed around 15-20% of total CO emissions from fires across the region, highlighting the need future work to quantify PM emissions in this region.

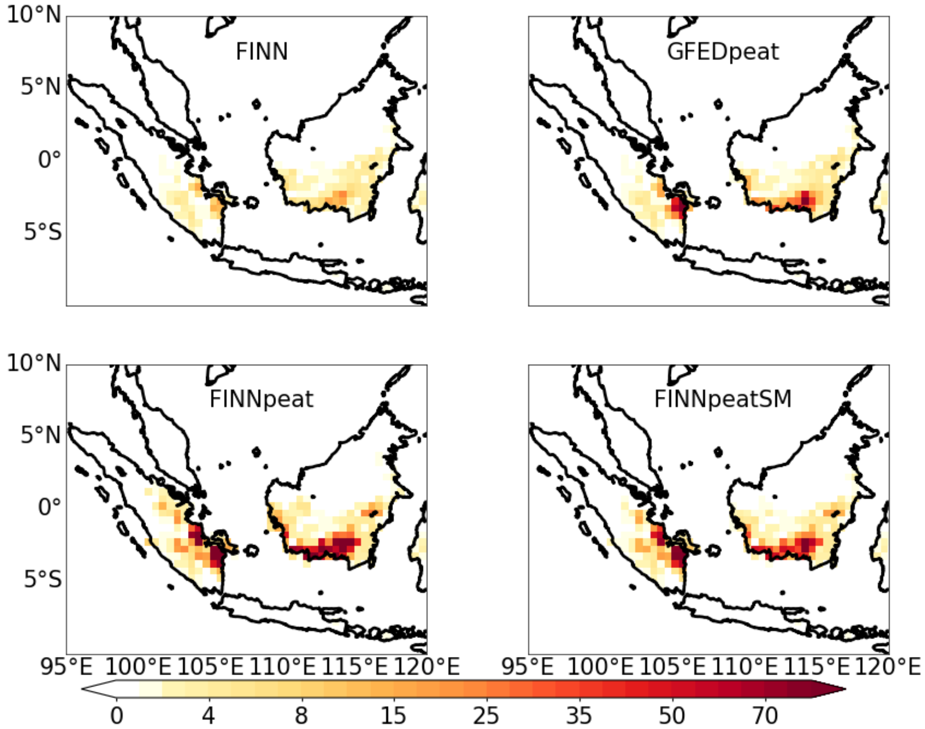

Figure 2.2: Total $PM_{2.5}$ fire emissions during September-October 2015 (g m^2).

FINN and GFED underestimate total emitted $PM_{2.5}$ and FINN underestimates total emitted CO_2 compared to the emissions found by Wooster et al. (2018) and Jayarathne et al. (2018), suggesting that peat fires are important contributors to these emissions. FINNpeatSM is the only emissions inventory that is consistent with these previous studies for both $PM_{2.5}$ and CO_2.

Figure 2.3 shows daily total $PM_{2.5}$ emissions from the different inventories over the study area. Temporally, the inventories follow a similar pattern, with 80-90% of the total $PM_{2.5}$ emissions for 2015 occurring in August-October. For all the emissions inventories the majority of emissions are in September, followed by October and then August. GFED has the largest difference between September and October emissions (58% in Sep and 17% in Oct), followed by FINN+GFEDpeat (47% and 24%), FINNpeat (36% and 30%), and finally FINN (33% and 29%) and FINNpeatSM (36% and 32%) which have the smallest differences between the two months. The reduced ratio of the fraction of emissions in September compared to October for FINNpeatSM is due to greater soil moisture in September resulting in a reduced peat burn depth.

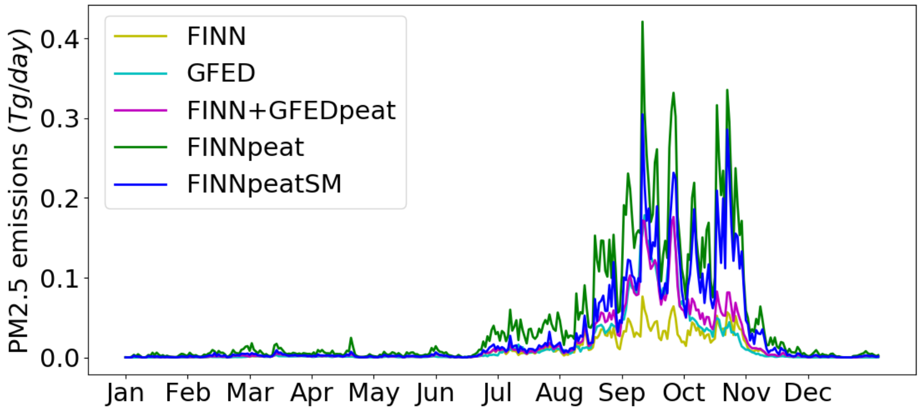

Figure 2.3: Total daily PM2.5 emissions from fires during 2015. Total shown for the area in Figure 2.1, 95-120°E and 10°S-10°N.

Another commonly used emissions inventory is the Global Fire Assimilation System (GFAS1). This uses satellite fire radiative power to detect fires, combined with EFs to calculate daily emissions (Kaiser et al., 2012). For peat fires, some EFs are from studies of Indonesian peat, although the PM2.5 EF (9.1 g/kg) is from tropical vegetation, as is used in GFED. Reddington et al. found that GFAS1 requires the same scaling as GFEDv3 to match observations in Indonesia. It is therefore likely that GFAS1 would show similar results to GFED in our assessment.

2.3.2 Comparison of model and observational data

We evaluated the WRF-chem simulations with the different emissions inventories and injection options against measured PM_{10}, $PM_{2.5}$ and PM_1 concentrations. Figure 2.4 and Figure 2.5 shows the comparison of simulated and observed PM concentrations. Comparisons of $PM_{2.5}$ and PM_1 measurements only, which were restricted to Singapore, are shown in Figure B.3.

PM concentrations are underestimated by the model with FINN emissions, with a fractional bias (FB) of -0.67 with surface injection and -0.77 with boundary layer injection of emissions, with an average across both simulations of -0.72. The model with FINN+GFEDpeat emissions also underestimates PM concentrations (average FB = -0.35) whilst the model with FINNpeat emissions overestimates PM concentrations (average FB = 0.2). The model with FINNpeatSM emissions has the smallest bias (average FB = -0.11, suggesting mean emissions from this inventory are closest to reality.

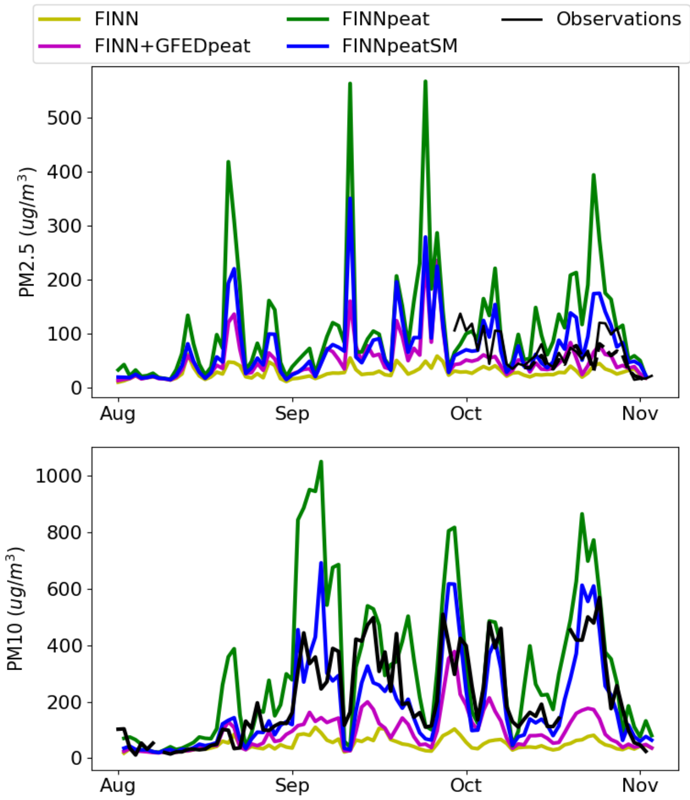

Figure 2.4: Daily observed and modelled (a) $PM_{2.5}$ in Singapore, and (b) PM_{10} in Pekanbaru, for WRF-chem runs with different fire emissions inventories and the surface injection option. (a) shows observations of $PM_{2.5}$ (solid) and PM_1 (dashed). The Pearson's correlation (r) for (a) is 0.47, 0.73, 0.52 and 0.50, and for (b) is 0.63, 0.60, 0.65 and 0.73 for FINN, FINN+GFEDpeat, FINNpeat and FINNpeatSM respectively.

The temporal pattern of measured PM is generally matched by the simulations, as shown in Figure 2.4. However, for many sites, the greatest PM concentrations were measured in October, whereas the model simulates greatest PM concentrations in September. This results in the model underestimating PM concentrations the most in October, with a smaller underestimate, or an overestimate in September (Figure 2.5).

Using a burn depth dependant on soil moisture alters the temporal pattern of simulated emissions, reducing the overestimation in September compared to October. When burn depth is constant, as in FINNpeat, 37% of regional $PM_{2.5}$ emissions for 2015 occur in September and 30% in October. In FINNpeatSM, where we assume a linear relationship between soil moisture and burn depth, the percentage of annual $PM_{2.5}$ emissions in September is 39% and 36% in October. A non-linear relationship between soil moisture and burn depth, would result in shallower burn depth in September and deeper burn depth in October, decreasing emissions in September and increasing emissions in

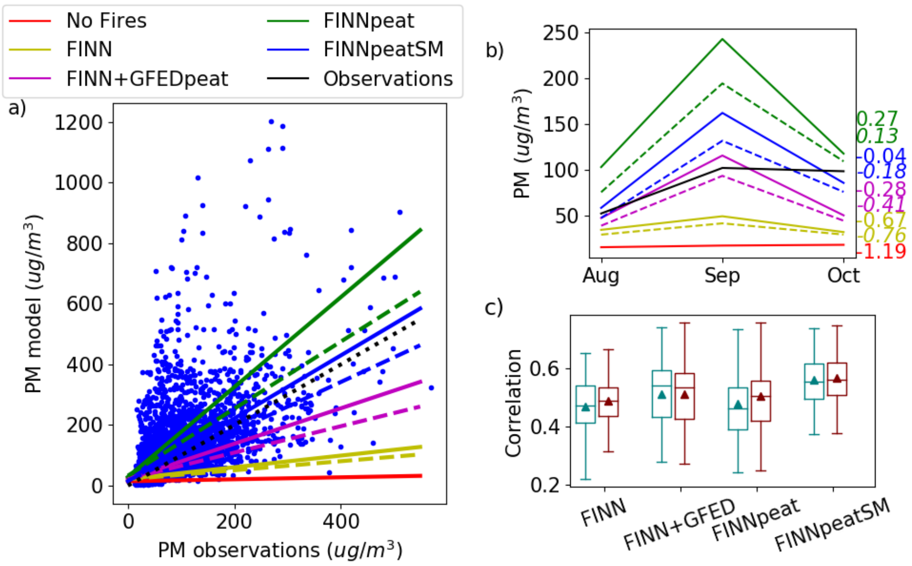

Figure 2.5: Comparison of simulated and observed PM concentrations during August to October 2015. Observations of PM_{10}, $PM_{2.5}$ and PM_1 from 55 sites in Indonesia, Singapore, and Malaysia. (a) Simulated and observed daily mean PM concentrations for FINNpeatSM emissions and surface injection (blue dots). Lines show the linear fit for the model with different emissions, solid lines are when emissions are emitted at the surface, dashed lines when emissions are injected into the boundary layer. The 1:1 line is shown in black dots. (b) The average monthly simulated and observed PM concentrations. The fractional bias for August to October is shown to the right of each line. (c) The correlation coefficient (r) for comparisons of daily mean simulated and observed PM concentrations for all 55 sites. For each simulation the box plots show the median (middle line of box), upper and lower quartiles (top and bottom of box), and the range of correlations (whiskers extend to min and max) across all sites are shown by the box plots, and the mean correlations are shown as triangles. Simulations with the surface injection are in light blue, and simulations with the boundary layer injection are in red.

October, which might further improve simulated PM concentrations. There is little information available on the measured relationship between soil moisture and burn depth.

The overestimation of modelled PM concentrations in September may also be due to our assumption that all the emissions from a fire are emitted on the day the fire was detected. In reality, peat fires can smoulder for weeks, and the emissions should be released over a longer time period. This could also reduce the simulated PM concentration in September and increase them in October. The overestimation in September could also be due to an issue with fire detection. Syaufina and Sitanggang (2018) found that only hotspots which last for at least 3 consecutive days indicate fires, something which is not considered when calculating the emissions. However, despite our simplified assumptions the model captures individual peaks in measured PM reasonably well (Figure 2.4). Alternately, an underestimation in October could be due to clouds, or haze caused by previous fires, blocking the detection of fires by the satellite.

Putriningrum et al. (2017) found that WRF-chem with FINNv1 or GFEDv4 emissions underestimated PM concentrations across Indonesia during October 2015, with GFEDv4 resulting in a better match compared to FINNv1. Putriningrum et al. (2017), suggested that emissions were underestimated due to haze from fires blocking the detection of burned area. While this is likely to effect the emissions, our work suggests that PM emissions in GFED4 could also be underestimated because EFs for peat combustion are too small.

Figure 2.5 also shows the correlation coefficients between model and measured PM concentrations across all the observation sites. The FINN simulation has the lowest average correlation across all sites (r = 0.47 and 0.49 with surface and boundary layer injection respectively), followed by FINNpeat (r = 0.48 and 0.51) and FINN+GFEDpeat (r = 0.51 for both injections). FINNpeatSM has the highest average correlation across all the sites (r = 0.56 to 0.57). Both FINN+GFEDpeat and FINNpeatSM, assume variable peat burn depth depending on soil moisture. This comparison therefore suggests that varying depth of peat burn based on surface soil moisture, as in FINNpeatSM and FINN+GFEDpeat, results in improved estimate of emissions. The height at which emissions are injected has little impact on the correlation, so there is limited evidence from this comparison to support either option.

Comparison with $PM_{2.5}$ concentrations measured in Singapore during October 2015 further supports the above analysis. WRF-chem underestimates $PM_{2.5}$ concentrations in Singapore both with FINN emissions (FB = -0.6 for surface emissions and -0.69 for boundary layer emissions) and FINN+GFED emissions (FB = -0.28 for both injections). With FINNpeat emissions the model overestimates $PM_{2.5}$ concentrations (FB = 0.45 to 0.53) and the best agreement with observations is with FINNpeatSM emissions (FB = 0.06 to 0.16).

Chemically-resolved PM_1 measurements from Singapore are available for 10^{th} to the 31st October 2015. Organic aerosols (OA) contributed 79% of the observed PM_1

between 10th and 31st October (Budisulistiorini et al., 2018). The FINN simulation underestimates the contribution of OA to PM_1 with 64% with BL injection (69% with surface injection). For the simulations with peat emissions, the model is improved with the contribution of OA to PM_1 varying (Figure B.4). With FINNpeatSM, 78% of PM_1 is OA with the boundary layer injection (82%, surface injection). For the simulations with FINNpeat it is 80% (84%), for FINN+GFED 78% (79%).

Figure 2.6 shows comparison of simulated and measured AOD. The comparisons are consistent with that seen for PM. The model with FINN emissions underestimates AOD (FB = -0.56 for surface emissions and -0.73 for boundary layer), as does the model with FINN+GFED emissions (FB = -0.09 and -0.29). FINNpeat overestimates for both injection options (FB = 0.54 and 0.35), and FINNpeatSM gives the lowest FB of -0.003 with boundary layer injection (0.19 with surface injection). The correlation coefficients between simulated and measured AOD are highest for simulations with FINNpeatSM (r = 0.64 with surface and 0.65 with BL injection) followed by FINN+GFEDpeat (r = 0.58 and 0.59), FINNpeat (r = 0.57 for both injections), and FINN (r = 0.53 and 0.52). The AOD simulated by the model exceeded 10 during September and Octobers similar to the values estimated by Eck et al (2019) for the same period. Previous work has found

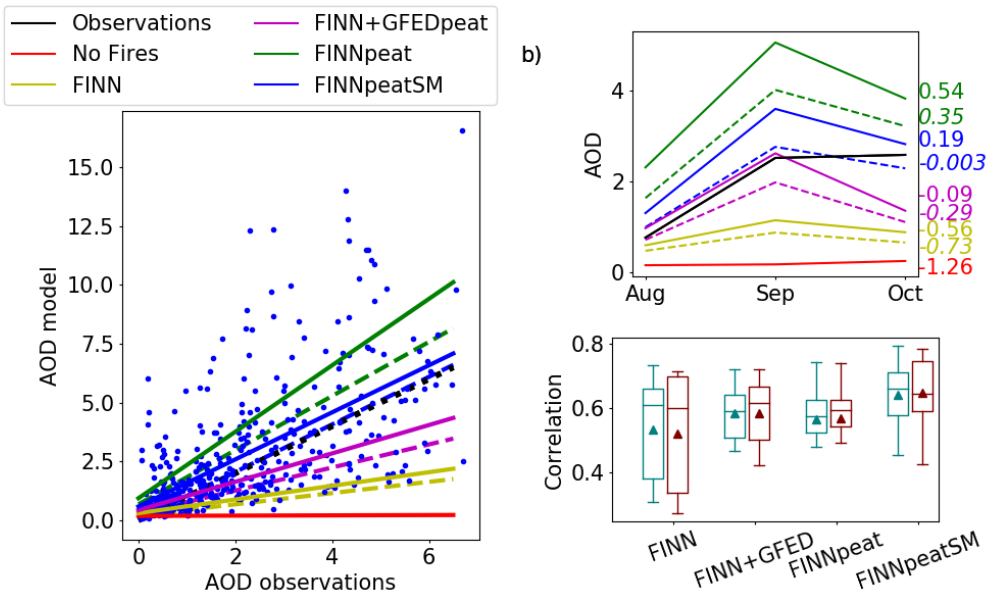

Figure 2.6: Comparison of simulated and observed AOD during August to October 2015, from 8 AERONET sites in Indonesia, Singapore, and Malaysia. Observed AOD is at 500 nm and simulated AOD is at 550 nm. (a), (b) and (c) show the same as in Figure 2.5, for AOD.

that models tend to better simulate $PM_{2.5}$ compared to AOD in regions influenced by fire emissions (Aouizerats et al., 2015; Crippa et al., 2016).

2.3.3 $PM_{2.5}$ concentrations and AOD

Figure 2.7 shows simulated surface $PM_{2.5}$ concentrations due to fires during September to October, (Figure B.5 shows results for the boundary layer injection). Simulated $PM_{2.5}$ concentrations from fires are greatest over Sumatra and southern Kalimantan, with simulated September-October mean concentrations exceeding 1800 μg m^{-3} in some grid cells in FINNpeatSM emissions. Enhanced regional $PM_{2.5}$ concentrations are simulated to the north east of the fires across peninsular Malaysia (50-150 μg m^{-3}), caused by regional transport of pollution. Simulated surface $PM_{2.5}$ concentrations from fires during September and October over Sumatra and Borneo are greatest with FINNpeat emissions (267 μg m^{-3}), followed by FINNpeatSM (183 μg m^{-3}), FINN+GFEDpeat (98 μg m^{-3}) and FINN (45 μg m^{-3}), matching the $PM_{2.5}$ emissions from the different inventories (Table 2.4).

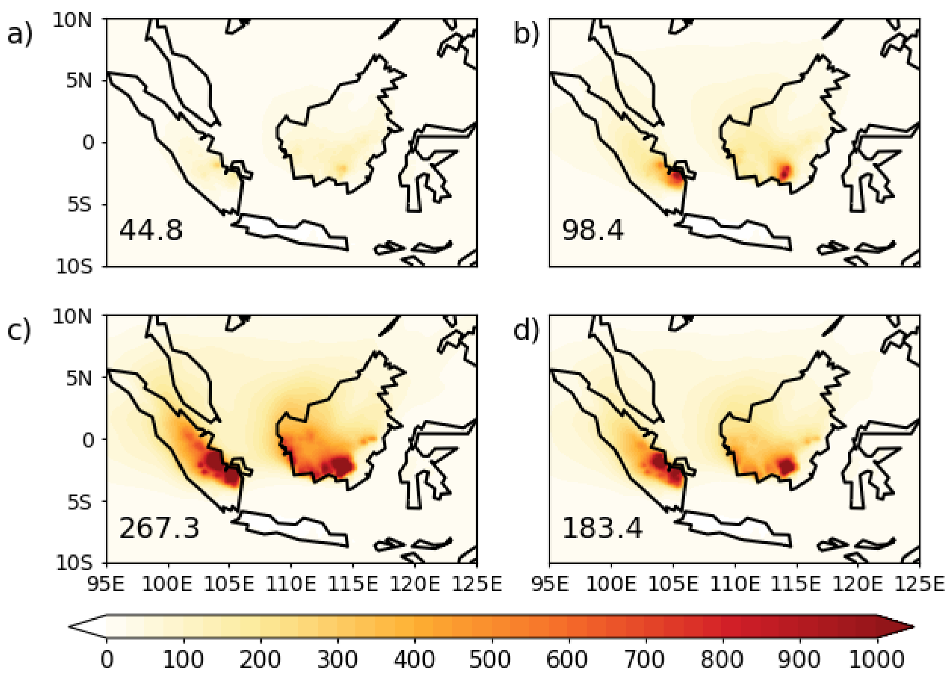

Figure 2.7: Mean simulated surface $PM_{2.5}$ concentration (μg m^{-3}) from fires for September to October 2015 with the surface injection and (a) FINN emissions, (b) FINN+GFEDpeat, (c) FINNpeat, (d) FINNpeatSM. The surface $PM_{2.5}$ concentration from fires, averaged over Kalimantan and Sumatra, is indicated on each panel.

Peat combustion contributes a substantial fraction of simulated $PM_{2.5}$ concentrations from fires, ranging from 55% in the model with FINN+GFEDpeat emissions, 76% with FINNpeatSM emissions, to 83% with FINNpeat emissions. Figure 2.8 shows the fraction of the simulated surface $PM_{2.5}$ concentration from peat fires for September to October 2015 using the FINNpeatSM emissions. The majority of simulated $PM_{2.5}$ concentrations across the study area are due to emissions from peat fires. Across Sumatra and Borneo, 96% of surface $PM_{2.5}$ concentrations are from fires with 73% from peat combustion. Peat fires therefore account for 76% of the fire contribution to $PM_{2.5}$. This is slightly larger than the contribution of peat fires to primary $PM_{2.5}$ emissions (71% in FINNpeatSM), likely due to atmospheric production of secondary organic aerosol from fire-emitted precursors. Reddington et al. (2014) used a combination of models to demonstrate that regional fire-derived PM concentrations during haze episodes are dominated by emissions from peatland regions. For 2015, Wiggins et al. (2018) suggest that ~85% of the smoke reaching Singapore was from peat fires, slightly higher than the contribution of peat fires to the simulated $PM_{2.5}$ concentration shown in Figure 2.8 (67%). Engling et al. (2014) found that in 2006, 76% of particulate matter in Singapore was from peat fires. At the Palangkaraya AERONET site in Kalimantan, Eck et al. (2019) found that 80-85% of AOD came from peat burning, consistent with the contribution of peat fires to $PM_{2.5}$ simulated by the model at that location (Figure 2.8).

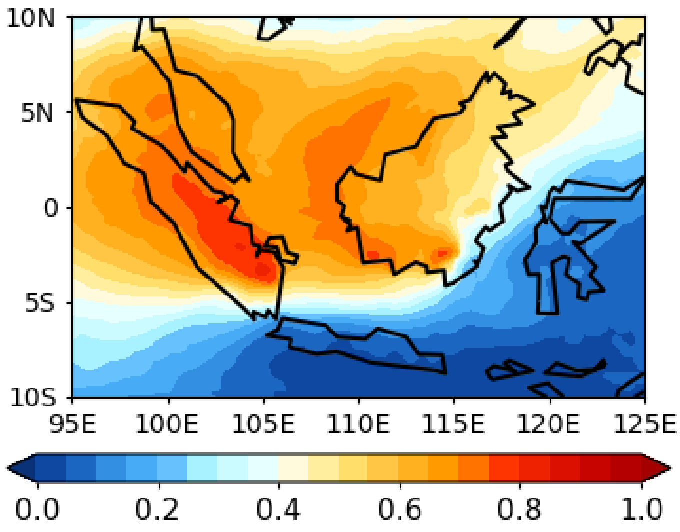

Figure 2.8: Fraction of simulated $PM_{2.5}$ concentrations originating from peat fire emissions. Simulations use the new FINNpeatSM fire emissions with surface injection.

Inclusion of emissions from peat fires gives largest fire emissions in Sumatra and western Kalimantan, where previously emissions were substantially lower (Figure 2.2). This leads to higher $PM_{2.5}$ concentrations across Singapore (Figure 2.5), which has a large impact on the population exposure to the $PM_{2.5}$. The location of fires can be an important factor of their contribution to air pollution in populated areas. Lee et al. (2017) found that the 2015 fires in Sumatra accounted for 50% of fire-derived $PM_{2.5}$ in Kuala Lumpur and 41% in Singapore, and Hansen et al. (2018), found that during August to October fires in South Sumatra and Central Kalimantan are the largest contributors to $PM_{2.5}$ in Singapore. Reddington et al. (2014) and Kim et al. (2015) found that for the 2006 fires Sumatran fires were responsible for the worst air quality across Equatorial Asia.

Injecting all fire emissions at the surface increases the average simulated surface $PM_{2.5}$ concentration by a factor of 1.34 to 1.36 compared to injecting 50% at the surface and 50% through the boundary layer. However, this factor varies spatially (Figure 2.9). Close to the fire locations, the surface injection option results in an increase in $PM_{2.5}$ concentrations by up to a factor of 2. Further away from the fires, however, the injection option has less impact on simulated $PM_{2.5}$ concentrations. Despite these differences in simulated PM, the available measurements of PM do not allow us to better constrain the vertical profile of fire emissions (Section 2.3.2).

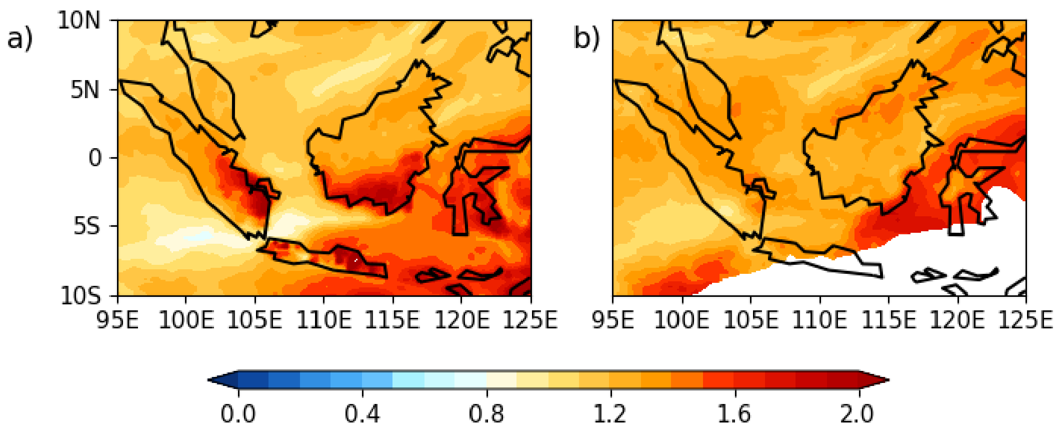

Figure 2.9: Ratio of simulated (a) surface $PM_{2.5}$ concentration and (b) AOD at 550 nm from fires for September to October, when using surface injection option compared to boundary layer injection option. Results are shown for the model with FINNpeatSM emissions. Zero values of average $PM_{2.5}$ and AOD have been removed.

Simulated AOD in Sumatra and Borneo during September to October (Figure B.6) follows a similar pattern to simulated $PM_{2.5}$, with the highest value for the model with FINNpeat (1.42) followed by FINNpeatSM (1.06), FINN+GFEDpeat (0.62) and FINN (0.31). Injecting fire emissions at the surface also results in greater simulated AOD compared to when emissions are spread through the boundary layer. The average AOD across Borneo and Sumatra increases by a factor of 1.32 for surface injected emissions compared to the boundary layer, which is similar to the difference seen in average $PM_{2.5}$ concentrations. However, spatially the difference between the injection options is different from that seen for $PM_{2.5}$ (Figure 2.8). Rather than seeing a larger increase around the fires in Sumatra and Kalimantan, the factor difference between the two injection options remains between 1.1 and 1.5 across the area effected by fires. Majdi et al. (2018) also found that the sensitivity of simulated surface $PM_{2.5}$ to injection method (up to 50%), was greater than the sensitivity of AOD (up to 20%), which is consistent with the differences seen here close to fires.

2.4 Conclusions

Vegetation and peat fires in Indonesia emit substantial amounts of trace gases and aerosol resulting in serious air pollution episodes. The magnitude of emissions from these fires is very uncertain, particularly for peat fires which are more difficult to detect using Earth observation methods. New measurements of tropical peat combustion have led to an upward revision of particulate emission factors, leading to a suggestion some fire emission inventories may underestimate particulate emissions from peat fires. Here we used the WRF-chem model along with extensive observations of PM to make a revised estimate of PM emissions from Indonesian fires during August – October 2015.

Current fire emission inventories either do not include peat fires, (FINNv1.5), or do not use updated peat emission factors (GFEDv4s). The WRF-chem model underestimated PM concentrations measured in Indonesia and Malaysia during August to October 2015, both with FINNv1.5 emissions (fractional bias = -0.7), and with a combination of FINN vegetation emissions and GFED4s peat emissions (fractional bias = -0.35). We created a new emissions inventory for Indonesia using updated emission factors for peat combustion and with variable assumptions relating the depth of peat burn to soil moisture (FINNpeatSM). Our best emissions estimate, FINNpeatSM, leads to an improved simulation of PM concentrations (fractional bias = -0.11). Estimated $PM_{2.5}$ emissions from fires across Sumatra and Borneo during September to October 2015 are 7.33 Tg (with FINNpeatSM), a factor 1.8 greater than in GFED4 (4.14 Tg) and a factor 3.5 greater than FINNv1.5 (2.1 Tg). Our total emissions agree with estimations by Wooster et al. (2018) (9.1±3.2) and Jayaranthe et al. (2018) (6±5.5 Tg from peat fires). Further work is needed to assess the impacts of secondary processes within the model on PM2.5 concentrations, and how this may affect the comparisons between model and observations made in this study. We estimate that fires contributed an additional 3.12 Tg of secondary organic aerosol emissions, equivalent to 31% of total emissions from fires. This brings the total PM from fire emissions to 10.45 Tg. Since updated CO_2 EFs for peat fires are similar to previous measurements, our estimated CO_2 emissions are consistent with GFED4s.

We find that emissions from peat combustion make up a substantial fraction of total fire emissions from the region. We estimate that peat combustion contributes 55% of total CO_2 emissions and 71% of primary $PM_{2.5}$ emissions during September to October 2015. Peat combustion contributes 76% of fire-derived surface $PM_{2.5}$ concentrations over Sumatra and Borneo during this period. This highlights the importance of peat fires and the need for better estimates of emissions from peat combustion.

The depth of peat burn is a crucial factor controlling emissions from peat fires, but it is poorly constrained. We found that using satellite remote sensed soil moisture to control the assumed depth of peat burn improved the simulation of PM, with the correlation between simulated and measured PM increasing from 0.48 with fixed peat burn depth to 0.56 with soil moisture control. There is little data available on the relationship between surface soil moisture and burn depth, more work on this could lead to further improvement in the simulation. Work is also needed to examine whether this is consistent for years other than 2015.

Our work suggests that existing emission inventories (GFED4 and FINNv1.5) underestimate particulate emissions from Indonesian fires, due to an underestimation of particulate emissions from peat combustion. Including updated emission factors from tropical peat combustion results in substantially increased PM emissions from

Indonesian fires. Measurements of emission factors from tropical peat combustion are still very limited, and additional measurements are required. Our comparison of simulated and measured PM concentrations across the region provides an additional and independent confirmation of updated emission factors from peat combustion. Our work suggests that previous studies may have underestimated the contribution of Indonesian fires on particulate air quality. We estimate that vegetation and peat fires increased PM2.5 concentrations over Sumatra and Borneo during September and October 2015 by an average of 127 $\mu g\ m^{-3}$. Future work needs to explore the impact of these fires on public health.

Code/Data availability. Code and data used in this study are available from authors upon request.

Author Contributions. Conceptualization by LK and DVS, with support from SRA and LS. LK carried out modelling work and analysis, with help from DVS and extra supervision from SRA. CK provided WRFotron modelling scripts and SAN and DL provided model code and technical support with modelling. LC and CLR provided technical support with modelling. LK and CW provided fire emissions, and MK, SHB, MFK and MTL all provided observations. LK prepared the manuscript with help from all authors.

Competing interests. The authors declare that they have no conflict of interest.

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Chapter 3 Air quality and health impacts of vegetation and peat fires in Equatorial Asia during 2004 – 2015

Kiely, Laura[1], Spracklen, Dominick V.[1], Wiedinmyer, Christine[2], Conibear, Luke[1], Reddington, Carly L.[1], Arnold, Stephen R.[1], Knote, Christoph[3], Khan, Md Firoz[4], Latif, Mohd Talib[5], Syaufina, Lailan[6], Adrianto, Hari A.[1,7]

1. School of Earth and Environment, University of Leeds, Leeds, UK

2. CIRES, University of Colorado, Boulder, Colorado, USA

3. Ludwig-Maximilians University, Munich, Germany

4. Department of Chemistry, University of Malaya, Malaysia

5. Department of Earth Sciences and Environment, University Kebangsaan Malaysia, Malaysia

6. Faculty of Forestry, IPB University, Bogor, Indonesia

7. Computer Science Department, IPB University, Bogor, Indonesia

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The reference style and the figure, table and section numbers have been formatted to be continuous throughout the thesis.

Abstract

Particulate matter (PM) emissions from vegetation and peat fires in Equatorial Asia cause poor regional air quality. Burning is greatest during drought years, resulting in strong inter-annual variability in emissions. We make the first consistent estimate of the emissions, air quality and public health impacts of Equatorial Asian fires during 2004-

2015. The largest dry season (August – October) emissions occurred in 2015, with PM emissions estimated as 9.4 Tg, more than triple the average dry season emission (2.7 Tg). Fires in Sumatra and Kalimantan caused 94% of PM emissions from fires in Equatorial Asia. Peat combustion in Indonesian peatlands contributed 45% of PM emissions, with a greater contribution of 68% in 2015. We used the WRF-chem model to simulate dry season PM for the 6 biggest fire years during this period (2004, 2006, 2009, 2012, 2014, 2015). The model reproduces PM concentrations from a measurement network across Malaysia and Indonesia, suggesting our PM emissions are realistic. We estimate long-term exposure to PM resulted in 44 040 excess deaths in 2015, with more than 15 000 excess deaths annually in 2004, 2006, and 2009. Exposure to PM from dry season fires resulted in an estimated 131 700 excess deaths during 2004-2015. Our work highlights that Indonesian vegetation and peat fires frequently cause adverse impacts to public health across the region.

3.1 Introduction

Vegetation and peat fires in Equatorial Asia contribute to climate change (Page et al., 2002; Tosca et al., 2013) and poor regional air quality (Field et al., 2009; Reddington et al., 2014; Lee et al., 2017). Fires in Equatorial Asia are influenced by climate, land-use and land management (van der Werf et al., 2008; Page and Hooijer, 2016), and air quality degradation is greatest in dry years when the most extensive fires occur (Marlier et al., 2012; Koplitz et al., 2016; Crippa et al., 2016). Large-scale deforestation, forest degradation and agricultural development have increased the occurrence of fire (Sloan et al., 2017) and extensive fires are no longer restricted to drought years (Gaveau et al., 2014). However, the air quality impact of fires outside of drought years has not been studied. Here we develop a new fire emissions estimate for Equatorial Asia and make a consistent estimate of the impacts of fire on air quality and health during 2004-2015.

Tropical peatlands store large amounts of organic carbon in peat soils (Page et al., 2002; Page et al., 2011). Fires on peatland can burn into the peat and combust substantial amounts of biomass (Hu et al., 2018; Roulston et al., 2018). The majority of peatland fires occur on deforested land (Cattau et al., 2016; Miettinen et al., 2017; Adrianto et al., 2019) or during deforestation (Adrianto et al., 2020). Drainage canals established during plantation development lower the water table, increasing the chances of the peat burning

(Wösten et al., 2008). Peat fires also have higher emission factors for many atmospheric pollutants than vegetation fires (Hu et al., 2018; Kiely et al., 2019). Together these factors result in peat fires contributing 71-86% of fire emissions in Equatorial Asia (Heil et al., 2007; Kiely et al., 2019).

Fire emission inventories combine uncertainties in area burned, fuel loads, biomass consumption and pollutant-specific emission factors resulting in substantial overall uncertainty (Reddington et al., 2016). Emissions estimates from Indonesian fires are particularly uncertain (Liu et al., 2020), due to difficulties in diagnosing peat burn depth and uncertainties around emission factors from peat combustion (Page et al., 2002; Van Der Werf et al., 2010; Kiely et al., 2019). Many previous studies scaled particulate matter (PM) emissions to improve simulated atmospheric concentrations in comparison to observations (Reddington et al., 2016).

In Equatorial Asia, fires occur predominantly in the dry season (August to October) and particularly during periods of drought, often associated with El Niño events, such as those in 1982-1983, 1997-1998, 2006 and 2015 (Ballhorn et al., 2009; Wooster et al., 2012; Field et al., 2016). Recent work has also highlighted the role played by the Indian Ocean Dipole (Pan et al., 2018). In 2015, an estimated 6 – 9.1 Tg PM was emitted from Indonesian fires (Wooster et al., 2018; Jayarathne et al., 2018; Kiely et al., 2019). Climate change may lead to increased frequency of extreme El Niño events (Cai et al., 2014) and increased future fire activity (Yin et al., 2016).

PM less than 2.5 μm in aerodynamic diameter ($PM_{2.5}$) has been associated with adverse health impacts and premature mortality (Emmanuel, 2000; Cohen et al., 2017). The World Health Organisation recommends that 24-hour mean $PM_{2.5}$ concentrations exceeding 25 μg m^{-3} could be detrimental to health; regions of Indonesia, Malaysia and Singapore frequently experience concentrations greater than this limit due to smoke from fires (Marlier et al., 2012; Crippa et al., 2016; Lee et al., 2017).

Previous studies that have estimated the premature mortality attributable to exposure to $PM_{2.5}$ from fires across Equatorial Asia, have focused on El Niño years, when fire emissions are greatest (Johnston et al., 2012; Sahani et al., 2014; Crippa et al., 2016;

Koplitz et al., 2016). Marlier et al. (2012) estimated that fires in 1997 resulted in 10 800 excess premature deaths from cardiovascular mortality. For the 2015 haze event, Crippa et al., (2016) found that long term exposure resulted in 75 600 excess premature mortalities (from respiratory, pulmonary and heart diseases, lung cancer and stroke). Koplitz et al., (2016) estimated premature mortality from all causes with 100 300 excess deaths in 2015 and 37 600 premature deaths in 2006.

Different methods of calculating PM emissions, concentrations and health effects, complicate comparisons across years. Here we use a consistent methodology to provide a multi-year comparison of fire emissions, population exposure to PM and excess premature mortality for Equatorial Asia between 2004 and 2015. Through studying a wide range of years we provide new information on the interannual variability and long-term impacts of fire on air quality and human health in Equatorial Asia.

3.2 Methods

In this study, we calculate emissions from Equatorial Asian fires for 2004-2015. We then use a regional air quality model to simulate PM concentrations for the 6 biggest dry-season fire episodes during this period. We evaluate simulated PM against observations across Indonesia and Malaysia. Finally, we use the simulated $PM_{2.5}$ to estimate the public health impacts of exposure to the particulate pollution.

3.2.1 Fire emissions

Fire emissions are from FINNpeatSM, described in detail in Kiely et al. (2019) and summarised briefly here. FINNpeatSM includes vegetation fire emissions from FINNv1.5 (Wiedinmyer et al., 2011). When MODIS fire hotspots are detected on peatland (World Resources Institute, 2017) we assume that fires burn into the peat. Emissions from peat fires are estimated from the burn area, peat burn depth, peat density and emission factors (EF). We assume 100 ha of surface burned area for each fire hotspot (as in FINNv1.5), but only 40 ha of peat burn to account for the fact that not all surface fires on peatland will burn into the peat. We estimate the burn depth of the peat based on daily soil moisture from the European Space Agency (ESA CCI SMv04.4) averaged to 2° degree resolution (Liu et al., 2012; Dorigo et al., 2017; Gruber et al., 2017). We assume peat burn depth scales linearly with soil moisture between a maximum burn depth of 37 cm (averaged from Page et al., 2002; Usup et al., 2004; Ballhorn et al., 2009) when soil moisture is low (< 0.15 $m^3 m^{-3}$) and a minimum burn depth of 5 cm when soil moisture is high (> 0.25 $m^3 m^{-3}$). Emission factors (EF) for peat burning are taken as an average of previous studies of burning of Indonesian peat (Christian et al., 2003; Hatch et al., 2015; Stockwell et al., 2016; Nara et al., 2017; Wooster et al., 2018; Jayarathne et al., 2018; Roulston et al., 2018). The (EF) for $PM_{2.5}$ used for peat fires (22.3 g kg^{-1}) is larger than in other fire emission inventories, such as the Global Fire Emissions Database (GFED4s) and the Global Fire Assimilation System (GFAS) which both use 9.1 g kg^{-1} (Van Der Werf et al., 2010; Kaiser et al., 2012).

3.2.2 WRF-chem

WRF-chemv3.7.1 was used to simulate PM concentrations across Equatorial Asia (Figure 3.1). The model has been run at 30 km resolution with 33 vertical levels, between the surface and 50 hPa. We used the model to simulate the 6 dry-seasons (August – October) with the greatest fire emissions over the 2004 to 2015 period: 2004, 2006, 2009, 2012, 2014 and 2015. Our domain excludes West Papua, where fires occurred in 2015 (Lohberger et al., 2017). All simulations included a 14 day spin up for chemistry at the start of the time period, and with a 24 hour spin up for meteorology every 15-16 days using National Centre Environmental Prediction Global Forecast System (NCEP, 2007). In between the meteorology was free running, to allow the

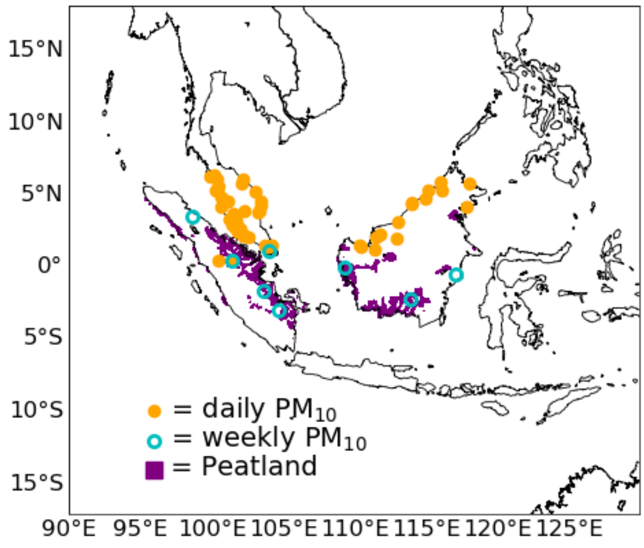

Figure 3.1: The WRF-chem model domain and locations of observations. Areas of peatland are shaded in purple.

model to simulate impacts of fire smoke on meteorology. The MOZART (Model for Ozone and Related Chemical Tracers, version 4; Emmons et al., 2010) chemistry scheme was used to calculate gas-phase reactions, with MOSAIC (Model for Simulating Aerosol Interactions and Chemistry; Zaveri et al., 2008; Hodzic and Knote, 2014) used to represent aerosol processes, separated into 4 bins; 0.039-0.156 µm, 0.156 – 0.625 µm, 0.625 – 2.5 µm and 2.5 – 10 µm. SOA formation from fires in the model is calculated as 4% of the fire emitted CO based on Spracklen et al. (2011). A more complete model description can be found in the Appendix C (Table C.1).

Anthropogenic emissions are from EDGAR-HTAP2 (Janssens-Maenhout et al., 2015) for 2010, biogenic emissions are from MEGAN (Model of Emissions of Gases and Aerosols from Nature; Guenther et al., 2006). Following Kiely et al. (2019), we inject half of the fire emissions at the surface with the rest spread throughout the boundary layer. For each year, model simulations were completed with and without fire emissions. The contribution of fires to PM concentrations is calculated as the difference between the simulations with and without fire.

3.2.3 Observations

Hourly measurements of PM_{10} (mass concentration of particulate matter < 10 µm aerodynamic diameter) are available from a network of 53 surface sites across Malaysia (Mead et al., 2018) for all the periods of this study (Figure 3.1). Hourly PM_{10} is also available from Pekanbaru in Indonesia for 2013 and 2015, and from Bukit Kototabang in Indonesia for 2004, 2006 and 2009. Weekly averaged PM_{10} measurements are available from six sites in Indonesia for 2014 and 2015. Hourly measurements of $PM_{2.5}$ from 5 locations in Singapore are available for 2014 and 2015, and are averaged to give mean concentrations for Singapore.

Measurements of PM are mainly from urban locations away from the locations of fires. To estimate the PM concentrations from fire at each measurement location we subtract the background PM concentration during months with little fire (months when $PM_{2.5}$ fire emissions are < 0.1 Tg month^{-1} across Indonesia).

We averaged hourly data to give daily means, and calculated the fractional bias (FB), Pearson correlation (r), the normalized mean bias factor (NMBF) and normalized mean absolute error factor (NMAEF) (Yu et al., 2006) to evaluate the model (Appendix C).

3.2.4 Population weighted $PM_{2.5}$

Population weighted $PM_{2.5}$ (PW), a metric of population exposure to $PM_{2.5}$ concentrations, was calculated as,

$$PW = \sum \frac{C_i * P_i}{P_{tot}}$$

where C_i is the $PM_{2.5}$ concentration and P_i is the population of grid cell i, and P_{tot} is the total population of the domain. The population data is from the Gridded Population of the World, Version 4 (GPWv4) (Center for International Earth Science Information Network and NASA Socioeconomic Data and Applications Center, 2016). The total population within the domain is 477 million, with 255 million in the Indonesian part of the domain (total Indonesian population is 263 million).

3.2.5 Mortality

The long term premature mortality was calculated using the simulated annual mean $PM_{2.5}$, with and without fire emissions. $PM_{2.5}$ from August from the simulation with no fires was used to represent January to July and November to December. Anthropogenic emissions in the tropics have little seasonal variation, and this method has been used previously to estimate population exposure to fires (Crippa et al., 2016; Koplitz et al. 2016).

Premature mortality per year, M, from disease j in grid cell i was calculated as,

$$M_{ij} = P_i I_j \, (RR_{jc} - 1)/RR_{jc}$$

where P_i is the population in i, I_j is the baseline mortality rate (deaths year^{-1}) for j, and RR_{jc} is the relative risk for j at $PM_{2.5}$ concentration, c (µg m^{-3}). The baseline mortality rates and the population age composition are from the GBD2017 (Institute for Health Metrics and Evaluation, 2019), and the relative risks are taken from the Global Exposure Mortality Model (GEMM) (Burnett et al., 2018) for non–accidental mortality (non–communicable disease and lower respiratory infections). The GEMM exposure function was calculated using the relationship between long-term exposure to outdoor $PM_{2.5}$ concentrations and mortality, from studies across many countries. The GEMM exposure function was chosen as it incorporates data from a study in China where PM concentrations are regularly high, as is the case in Equatorial Asia. Mean, upper and lower uncertainty intervals from the GEMM have been used to produce mortality estimates with a 95% uncertainty interval. Population count, population age, and baseline mortality rates were kept constant for 2004-2015 to estimate the variation due to changes in exposure only.

To explore differences with previous studies, we also estimate mortality following the method used in Koplitz et al. (2016), where the baseline mortality for all causes increases by 1% for every 1 $\mu g\ m^{-3}$ increase in annual mean $PM_{2.5}$ concentrations below 50 $\mu g\ m^{-3}$.

3.3 Results and Discussion

3.3.1 Emissions

The greatest fire emissions occur between August and October each year, with a secondary peak in January to April (Figure 3.2). The largest dry season emissions occurred in 2015, followed by 2006, 2009 and 2004. All of these years experienced monthly total fire emissions that were greater than 1 standard deviation above the long-term monthly mean. Other years with total dry season emissions above the median were 2012 and 2014.

Table 3.1 compares dry season (August to October) burned area, biomass consumption and emissions for FINNpeatSM and GFED4s inventories (van der Werf et al., 2017). Averaged across 2004-2015, FINNpeatSM has a greater burned area compared to GFED4s (fractional bias, FB = 1.01). Dry matter fuel consumption is more comparable (FB = 0.15) due to greater average dry matter consumption per unit area burned in GFED4s (15 189 g m^{-2}) compared to FINNpeatSM (6476 g m^{-2}), as a result of greater average peat burn depth in GFED4s. Peat makes up half of the average dry matter consumption in GFED, compared to a quarter of the dry matter consumption in

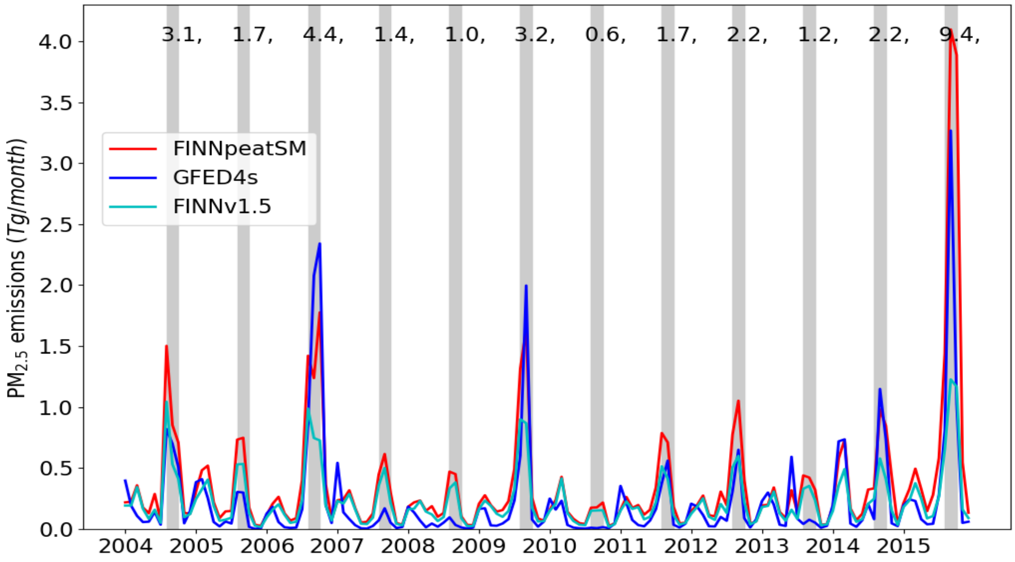

Figure 3.2: Monthly primary $PM_{2.5}$ fire emissions from Indonesia between 2004 and 2015, from the FINNv1.5, GFED4s and FINNpeatSM inventories. Grey shaded regions show the dry season (August-October) each year. Dry season primary $PM_{2.5}$ emissions (Tg) from FINNpeatSM are shown at the top of the figure.

FINNpeatSM. The average emissions of CO and CO_2 are similar (FB = -0.04 and FB = 0.07) for the two inventories, while FINNpeatSM has greater dry season $PM_{2.5}$ emissions (FB = 0.48) (Table 3.1), due to higher $PM_{2.5}$ EF for peat combustion applied in FINNpeatSM (22.3 g kg^{-1}) compared to GFED4s (9.1 g kg^{-1}). The total emissions from fires depends on the percentage of peat burned, as well as the overall dry matter consumption (see Appendix C).

GFED4s uses MODIS burned area (Giglio et al., 2013) whereas FINNpeatSM applies a 1km^2 burned area to detected hotspots. Previous studies have also found that this method results in FINN having a larger burned area than other emissions inventories in Asia (Vongruang et al., 2017), while Liu et al. (2020) suggest thick haze in Indonesia in 2015 prevented detection of fires and that MODIS burned area may be underestimated by 93%. In FINNpeatSM, average burn depth is 7.3±3.7 cm, compared to 10.8±4.8 cm in GFED4s. These estimates are lower than many burn depths recorded in the field (Ballhorn et al., 2009; Stockwell et al., 2016), however field measurements are likely to be taken at large fires where burn depths may be deeper than average (Stockwell et al., 2016).

Table 3.1: Total burned area, dry matter consumed and emissions of $PM_{2.5}$, CO_2 and CO for Equatorial Asian fires during August – October from FINNpeatSM. The fraction of emissions from peat fires is shown in brackets after each value. For burned area the fraction of fires which occurred on peatland is shown. The average burn depth and emissions per m^2 burned area is also given. Also detailed are average ± standard deviation burned area, dry matter consumption and emissions for August-October across all years for 2004-2015 for FINNpeatSM and GFED4s, with the correlation and the fractional bias between interannual averages.

		Burned Area (km^2)	Mean burn depth (cm)	Dry Matter (Tg)	(g /m^2)	$PM_{2.5}$ (Tg)	(g /m^2)	CO_2 (Tg)	(g /m^2)	CO (Tg)	(g /m^2)
2004:	FINNpeatSM	47 600 (39%)	5.8	267 (18%)	5604	3.1 (35%)	65.1	422 (19%)	8858	30.0 (38%)	629
2006:	FINNpeatSM	66 700 (46%)	6.2	361 (25%)	5414	4.5 (45%)	67.5	573 (26%)	8593	44.3 (48%)	664
2009:	FINNpeatSM	39 800 (43%)	7.6	266 (21%)	6683	3.2 (40%)	80.4	419 (22%)	10,527	31.2 (43%)	784
2012:	FINNpeatSM	29 700 (37%)	7.9	186 (22%)	6252	2.2 (40%)	74.0	295 (23%)	9916	22.0 (43%)	739
2014:	FINNpeatSM	33 400 (40%)	7.7	184 (25%)	5517	2.2 (45%)	66.0	293 (26%)	8785	22.7 (48%)	681
2015:	FINNpeatSM	68 000 (50%)	19.0	623 (46%)	9160	9.4 (68%)	138.2	999 (48%)	14,688	96.4 (70%)	1417
2004-2015 Mean:	FINNpeatSM	33 275±18250 (36%)	7.3 ± 3.7	215 ± 147 (25%)	6476	2.7 ±2.3 (45%)	80.2	340± 265 (27%)	10,228	27 ± 24 (49%)	798
	GFED4s	12 246 ±8895 (51%)	10.8 ± 4.8	186 ± 193 (52%)	15189	1.7±1.8 (52%)	138.8	318± 329 (51%)	25,968	28 ± 31 (71%)	2286
Correlation (r)		0.98		0.91		0.87		0.91		0.89	
Fractional Bias (FB)		1.01		0.15		0.45		0.07		-0.04	

There is a strong correlation between the dry season emissions simulated by FINNpeatSM and GFED4s (r = 0.87 – 0.98 for different pollutants, Appendix C), although GFED4s emissions have greater interannual variability (Figure C.1), due to greater variability in peat burn depth (Figure C.2). Emissions are a product of burned area, burn depth and emissions factors. Compensating differences amongst these variables mean that two emission datasets can predict similar emissions for different reasons. Measurements of burned area, burn depth, and emission factors are needed to help further constrain the emission models.

Figure 3.3 compares the spatial pattern of average dry season $PM_{2.5}$ emissions in FINNpeatSM and GFED4s. In both datasets South Sumatra and Kalimantan are responsible for the majority of fire emissions, with Sumatra accounting for 33-42% of $PM_{2.5}$ emissions and Kalimantan accounting for 52-63%, in agreement with previous studies (Kim et al., 2015; Wooster et al., 2018).

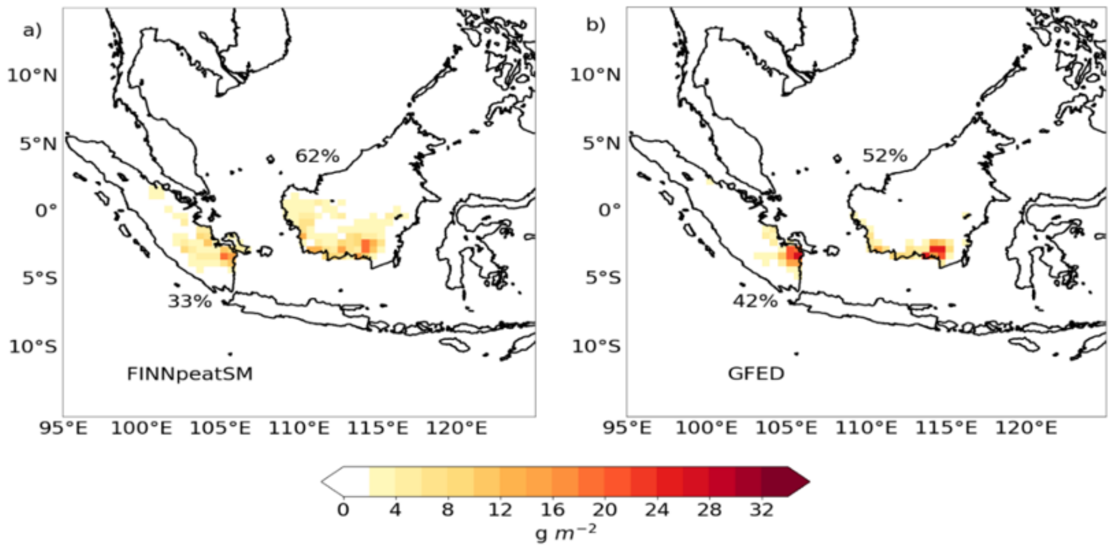

Figure 3.3: Average dry season (August – October) $PM_{2.5}$ emissions (g/m^2) during 2004-2015 for (a) FINNpeatSM and (b) GFED4s. Emissions are plotted at a resolution of 0.5°. The percentage of emissions from Sumatra and Kalimantan are shown next to the regions.

3.3.2 Model evaluation

Without fire emissions, the model greatly underestimates PM concentrations across Malaysia and Indonesia (NMBF = -3.72) and the temporal variability across the sites with daily data is poorly simulated (r = 0.27). When fire emissions are included, the model still underestimates observed PM (NMBF = -0.47), although the temporal variability is better simulated (r = 0.51) (Figure C.3). Most measurements are in urban locations and issues resolving urban-scale pollution are likely to contribute to model underestimation. To overcome this we estimated fire-derived PM from the observations by subtracting measured PM concentrations during periods without fire (see Methods), and compared with the simulated PM concentration from fires (the difference between simulations with and without fires). Figure 3.4 shows the comparison of simulated and observed fire-derived PM at each site. Across all years, the simulation of fire-derived PM is unbiased (NMBF = 0.14) and the model has reasonable skill in simulating the temporal variability at each site (r = 0.43), although there is year to year and site to site variability (see Appendix C). The NMAEF and FB for the comparison of fires derived PM are also low for each year (NMAEF = 1.07, FB = -0.02; Figure C.4). Our model skill in comparison against PM_{10} observations at 52 sites is similar to a previous comparison by Crippa et al. (2016) who reported a NMBF of -0.24 for comparison against PM_{10} observations at two sites in 2015.

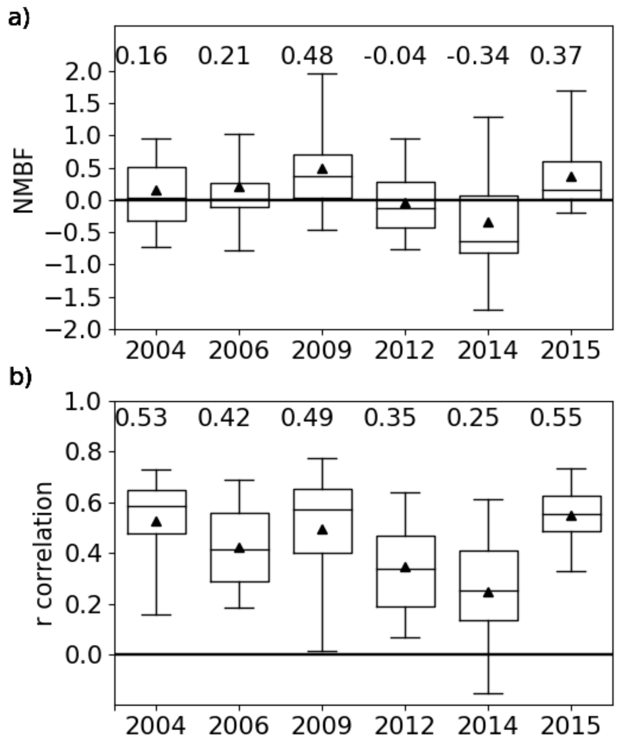

Figure 3.4: Box plot showing (a) the normalized mean bias factor (NMBF) and (b) the correlation coefficient (r) between simulated and measured fire-derived PM concentration. NMBF and r were calculated at each of the sites in Malaysia and Indonesia. The box plots show the mean value as a triangle, the median as the middle of the box, the box showing the upper and lower quartiles and the whiskers showing the range of values without outliers. The mean NMBF and r across all sites is given on the plots. Measured fire-derived PM_{10} is estimated at each site by subtracting measured PM_{10} from periods without fire (see Methods).

3.3.3 $PM_{2.5}$ exposure

Table 3.2 gives the average $PM_{2.5}$ concentration across the domain and the population-weighted $PM_{2.5}$ exposure for Equatorial Asia due to emissions from fires. $PM_{2.5}$ and population-weighted $PM_{2.5}$ concentrations are greatest in 2015. In 2004 and 2012 there is greater average population weighted $PM_{2.5}$ from fires than for 2009, despite 2004 and 2012 having lower total $PM_{2.5}$ fire emissions. This is due to there being more fires in Sumatra in 2012 than in 2009, close to populated areas. Despite having lower emissions than Kalimantan, fires in Sumatra can expose a greater population to poor air quality (Reddington et al., 2014; Kim et al., 2015; Marlier et al., 2015; Koplitz et al., 2016). We estimated a population-weighted smoke exposure over July to October of 8.8 µg m^{-3} in 2006 (compared to 8 µg m^{-3} simulated by Koplitz et al. (2016)) and 25.6 µg m^{-3} in 2015 (compared to 19 µg m^{-3} by Koplitz et al. (2016)).

Fires increase exposure to $PM_{2.5}$ concentrations above the WHO recommended limit of 25 µg m^{-3} (World Health Organization, 2005) (Figure 3.5). In 2015 fires resulted in an average of 20 million people being exposed to a daily $PM_{2.5}$ concentration > 150 µg m^{-3} (Figure 3.5), and 66.5 million people being exposed to daily $PM_{2.5}$ concentrations > 25 µg m^{-3} for at least one in two days during August – October (Figure 3.5). Crippa et al. (2016) found that 69 million people in Equatorial Asia were exposed to unhealthy air quality for one day in two in 2015, and Mead et al. (2018) found that 26 million people in Malaysia were exposed to PM_{10} levels above the WHO recommended limit of 50 µg m^{-3}. For other years we estimate 22.2 – 51.7 million people were exposed to $PM_{2.5}$ concentrations above 25 µg m^{-3} for one day in two (Figure 3.5). The majority of people exposed to poor air quality from fires live in Indonesia (51-80% of people exposed) and Malaysia (15-30%).

Table 3.2: The average simulated $PM_{2.5}$ concentration over Indonesia and population weighted $PM_{2.5}$ concentration from fires over August to October; the number of people exposed to $PM_{2.5}$ > 25 µg m^{-3} for at least half the days in August to October due to fires; the mortality, years of life lost (YLL) and disability adjusted life years (DALY) resulting from exposure to $PM_{2.5}$ from fires in each year (calculated using GEMM). Descriptions of the calculation of YLL and DALY are in Appendix C. The upper and lower estimates are shown in brackets.

Year	Average $PM_{2.5}$ (µg m^{-3})	Average population-weighted $PM_{2.5}$ (µg m^{-3})	People exposed to $PM_{2.5}$ > 25 µg m^{-3} for at least half the days (million people)	Mortality (deaths)	YLL (years)	DALY (years)
2004	14.3	5.7	30.0	16,219 (12562 – 20191)	392,761 (303728 – 489295)	637,727 (456836 – 856074)
2006	21.0	8.8	51.7	22,088 (17145 – 27427)	532,655 (412927 – 661631)	867,220 (622619 – 1161097)
2009	15.4	5.2	22.2	16,656 (12868 – 20768)	404,715 (312146 – 505219)	654,733 (468340 – 879776)
2012	11.7	5.2	26.7	14,573 (11287 – 18132)	353,026 (273043 – 439511)	573, 084 (410643 – 768854)
2014	11.7	4.7	27.9	13,705 (10598 – 17085)	333,931 (257964 – 416406)	541,086 (387007 – 727671)
2015	65.8	25.6	66.5	44,041 (34672 – 53948)	1,057,573 (832357 – 1294657)	1,725,203 (1256322– 2278572)

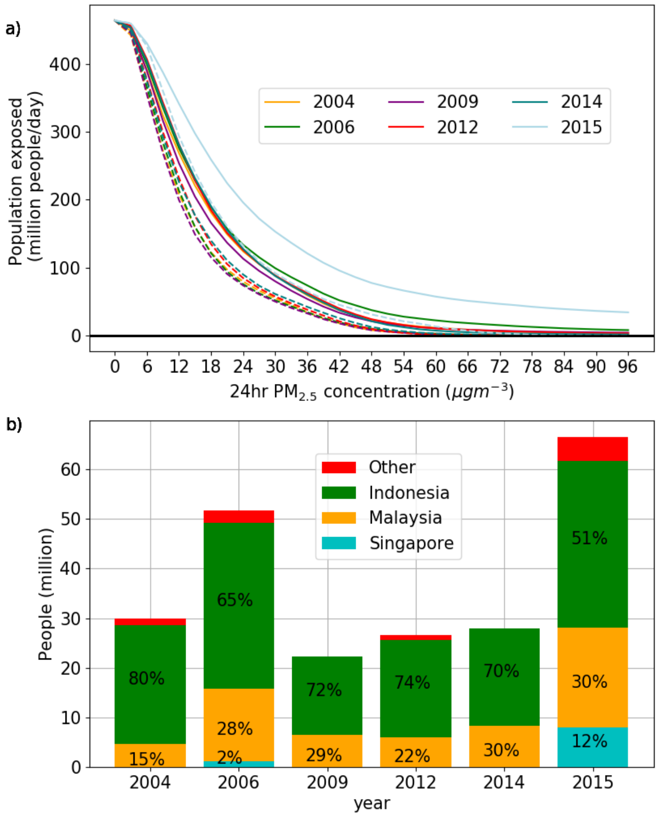

Figure 3.5: Population exposure to poor air quality. (a) The average population per day exposed to 24-hr $PM_{2.5}$ concentrations above levels shown on x axis, for simulation with fires (solid lines) and without fires (dashed lines). (b) The number of people exposed to 24-hr $PM_{2.5}$ concentrations over 25 µg m^{-3} for at least half the days in August-October.

3.3.4 Public Health Impacts

Table 3.2 shows the estimated excess premature mortality, years of life lost, and disability affected life years across the domain resulting from exposure to $PM_{2.5}$ from fires. For each year studied, exposure to $PM_{2.5}$ from fires resulted in over 13 000 excess premature deaths, 300 000 years of life lost and 500 000 disability affected life years.

The greatest number of excess deaths resulting from fires was in 2015. We estimate exposure to $PM_{2.5}$ from fires caused 44 000 excess deaths in 2015, less than the 75 600 excess deaths estimated by Crippa et al. (2016) or the 100 300 excess deaths estimated by Koplitz et al. (2016). This difference is due to different methods of estimating the health impacts of exposure to $PM_{2.5}$. Koplitz et al. (2016) applied a 1% increase in baseline mortality for all causes of non-accidental death, for every 1 µg m^{-3} increase in annual mean $PM_{2.5}$ concentration. When we apply the same function with our simulated PM concentrations we estimate 106 000 premature mortalities in 2015, similar to that estimated by Koplitz et al. (2016). In 2006, we estimate exposure to smoke from fires results in 22 100 premature mortalities, greater that the 6 000 excess deaths from cardiovascular mortality estimated by Marlier et al. (2012) but less than the 37 600 deaths estimated by Koplitz et al. (2016). Using the same relative risk as Koplitz et al. (2016), we estimate 42 520 excess premature deaths from the 2006 fires, similar to their estimate. This comparison suggests that the largest uncertainty in health impacts is due to uncertainty in exposure response function (i.e., the sensitivity of health to PM exposure) rather than uncertainty in emissions or PM concentrations. Kushta et al. (2018) found that the majority of uncertainty in long term mortality estimates for Europe is related to the relative risk function. There may also be mortalities from exposure to fire related air pollution which have not been considered in our study. Jayachandran (2013) suggests that the pollution from the 1997 fires in Indonesia may result in early-life mortality, while we have only calculated health impacts for adults.

Figure 3.6 shows the regional distribution of excess mortality due to $PM_{2.5}$ exposure from fires. The largest mortality occurs in Sumatra, with 38% of the total mortalities due to $PM_{2.5}$ exposure from fire. This is due to a large population with close proximity to the fires. Kalimantan, which has a higher proportion of the $PM_{2.5}$ emissions than Sumatra (Table 3.1), has an average of 23% of the total mortalities. Averaged across the years, Malaysia accounts for 18% of the mortalities and Singapore accounts for 4%.

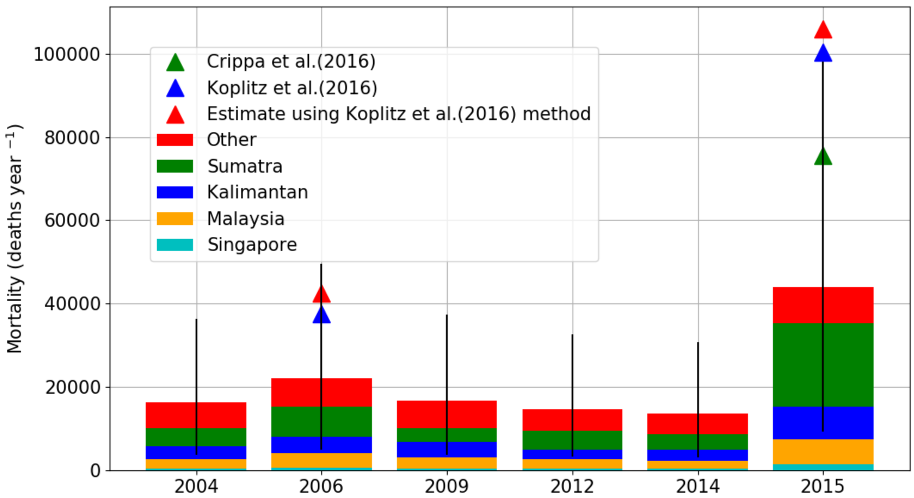

Figure 3.6: Excess premature mortality due to exposure to $PM_{2.5}$ from fires. The upper and lower 95% uncertainty interval for the total domain is shown as black lines. Symbols show comparison against previous studies as well as an estimate using our PM exposure combined with the health function used by Koplitz et al. (2016).

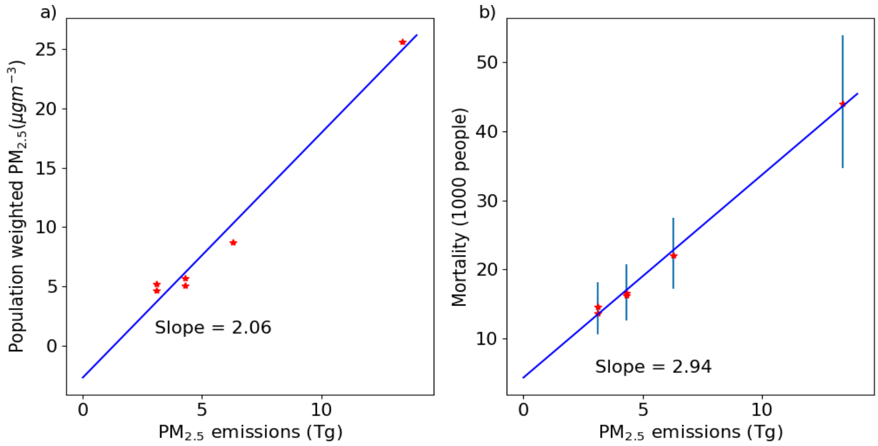

Figure 3.7: The total dry season $PM_{2.5}$ emissions (primary emissions and SOA formation) from fires against (a) the population-weighted $PM_{2.5}$, and (b) the total mortality from exposure to $PM_{2.5}$ from fires. Error bars show the upper and lower estimates of mortality. The gradient of the linear least squares regression, is given on the plot. The Pearson's correlation is 0.987 for (a) and 0.997 for (b).

Figure 3.7 shows the annual mean population-weighted $PM_{2.5}$ and the annual mortality resulting from exposure to $PM_{2.5}$ from fires as a function of particulate emission (primary $PM_{2.5}$ emissions and SOA formation; see Methods) from fires. For the years we have studied there is a linear relationship between particulate emission and population-weighted $PM_{2.5}$ (r = 0.99) and between emission and estimated premature mortality (r = 0.99). For each Tg of particulates emitted from fires, population weighted $PM_{2.5}$ increases by 2.1 µg m^{-3}, and excess annual premature mortality increases by 2950.

A linear relationship between emission and exposure may not be expected; exposure to $PM_{2.5}$ and resulting impacts on health depend on the location and magnitude of the emissions, as well as the atmospheric transport of pollution. However, in Equatorial Asia, the location of fires and the direction of pollution transport varies little year to year. Each year, dry season fires occur in similar regions of Equatorial Asia (Figure 3.3), consistent south-easterly winds over South Kalimantan and Sumatra result in similar atmospheric transport patterns (Chang et al., 2005; Heil et al., 2007; Wang et al., 2013; Lee et al., 2017), and the same areas are exposed to poor air quality (Figure C.6). This leads to the strong linearity between $PM_{2.5}$ emissions, PM exposure, and mortality. The sample size used here is small (n = 6), however, our results indicate that it may be possible to make a simple estimate of PM exposure and health impacts from emissions alone. We used the relationship between PM emission and mortality, to estimate the health impacts from fires across 2004 – 2015. Total August – October $PM_{2.5}$ emissions from 2004 to 2015 were 44.8 Tg, resulting in an estimated 131 700 excess premature mortalities in this period. We note the 6 years studied in detail resulted in a combined total of 113 600 excess premature deaths. We also used this relationship combined with the particulate emission per unit area burned (Table 3.1) to estimate the premature mortality resulting from each 1 km^2 of land burned. For 2004-2014, we estimate 0.25 – 0.33 deaths per km^2 of burned area. For 2015, we estimate 0.58 deaths km^{-2}, due to the deeper peat burn depth in that year. These numbers provide an indication of the potential magnitude of public health benefits from reductions in fire arising from the moratorium on granting new concession licences for industrial agriculture (Wijedasa et al., 2018), peatland restoration (Harrison et al., 2019) and fire management (Carmenta et al., 2017; Jefferson et al., 2020).

3.4 Conclusion

We combined a new method of calculating emissions from peat fires (FINNpeatSM), a regional air quality model and a concentration-response function to make the first consistent estimate of the impacts of smoke from Equatorial Asian fires on human health over the period 2004 to 2015. Over this period, FINNpeatSM has a larger burned area but shallower peat burn depth compared to GFED4s, leading to similar biomass consumption, CO and CO_2 emissions for both inventories. We estimate average August - October $PM_{2.5}$ emissions were 2.7 Tg yr^{-1}, 59% greater than in the GFED4s dataset, largely due to greater $PM_{2.5}$ emission factor for peat combustion in our estimates. We estimate that the largest fire emissions occurred in 2015, due to the greater area burned and deeper peat burn depth compared to other years. Deeper peat burn depth is a result of low soil moisture in 2015, confirming that soil moisture plays an important role in controlling emissions from peat fires. We estimate that 94% of $PM_{2.5}$ emissions from fire across Equatorial Asia are from Indonesian fires, with 60% – 82% due to fires in Kalimantan. Improving emission estimates requires better estimates of both area burned and peat burn depth, including how this varies with soil moisture. A detailed evaluation against multiple in-situ and remote sensed data is needed to constrain emissions and better understand interannual variability.

We used the WRF-chem model to simulate PM concentrations for the six years during 2004-2015 with the largest fire emissions. Simulated PM concentrations resulting from these fire emissions reproduced measured concentrations across Indonesia and

Malaysia, supporting our new emissions estimates. In contrast, previous studies have resorted to scaling PM emissions to better match surface concentrations (Koplitz et al, 2015; Marlier et al., 2012). In 2015, we estimate fires exposed 66.5 million people to daily mean $PM_{2.5}$ concentrations exceeding the WHO limit of 25 µg m^{-3}, for at least half of the August to October period. Measurements of $PM_{2.5}$ concentrations in regions impacted by fires are needed to evaluate these exposure estimates.

We used simulated $PM_{2.5}$ to estimate the health impact of fires across the different years. We estimate that exposure to $PM_{2.5}$ from fires resulted in 44 000 excess deaths in 2015, less than in previous studies due to the less sensitive relative risk function we used. New analysis is needed to help constrain the public health impacts of exposure to PM from fires. In other years (2004, 2006, 2009 and 2012) we estimate exposure to PM resulted in 14 000 – 22 000 premature deaths annually, with a total of 131 700 premature mortalities resulting from August-October fires during 2004-2015. Our work confirms that smoke from Indonesian fires regularly cause substantial impacts on human health across the region. Unless further action is taken to reduce fires, air pollution from fires will continue to cause substantial health burden across Equatorial Asia over the next decade (Marlier et al., 2019).

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Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Chapter 4 Economic cost of Indonesian fires and the benefits of restoring peatland

Kiely, L.[1], Spracklen, D.V.[1], Arnold, S. R.[1], Papargyropoulou. E[2], Conibear, L.[1], Wiedinmyer, C.[3], Knote, C.[4], Adrianto, H. A.[1, 5]

1. Institute Climate Atmospheric Science, School of Earth and Environment, University of Leeds, UK

2. Sustainability Research Institute, School of Earth and Environment, University of Leeds, UK

3. CIRES, University of Colorado, Boulder, Colorado, USA

4. Ludwig-Maximilians University, Munich, Germany

5. IPB University, Bogor, Indonesia

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The reference style and the figure, table and section numbers have been formatted to be continuous throughout the thesis.

Abstract

Deforestation and drainage has made Indonesian peatlands susceptible to burning. Large fires occur regularly, destroying agricultural crops and forest, emitting large amounts of CO_2 and air pollutants, resulting in adverse health effects. These impacts have an economic cost. We estimate the 2015 fires, the largest in recent years, resulted in costs totalling US$28.8 billion, whilst the six largest fire events between 2004 and 2015 cost US$93.7 billion in total. In order to reduce fire, the Indonesian government has

committed to restore 2.49 Mha of degraded peatland. We estimate that if this restoration had already been completed, the area burned in 2015 would have been reduced by 6%, reducing CO_2 emissions by 18%, and $PM_{2.5}$ emissions by 24%, preventing 12,000 premature mortalities. Peatland restoration could have resulted in economic savings of US$8.6 billion for 2004-2015, making it a cost effective option for reducing impacts to the environment, climate and human health.

4.1 Introduction

Large fires have been a regular occurrence in Indonesia in recent decades (Field et al., 2009). Fires generally occur during periods of drought (Taufik et al., 2017), and are closely linked with land-use change (Adrianto et al., 2019). Drainage of extensive areas of peatland in Indonesia make the naturally fire-resilient land susceptible to fire (Taufik et al., 2018).

Indonesian peatlands store vast amounts of carbon (Page et al., 2011), and the CO_2 emissions from fires are large (Page and Hooijer, 2016; Heymann et al., 2017; Hu et al., 2018), contributing substantially to Indonesia's greenhouse gas emissions (World Bank, 2016b). Fires also emit large quantities of fine particulate matter ($PM_{2.5}$) and other pollutants, resulting in poor air quality and negative health effects (Koplitz et al., 2016; Crippa et al., 2016; Kiely et al., 2020). Fires destroy agricultural land and forest resources, while haze can disrupt transport, tourism and trade, slowing the economic performance of a region (Kusumaningtyas and Aldrian, 2016). Varma (2003) estimates that fires in 1997-1998 resulted in economic cost of US$19.7 billion through damage to agriculture and forest. In comparison, fires in the Amazon during the same year cost US$9.5 billion through damage to agriculture and forest, CO_2 emissions and health impacts from exposure to fire haze (De Mendonça et al., 2004). More recently, the 2015 fires in Indonesia are estimated to have cost US$16.1 billion (World Bank, 2016b) whilst the 2019 fires cost US$5.2 billion (World Bank, 2019) in damages and economic losses to agriculture, forestry, trade, tourism, transportation, manufacturing and the environment, and through the costs of fire suppression, short-term health impacts and school closures. These estimates did not include the economic costs of long-term health impacts from exposure to haze from the fires, meaning the actual cost is likely to be much higher (Tacconi, 2016).

Due to the detrimental impacts of fires, a moratorium on any new land conversion on peatland has been brought into effect in Indonesia (Republic of Indonesia, 2016), and the Peatland Restoration Agency has been established to restore and re-wet 2.49 million hectares of peatland (Peatland Restoration Agency, 2016). Fires are more likely to occur on degraded land than in protected areas of forest (Adrianto et al., 2020), and drainage canals can make fires 4.5 times as likely (Taufik et al., 2018). Controlling land use and drainage on peatland should therefore reduce fire and associated emissions. Since the spread of peatland fires is dependent on the water content of the peat (Rein et al., 2008), re-wetting peatlands can be important for controlling fires. However, there have been no comprehensive estimates of the potential impacts of peatland restoration initiatives on fire occurrence. Crucially, large-scale restoration efforts to address fire-related problems lack a cost-benefit analysis (Tacconi, 2002).

4.2 Results

4.2.1 Costs of fires

We estimated the economic costs of Indonesian fires, focusing on the six largest dry season (August – October) fire events from 2004 to 2015 (Figure 4.1). Previous estimates of fire cost have included different economic losses (Varma, 2003; World Bank, 2016b). The World Bank (2016) estimates the cost across many sectors, including damage to agricultural land and equipment, CO_2 emissions, short-term health effects, reduced transport, trade and tourism, and school closures and fire suppression. Damages caused by fire have a direct cost, as do fire suppression and hospital visits. A loss in productivity, through reduced business, illness and school closures, has a cost through reduced income and economic activity. CO2 emissions have an environmental impact, the cost of which is represented by the lost capacity for carbon storage. Of these sectors, health impacts, CO_2 emissions and damage to land cover caused 79% of the total costs, despite long-term health impacts not being included and the low cost applied to carbon emissions (Tacconi, 2016). For this study we have therefore focused on these three main contributing sectors; damages to land cover, CO_2 emissions, and health impacts from $PM_{2.5}$ (Table D.1).

Costs due to damages to agriculture, plantation, natural forest and other land covers were estimated by combining the area burnt with the net present value of each land use.

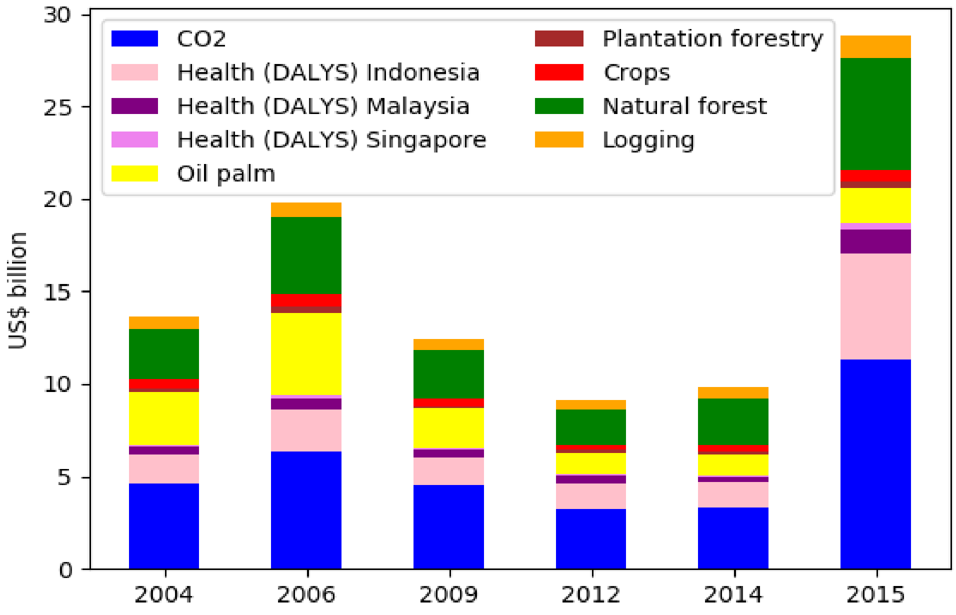

Figure 4.1: The economic cost of Indonesian fires, in US$ billion, split by category. The health costs are split by the country being affected.

The greatest cost from damages to land cover occurred in 2006 (US$10.5 billion) and 2015 (US$10.4 billion), with costs in other years between US$4 billion and US$7 billion. The damages to plantation crops and natural forest made up the majority of this cost (Figure 4.1).

The costs associated with CO_2 emissions were estimated by combining CO_2 emissions from a fire emission inventory (Kiely et al., 2020), with the 2009-2020 average value of CO_2 from the European Union Emissions Trading System. The 2015 fires resulted in the largest CO_2 emissions (962 Tg) with a cost of US$11.3 billion. Our estimate of the CO_2 emissions from the 2015 fires lies within the range from previous studies (547 – 1100 Tg) (Huijnen et al., 2016; Heymann et al., 2017; Jayarathne et al., 2018). In other years CO_2 emissions varied between 272 Tg and 542 Tg with costs of US$3.2 – 6.4 billion.

The economic cost of the health effects caused by exposure to haze from fires was calculated based on the number of Disability Adjusted Life Years (DALY) caused by smoke exposure multiplied by the economic value of a DALY in Indonesia. The 2015 fires caused the largest health costs (US$7.3 billion), with US$5.7 billion for Indonesia, US$1.3 billion for Malaysia and US$0.3 billion for Singapore. In other years, the total health related costs were US$1.8 – 3 billion.

The total costs of the fires from damage to land cover, CO_2 emissions, and long term health impacts were greatest for the 2015 fires, which resulted in a cost of US$28.8 billion (Figure 4.1). Of the total costs, 35% were due to land cover damage, 39% from the CO_2 emissions, and 25% from the long-term health costs. In other years total costs were US$9.1 – 19.8 billion, with the damage to land cover contributing around half of the total cost, and CO_2 costs contributing around a third. In 2015 severe drought caused fires to burn deeper into the peat resulting in larger emissions per area burned (Kiely et al., 2020), causing the costs associated with CO_2 and $PM_{2.5}$ to be greater.

The World Bank (World Bank, 2016b) estimates the cost of the 2015 fire event to be US$16.1 billion, less than suggested in our study, largely due to the lack of long-term health impacts in the World Bank estimate. The estimate of costs due to damage to agriculture and forest in the World Bank study (US$8.7 billion) is similar but smaller than our estimate (US$10.4 billion), despite them also including equipment damage in this cost. This could be because the World Bank used burned area from the Global Fire Emissions Dataset, which has previously been found to be underestimated in the region (Lohberger et al., 2017). The cost from sectors not included in our study has been estimated at US$3.4 billion (World Bank, 2016b).

4.2.2 Economic benefit of using fire for land clearing

Landowners use fire to clear land because it is can be easier and cheaper than other methods. Guyon and Simorangkir (2002) find that clearing heavily forested land without the use of fire has increased labour and equipment cost. We estimate the economic benefit of using fire to clear primary forest, compared to other mechanical clearance options, to be US$1.2 billion across the six years studied. The cost most likely to directly affect land owners is the damages to agriculture, which totals US$17.8 billion over the six years, much greater than the benefit of fires. Although the cost of fire (due to damages to agricultural land) exceeds the economic benefit, small scale farmers may not have access to the mechanical equipment needed to clear land without fire (Simorangkir, 2007). Morello et al. (2019) suggested that for the Amazon, a policy of subsidizing mechanical clearing equipment is effective in improving the cost effectiveness of banning fire.

The costs of fires can affect many people. Damages to planted land will cost the land owner while damages to forest may affect local people using forest resources. Income losses through illness caused by fire can affect anyone exposed to smoke. The economic benefits of using fire, however, come to those profiting from the land use, mainly land owners and stakeholders in plantation companies.

4.2.3 Fires in protected areas

Peatland restoration involves blocking drainage canals to restore water levels and re-establishing vegetation cover. Large-scale peatland restoration in Indonesia has just begun, and it is too early to measure the effect on fire. Instead, we used fires observed within protected areas as a proxy for fire occurrence on restored peatland. Peatland in protected areas is largely undrained and still covered in vegetation and therefore provides an indication of the susceptibility of restored and re-wetted peatlands to fire.

We compared the occurrence of fire inside protected areas in Indonesia with the surrounding area. For each year we calculated the ratio of peatland burned area inside and outside of protected areas. Comparing directly with the surrounding area avoids issues connected to bias in the location of protected areas (Spracklen et al., 2015). We find that protected areas typically reduce the occurrence of fire, though the effects are variable depending on location and protected area type (Figure 4.2, Table D.2) as found previously for both deforestation (Curran et al., 2004; Gaveau et al., 2009; Spracklen et al., 2015) and fire (Nelson and Chomitz, 2011). National Parks in Kalimantan result in the greatest reduction in fire. This is likely due to the fact that National Parks are generally larger than other types of protected areas, reducing outside influences such as drainage, although the management of National Parks could also be important (see Appendix D). We find that for National Parks in Kalimantan total dry season burned area on peatland in 2004 – 2015 was reduced by 37-79% compared to the surrounding areas, depending on the year.

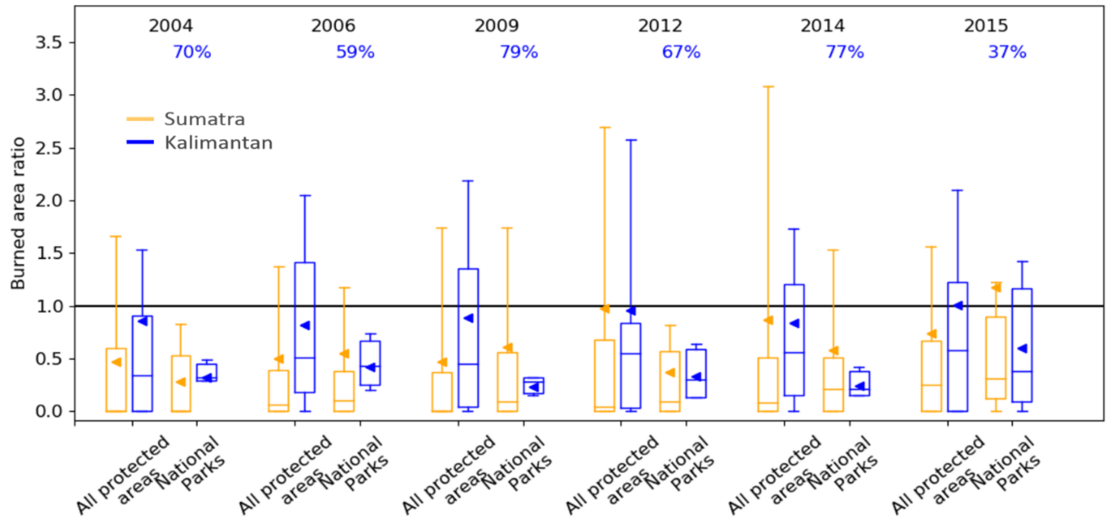

Figure 4.2: The ratio of peatland burned area inside protected areas to outside of protected areas. For each protected area we compare fraction of peatland burned inside to outside (within 0.25° of the protected area). Results are shown for Sumatra (orange) and Kalimantan (blue) for all protected area categories and for National Parks separately in each year. The box shows the upper and lower quartiles, the whiskers show the 95th percentiles, the lines show the median and the triangles the mean. The average percentage reduction in burned area inside the National Parks in Kalimantan in each year is shown

Depth of peat burn and emissions from peat fires depends on water levels in peatlands, which can be heavily impacted by land-use change and drainage. To explore how protection of peatlands can modify water storage, we compared soil moisture inside and outside of protected areas. We used satellite soil moisture from the Soil Moisture Active Passive product (SMAP) from NASA, which is available for 2015 onwards (O'Neill et al., 2019). This product combines satellite radar and radiometer measurements to produce daily soil moisture at 9 km resolution. Monthly average soil moisture in August – October 2015 was 48-57% greater inside National Parks compared to outside, likely due to reduced drainage inside the protected areas.

4.2.4 Effects of peatland restoration on emissions

We used the reduction in fire occurrence and increase in soil moisture in protected areas in Kalimantan to estimate the potential reductions in fire emissions that would have been achieved under a policy of peatland restoration. We estimated the burned area and emissions under a scenario where 2.49 Mha of degraded peatland was restored, the area planned for restoration by the Indonesian peatland restoration agency. We selected locations for peatland restoration by identifying peatlands with the greatest $PM_{2.5}$ emissions during 2004-2015. We assumed restoration areas of ~500 km^2, with 2.49 Mha equivalent to 51 restoration areas. Regions selected for restoration are all located in Kalimantan and Sumatra, with the majority in southern Central Kalimantan or South Sumatra (Figure 4.3). For each of the years we studied between 2004 and 2015, we calculated the change in fire and associated emissions that would have occurred if 2.49 MHa had been restored prior to the occurrence of fires. For each year, we recalculated fire emissions with the burned area and soil moisture inside restored peatland areas scaled by the ratios of burned area and soil moisture inside and outside of National Parks in Kalimantan for that year.

To assess the uncertainty around our treatment of fire on restored areas, we explored the effect of two other scenarios on fire emissions. For one option (no fire), we assumed all fires are prevented on the restored peatland. Studies have found that fires continue to occur after peatland restoration (Jaenicke et al., 2010; Ritzema et al., 2014), suggesting that ‘no fire’ is an unlikely scenario; however, it shows the maximum reduction which could be achieved by the restoration. For the other option (no peat fire) we assumed all peat fires are prevented, so only emissions from surface vegetation fires remain. This ‘no peat fire’ scenario could occur if peatlands are re-wetted, and remain saturated throughout the dry season preventing the peat from burning, but fires continue on the surface.

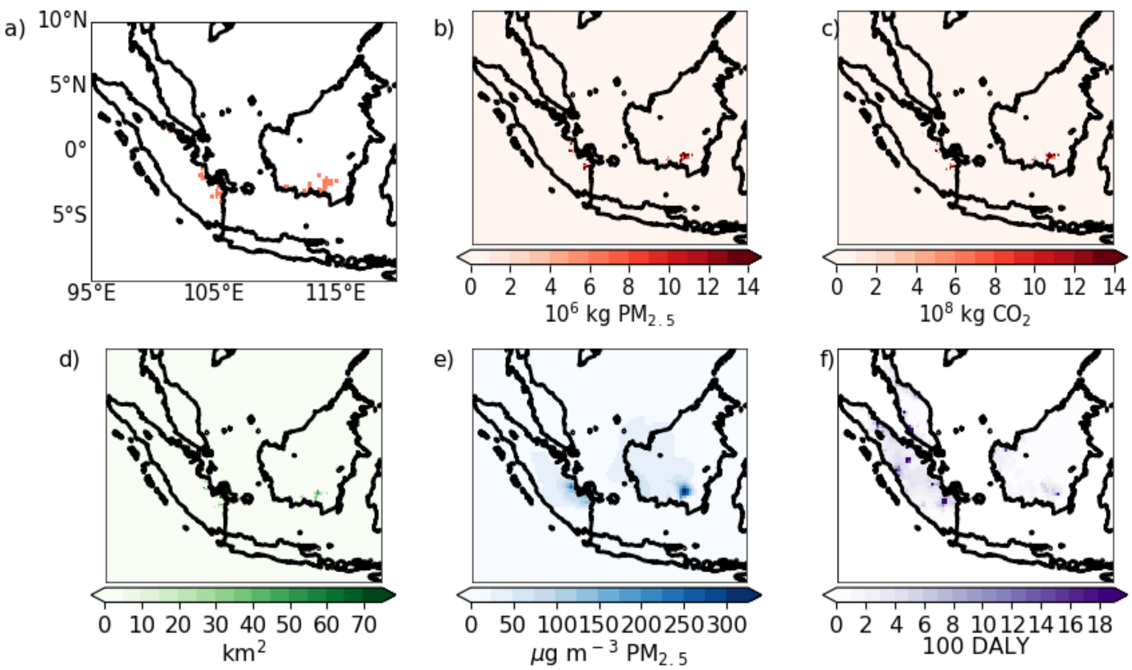

Figure 4.3: Locations of peatland restored in this study (a), and the potential impacts of peatland restoration on August – October 2015 fires (b-f). Reduction in PM2.5 (b) and CO2 (c) emissions, burned area (d), average PM2.5 concentrations (e), and DALYs from PM2.5 exposure (f) due to peatland restoration.

In 2015, 15% of total burned area occurred on areas selected for restoration. Our analysis suggests restoration to the level of National parks would have reduced peatland area burned in 2015 by 37% (Figure 4.2), resulting in an overall reduction in area burned across Kalimantan and Sumatra by 6%. Restoration reduces total August-October $PM_{2.5}$ emissions by 24% from 9.45 Tg to 7.27 Tg, and CO_2 emissions were reduced by 18% from 962 Tg to 790 Tg (Figure 4.3). The percentage reduction of CO_2 is less than of $PM_{2.5}$ as the latter has a greater contribution from peat fires, which are reduced by both reduction in burned area and burn depth. Restoration causes smaller reductions in other years, between 8-15% for $PM_{2.5}$ and 6-11% for CO_2 (Figure 4.4). Restoring peatland would also reduce the carbon emitted through peatland degradation (Irawan et al., 2019); however, this benefit has not been included in our study.

Figure 4.4 shows $PM_{2.5}$ and CO_2 emissions under our different peatland restoration scenarios. The ‘no fire’ scenario on restored peatlands results in the largest reduction in emissions (Figure 4.4). Under the scenario of 2.49 MHa restored, the ‘no fire’ scenario reduced $PM_{2.5}$ emissions in 2015 by 32% and CO_2 emissions by 26%. In other year emissions were reduced by 9-19%. The ‘no peat fire’ scenario gives a similar reduction in CO_2 emission to the ‘National Parks’ scenario, but for $PM_{2.5}$ emissions it varies. In 2015, when intense drought meant that peat fires burnt deep into the ground, the ‘no peat fire’ scenario is more effective than the ‘National Parks’ scenario, with a 27% reduction in $PM_{2.5}$ emissions compared to a 23% reduction under the ‘National Parks’ scenario. For other years when peat fires had a smaller contribution to emissions, the ‘no peat fire’ and ‘National Parks’ scenarios for restoration show similar reductions in emissions: 5-14% and 6-15% respectively (Figure 4.4).

This suggests that for strong drought years re-wetting peatland to prevent fires from burning into the peat is the most effective action. For less intense drought years, reducing the number of fires and area burnt could be more important. Since the National Parks restoration scenario predicts the lowest emissions reduction in most years (Figure 4.4), this is a conservative estimate of emissions reduction. For this reason, we apply this scenario in our estimates of the benefits of peatland restoration.

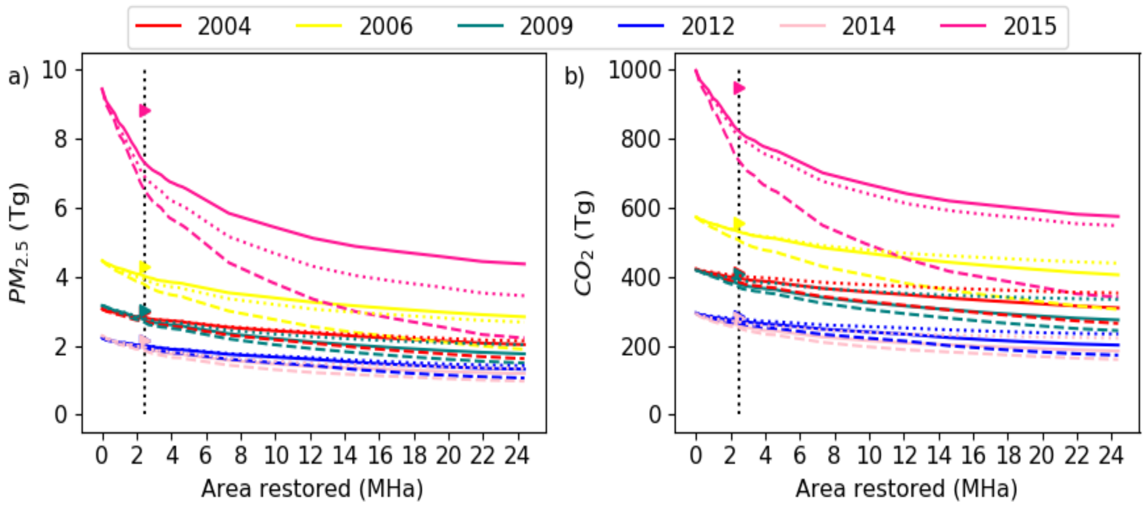

Figure 4.4: Emissions of $PM_{2.5}$ (a) and CO_2 (b) under different peatland restoration scenarios. The number of 488 km^2 cells restored has been increased in intervals of 5 up to 100, and then in intervals of 50 up to 500. The solid lines show the restoration to the level of National parks, the dotted lines show the restoration with 'no peat fire', and the dashed lines show the restoration with 'no fire'. The triangles show the emissions when 2.49 Mha is randomly located, restored to the level of National Parks. The black dotted vertical line shows 2.49 Mha restored.

We used a regional atmospheric chemistry model to simulate the impacts of peatland restoration on regional air quality in 2015. Reduced emissions under peatland restoration result in average $PM_{2.5}$ concentrations across the domain being reduced by 28% (from 76 µg m^{-3} to 55 µg m^{-3}) and population-weighted $PM_{2.5}$ being reduced by 26% (from 27 µg m^{-3} to 20 µg m^{-3}). We estimated the number of excess deaths in the region resulting from exposure to $PM_{2.5}$ from fires is reduced by 11,914 (21%), from 55,819 to 43,905 with peatland restoration. The number of Disability Affected Life Years (DALYs) caused by exposure to $PM_{2.5}$ is reduced by 0.46 million (21%), from 2.19 million to 1.72 million. While the reduction in $PM_{2.5}$ concentration is greatest near the locations of the restored land, the reduction in exposure and associated DALYs is more regionally dispersed (Figure 4.3). For other years we estimate restoration reduces the number of DALYS by 17,000 – 94,000.

4.2.5 Potential for scaling up peatland restoration

Indonesia has around 21 Mha of peatland, with 13 Mha in Sumatra and Kalimantan (Page et al., 2011; Warren et al., 2017) and 11.5 Mha of this is estimated to have been degraded (Miettinen et al., 2016). We explored how the benefits of peatland restoration would likely change with the scale of restoration (Figure 4.4). Under each scenario, the peatland with the greatest $PM_{2.5}$ emissions over 2005-2015 period are prioritised for restoration first. As $PM_{2.5}$ emissions reflect the amount of peat burnt, these areas also have the greatest CO_2 emissions. $PM_{2.5}$ and CO_2 emissions decrease steeply as the area of peatland restoration is expanded. Although the 2.49 Mha of peatland the government plans to restore results in a substantial emission reduction, further reductions would still occur if more land is restored, particularly in a high fire year such as 2015. Restoration of all peatlands results in a 54% reduction in $PM_{2.5}$ emissions when peatlands are restored to the state of National Parks and a 77% reduction under the 'no fire' scenario.

Fires are heavily concentrated in regions of peatland degradation and land use change. In 2015, 53% of fire detections occurred on peatlands which covered only 12% of the land, with the greatest fire detection over degraded peatlands (Miettinen et al., 2017). Prioritising areas for peatland restoration is therefore important. We selected locations with the greatest emissions from fires in previous years, which optimised the reduction in emissions. Randomly allocating the 2.49 MHa of restoration reduces emission reductions by more than half (Figure 4.4) demonstrating that targeting restoration is important if benefits are to be maximised. The peatland being targeted by the Peatland Restoration Agency is degraded, meaning that past fire occurrence is likely (Taufik et al., 2018). Therefore the locations of the 2.49 Mha of peatland being restored is more likely to coincide with the highest emitting peatland areas than the randomly allocated peatland areas.

4.2.6 Economic costs and benefits of peatland restoration

Peatland restoration reduces fire occurrence, leading to economic benefits in the form of reduction in costs due to fire. Figure 4.5 shows the reduction in the costs of the fires if 2.49 Mha of peatland had been restored prior to the 2004-2015 fires. The total reduction over the 6 years studied is estimated to be US$8.6 billion, with the largest reduction in cost in 2015 (US$4.0 billion). Peatland restoration would have reduced fire costs by 9% across all years, with a 14% reduction in 2015. The reduction in CO_2 emissions contributed the largest reduction in cost over all the years (45%) followed by the reduction in health related losses (29%) and the reduction in land cover losses (26%). Other haze related costs such as disruptions to transport and tourism are also likely to be reduced with the reduction to $PM_{2.5}$ emissions, but have not been considered in this study.

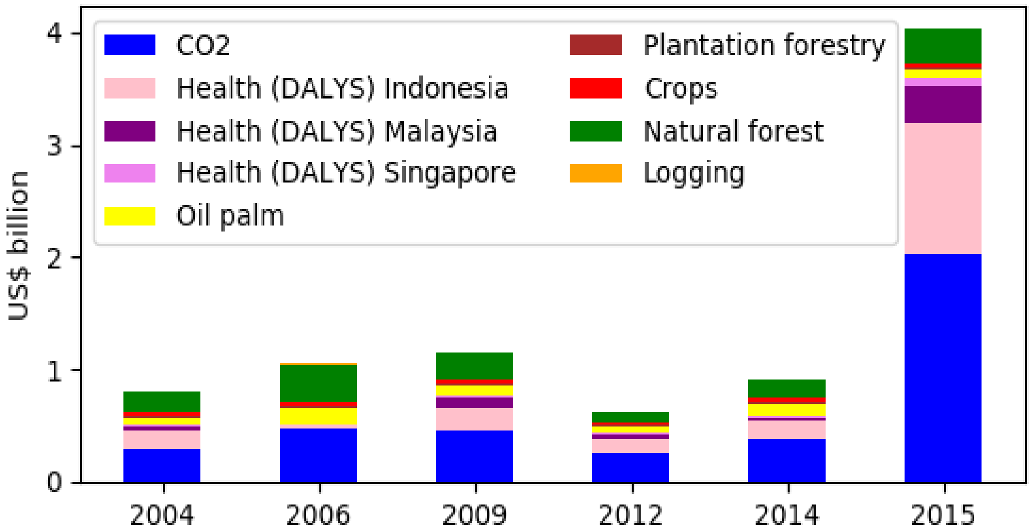

Figure 4.5: The estimated reduction in economic costs of fires after peatland restoration, split by category. The DALY costs are split by the country being affected.

We have treated each year individually, and calculated the reduction in costs that could have been achieved if the peatland had been restored prior to each fire event. This provides an indication of the potential savings that restoration could provide for similar fire events in future years. Predicting the cost of fires in the future under business as usual and peatland restoration scenarios is challenging, due to the complex combination of meteorological and anthropogenic drivers of fire. In addition, a range of physical, social and economic feedbacks in the system (Page and Hooijer, 2016), further complicate the response and have not been assessed here.

The World Bank (World Bank, 2016b) suggest that restoring 2 Mha of peatland would cost US$1.9 billion, considerably lower than our estimate of economic benefit. If we account for the buy-back value of agricultural land and plantations within the restored areas, costs of restoration rise. Of the land restored in this study, 0.3 Mha is on oil palm concessions, 0.4 Mha is on wood fibre concessions and 0.6 Mha is other agricultural crops. Depending on the land value we estimate a onetime buy-back of the land suggested for restoration in this study would cost US$1.3-6.1 billion, bringing the total cost of restoring 2.49 Mha of peatland to US$3.2-7 billion. Using either value, the cost associated with restoring peatland is less than the associated reduction in fire costs.

The cost of peatland restoration may not have to be fully borne by Indonesia. A reduction in fires yields health benefits across Indonesia, Malaysia and Singapore. Lin et al. (2017) suggests that Singaporeans are willing to pay US$643.5 million for the health benefits of reduced fire. Carbon emissions and climate change are also a global problem. Using the European Union (EU) emissions trading system (ETS) carbon price shows the international value placed on carbon emissions, suggesting global support should be provided for fire prevention.

4.2.7 Policy implications of this research

Our research contributes three main findings with significant implications for land management policy in terms of i) the cost effectiveness of fire as a land clearing technique, ii) the cost effectiveness of peatland restoration as a fire prevention strategy, and iii) the conditions under which peatland restoration can deliver the maximum environmental, economic and health benefits.

We have shown that the costs associated with fires outweigh the savings made by farmers and stakeholders. The economic benefit of fires is often stated as a reason for clearing land with fire (Tacconi, 2002; Simorangkir, 2007), but potential damage to crops is rarely considered as an incentive to reduce the use of fire (Jefferson et al., 2020; Carmenta et al., 2020). Local support of fire reduction schemes is a key factor to their success (Harrison et al., 2019; Watts et al., 2019), and schemes need to identify incentives and sanctions which are important to local people (Carmenta et al., 2020).

Our analysis shows that peatland restoration is a cost effective strategy for prevention of peatland fire in support of existing policies. The economic benefits in the form of reduction of fire related costs, linked to CO_2 emissions, long term health impacts and damage to land cover, outweigh the cost associated with peatland restoration. The benefit of restoration depends on the amount of land restored and where the restoration occurs. We therefore recommend that peatland targeted for restoration should be in areas which have proven to be susceptible to fires in the past, something which may not be the case for the current restoration plan (Peatland Restoration Agency, 2016).

The different fire scenarios we have considered for restored peatland show the variability in possible restoration benefits. Future studies measuring the effect of peatland restoration on fires are needed to better inform the cost-benefit analysis. Restoration can include canal blocking to re-wet the peat and re-vegetation of degraded peatlands. Re-wetted peatland is unlikely to re-vegetate naturally (Hansson and Dargusch, 2018) and so re-vegetation should be included in restoration plans. Re-vegetation can be expensive and current plans include reforesting only 27% of the restoration area (Peatland Restoration Agency, 2016). Our work also shows the importance of preventing degradation of intact peatlands. Indonesia has a moratorium on deforesting primary forest; however, this only covers 32% of Indonesia’s peatlands, leaving many vulnerable (Wijedasa et al., 2017).

In conclusion, we demonstrate the substantial national and international benefits of peatland restoration (including both re-wetting and re-vegetation). Our work provides evidence to support Indonesia’s plans to restore 2.49 Mha of degraded peatland. We show that a more ambitious programme of restoration would yield even greater benefits, especially if restoration was targeted to areas proven to be susceptible to fires in the past, in order to maximise the fire prevention and environmental, health and economic benefits of peatland restoration.

4.3 Methods

4.3.1 Fire emissions

We used fire emissions and burned area from FINNpeatSM, an extension of the Fire Inventory from NCAR (FINNv1.5; Wiedinmyer et al., 2011). FINNpeatSM emissions were created specifically for Indonesian fires using recently calculated emissions factors for Indonesian peat fires and a peat burn depth scaled according to the surface soil moisture. The location and area burned by fires in FINN is based on MODIS hotpots. This emission inventory is described in Kiely et al. (2019) and has been comprehensively evaluated for all the years explored here (Kiely et al., 2020). We focus our analysis on the major fire season in Indonesia, and report values for fire occurring from August 1st through to October 31st for each year.

4.3.2 Cost of fires

To calculate the economic cost of fire due to damages to agriculture and other land uses, we used the locations of fires combined with land cover data to calculate the area of each land cover that was burned, which was then multiplied by the value of that land cover. We used FINNpeatSM to provide the locations of fires at 1 km^2 resolution. To account for heterogeneity in fire damage at smaller spatial scales, we scaled the area burned estimated by FINNpeatSM for Sumatra and Kalimantan in 2015 (63938 km^2) by 0.59 to match the area burned estimated from analysis of Sentinel-1 (37860 km^2), as found by Lohberger et al. (2017). We scaled FINNpeatSM burned area in other years by the same factor.

We identified the locations of oil palm plantations, wood fibre plantations, rubber plantations, crops, logging concessions and natural forest. The locations of oil palm, wood fibre and rubber plantations come from the tree plantations data created by Transparent World, accessed from the Global Forest Watch (Transparent World, 2015). We used cropland categories from the European Space Agency Climate Change Initiative (ESA CCI) land cover (ESA, 2017) downloaded from Global Forest Watch, with the oil palm plantation area from the tree plantations data removed. The logging concessions data is from the Ministry of Environment and Forestry (2019). We identified natural forest as the primary forest categories in the ESA land cover data, with the logging concessions removed.

There are uncertainties in the spatial distribution of land use. Combining land cover categories from different datasets may result in some discrepancies. Dates of the land cover data vary and it is possible that some land use types may have been established after the occurrence of fire. Remote sensing of land cover types is also uncertain, for example the tree plantations data claims an overall accuracy of 79% (Transparent World, 2015).

We estimated the value of land as the net present value (NPV) of that land use. The NPV of the oil palm and rubber plantations and logging concessions are from Sofiyuddin et al. (2012), at US\$650,000 km^{-2}, US\$200,000 km^{-2} and US\$611,400 km^{-2} respectively. The NPV for Acacia plantations (US\$104,000 km^{-2}) from Sofiyuddin et al.

(2012) has been used for all wood fibre, and the NPV for rice and maize (US$70,000 km^{-2}) used for all other crops. The value of natural forest was taken from Beukering et al. (2003), who included multiple economic benefits. We remove the value attributed to benefits related to reduced emissions, as we are counting these separately, and the remaining value of US$56,500 km^{-2} year^{-1} includes benefits to the water supply, flood prevention, biodiversity and tourism. This value equates to US$609,300 km^{-2} over 20 years allowing for discount rate and inflation. The value of tourism here refers to the lost revenue of tourists visiting forests, whereas the loss caused by fires to the tourism sector calculated by some other studies (Glover and Jessup, 2006; World Bank, 2016b) refers to reductions in tourism to Indonesia due to haze.

To calculate the economic cost of CO_2 emissions, we multiplied CO_2 emissions from the FINNpeatSM emissions inventory (Kiely et al., 2020) by the average 2009 – 2020 closing price of CO_2 in the EU ETS (Business Insider, 2020) (€10.8 tCO_2^{-1}) converted to US$ using an exchange rate of 1.09 to give US$11.8 tCO_2^{-1}. This is the value at which CO2 emissions can be traded within the system, and demonstrates the market value of reducing carbon emissions. Indonesia is not currently part of an emissions trading system and there is no available payment for carbon services, although a trial of this is underway (Ekawati et al., 2019). This value is similar to the US$10 tCO_2^{-1} used in other studies (Busch et al., 2012; Yusuf et al., 2018).

To calculate the economic cost of the health impacts of fires, we multiplied the number of the disability adjusted life years (DALYS) due to smoke exposure by the economic value of a DALY. To estimate the economic value of a DALY we used the economic loss due to non-communicable diseases (NCDs) in Indonesia from 2012 through 2030 (World Economic Forum, 2015), estimated as US$4.47 trillion which equates to US$235 billon yr^{-1}. We assume 50 million DALYS per year from NCD (Mboi et al., 2018) to calculate a cost per DALY of US$4710. Compared with welfare-based and income-based methods for estimating the cost of air pollution, as described in the World Bank and Institute for Health Metrics and Evaluation report (World Bank, 2016a), our method allows us to consider the cost from all health impacts of fires, rather than mortality only. It also uses data specific for Indonesia, whereas a welfare-based method would require adjusting from studies in other countries.

We apply the same economic value to DALYs in all countries, so the cost to Malaysia and Singapore may be underestimated. While the other costs estimated in this study are from Indonesian fires only, the simulations which the DALYs are calculated from also include some fires in Malaysia, Brunei and Thailand. These non-Indonesian fires contribute only 3-7% of the $PM_{2.5}$ emissions in different years. For 2015, simulated $PM_{2.5}$ from non-Indonesian fires only has been used to estimate that these fires cause 3% of the mortalities and DALYs from fires, and in other years this is likely to be similar (see Appendix D).

For this study we are comparing fire events in different years, rather than considering a period of time. We therefore keep NPV, CO_2 and DALY costs constant for each year rather than adjust for inflation, so that the only difference between costs in different years are due to differences in fires. This means the costs are relative only to the magnitude of each fire event, rather than to when the event occurred.

The economic benefit of using fire to clear land has also been calculated. The difference in cost of fire and zero-burning clearing methods have been taken from Guyon and Simorangkir (2002) and inflation has been applied to get an average 2004 – 2015 benefit of US$156 ha^{-1} for non-peatland and US$848 ha^{-1} for peatland, which has been used for all years. This economic benefit has been multiplied by the area burnt on primary forest, assuming that this was all intentionally burnt for land conversion. Guyon and Simorangkir (2002) suggest that the cost of clearing anything but primary forest is similar with and without the use of fire, which is why only fires on primary forest have been considered to give an economic benefit. The economic benefit when using fire as a land clearing method varies depending on the land and region, and we have used the upper estimate where multiple values are given.

4.3.3 Health Impacts

We estimate DALYs from fires using the same method as Kiely et al. (2020), which is described briefly here. $PM_{2.5}$ concentrations have been simulated by WRF-chemv3.7.1, run at 30 km resolution with 33 vertical levels between the surface and 50 hPa. The simulation was run for August – October each year, after a 14 day spin up for chemistry. Meteorology was reinitialised every 15-16 days using National Centre

Environmental Prediction Global Forecast System data (NCEP, 2007), with the meteorology free running between. Fire emissions are represented by FINNpeatSM, anthropogenic emissions are from EDGAR-HTAP2 (Janssens-Maenhout et al., 2015) for 2010 and biogenic emissions are from MEGAN (Model of Emissions of Gases and Aerosols from Nature; Guenther et al., 2006). Gas-phase reactions were calculated by the MOZART (Model for Ozone and Related Chemical Tracers, version 4; Emmons et al., 2010) chemistry scheme and aerosol processes, binned into 0.039 - 0.156 μm, 0.156 – 0.625 μm, 0.625 – 2.5 μm and 2.5 – 10 μm, were represented by MOSAIC (Model for Simulating Aerosol Interactions and Chemistry; Zaveri et al., 2008; Hodzic and Knote, 2014). Secondary organic aerosol (SOA) formation from fires in the model is calculated as 4% of the fire emitted CO based on Spracklen et al. (2011) and Hodzic and Jimenez (2011)(Hodzic and Jimenez, 2011)(Hodzic and Jimenez, 2011)(Hodzic and Jimenez, 2011)(Hodzic and Jimenez, 2011)(Hodzic and Jimenez, 2011). The contribution of fires to PM concentrations is calculated as the difference between simulations with and without fire. These simulations are the same as those from Kiely et al. (2020), except for 2015, which in Kiely et al. (2020) was run with meteorology reinitialised once every month. This causes some differences to the health impact estimates for 2015.

The population weighted $PM_{2.5}$ (PW) is calculated using population data from the Gridded Population of the World, Version 4 (GPWv4; Center for International Earth Science Information Network and NASA Socioeconomic Data and Applications Center, 2016).

$$PW = \Sigma C_i * P_i / P_{tot}$$

Where Ci is the $PM_{2.5}$ concentration in a grid cell, P_i is the population of a grid cell and P_{tot} is the total population of the area.

Premature mortality per year, M, from disease j in grid cell i was calculated as,

$$M_{ij} = P_i I_j \, (RR_{jc} - 1) / RR_{jc},$$

where P_i is the population in i, I_j is the baseline mortality rate (deaths $year^{-1}$) for j, and RR_{jc} is the relative risk for j at $PM_{2.5}$ concentration, c ($\mu g\ m^{-3}$). The $PM_{2.5}$ concentration is an annual average, and the average $PM_{2.5}$ from August from the simulation with no fires has been used to represent January to July and November to December. The baseline mortality rates and the population age composition are from the GBD2017 (Institute for Health Metrics and Evaluation, 2019), and the relative risks are taken from the Global Exposure Mortality Model (GEMM; Burnett et al., 2018) for non–accidental mortality (non–communicable disease and lower respiratory infections). The DALYs have been calculated as

$$DALY = YLL + YLD,$$

where,

$$YLL = PI_{\mathrm{YLL}}\,(RR_{jc} - 1)/\,\mathrm{RR}_{\mathrm{jc}} \quad \text{and}$$

$$YLD = PI_{\mathrm{YLD}}\,(RR_{jc} - 1)/\,\mathrm{RR}_{\mathrm{jc}} \;,$$

where P is the population, I_{YLL} and I_{YLD} are the corresponding Years of Life Lost and Years Lived with Disability baseline rate (deaths $year^{-1}$), taken from GBD2017. RRc is the relative risk at $PM_{2.5}$ concentration, c (µg m^{-3}), from the GEMM.

4.3.4 Peatland restoration

To estimate the potential impacts of peatland restoration, we assumed that peatland areas could be restored to the conditions currently found within protected areas. To determine the effects of protecting land, we analysed the burned area and soil moisture inside and outside of protected areas. We used the peatland distribution map from the World Resources Institute (2017) to determine peatland extent. The soil moisture is the Soil Moisture Active Passive (SMAP) product from NASA (O’Neill et al., 2019). The protected area data comes from the World Database on Protected Areas (IUCN and UNEP-WCMC, 2018), downloaded from the Global Forest Watch. The protected areas are split into 9 categories; Game Reserve, Grand Forest Park, Hunting Park, National Park, Nature Recreation Park, Nature Reserve, Protection Forest, Wildlife Reserve, and Undesignated. We have included World Heritage Parks, Ramsar Wetlands of International Importance and UNESCO biosphere reserves as National Parks. For each protected area the August – October peatland burned area per km^2 inside each protected area was compared with the August-October peatland burned area per km^2 within a 0.25° boundary of the protected area. The ratio of these two values was calculated for each protected area, for each year. The average peatland soil moisture inside each protected area for each month in August – October 2015 was compared with the average peatland soil moisture within the 0.25° boundary of the protected area, giving a soil moisture ratio for each protected area for each month.

The average ratio of peatland and non-peatland burned area and soil moisture was found across all protected areas in each category, for Sumatra and Kalimantan separately (Table D.2). We used the average burned areas and soil moisture ratios from National Parks in Kalimantan to estimate the area burned and emissions after restoration. The FINNpeatSM emissions were re-calculated with the burned area and soil moisture in restored areas scaled by these ratios. Where the restored areas are only partially peatland, fires not on peatland are scaled by the non-peatland ratio for burned area (Table D.2).

The areas to be restored were selected by finding the 0.2x0.2° (48,800 ha, 488 km^2) gridcells with the greatest total dry season emissions between 2004 and 2015. Only grid cells containing at least 25% peatland were considered for restoration. For the case when 2.49 Mha of land is restored, 2.25 Mha of this is peatland. Smaller gridcells at 0.1x0.1° (122 km^2) were also considered; however, evaluation of the benefits of protected areas based on size suggests that larger protected areas have greater fire reduction than smaller protected areas (see Appendix D). Emissions were also calculated when areas for restoration were randomly placed on peatland in Sumatra and Kalimantan. To get a random allocation of gridcells the random python module was used, which uses the Mersenne Twister pseudorandom number generator. This random allocation was repeated 10 times, and the average emissions across all these scenarios calculated. The range between the 10 scenarios is small (<3%).

To calculate the cost of peatland restoration an estimated cost of canal blocking was combined with the buy-back cost of land to be restored. Oil palm in Riau (Sumatra) that is ready to harvest sells for US\$3077 ha^{-1} (Purnomo et al., 2017). The World Bank (2016), suggests a greater onetime buy back cost for oil palm of US\$10,000 ha^{-1}. These two values have been used as lower and upper estimate of the buy-back cost. We assume a buy-back cost of other land uses based on the NPV US\$492 – 1394 ha^{-1} for wood fibre and US\$313 – 1017 ha^{-1} for cropland.

4.3.5 Health impacts after restoration

For 2015, we simulated $PM_{2.5}$ concentrations using the WRF-chem model with emissions from the peatland restoration scenario. We then recalculated health impacts calculations using these simulations. The impact of restoration on public health is estimated as the difference in health impacts between the baseline simulation and the simulation with emissions from the restoration scenario.

For years other than 2015, we estimate the reduction in DALYs from restoration directly from the reduction in $PM_{2.5}$ emissions. The DALYs from fires decrease linearly with the $PM_{2.5}$ emissions, at a rate of 0.16 million DALY Tg^{-1} $PM_{2.5}$ (see Appendix D). We use this relationship to estimate the DALYs under the restoration scenarios, as was done for premature mortality in Kiely et al. (2020). For 2015, using $PM_{2.5}$ emissions and the linear relationship results in post-restoration DALYs within 1% of those estimated using exposure to simulated $PM_{2.5}$ concentrations simulated by WRF-chem, demonstrating that this simple approach is sufficient to estimate DALYS.

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Chapter 5 Conclusion

The overall aim for this thesis, as detailed in section 1.7, was to improve understanding of Indonesian fire events and the subsequent social and economic impacts. The first publication included in this thesis (Chapter 2) evaluated how Indonesian peat fire emissions in 2015 are considered in current fire emissions inventories, and presented FINNpeatSM, a new extension of the FINN fire emissions inventory, specifically for Indonesian fires. The second publication (Chapter 3) used FINNpeatSM to demonstrate the detrimental effect of fires on air quality and human health, expanding the study period to 2004-2015. The third publication (Chapter 4) used FINNpeatSM and the estimated health impacts to estimate the economic impacts of fires. This publication also investigated the potential of peatland restoration to reduce the impacts of fires, using the peat fire dynamics recognized in Chapter 2 to estimate the change in fire emissions which might be seen after restoration. Together, these three papers advance knowledge of Indonesian fire emissions and the resulting social and economic impacts, allowing for a better understanding of the impact of future events. The findings demonstrate the importance of reducing future emissions and provide evidence of how this can be achieved. This work is the first time that the emissions, health impacts and economic costs of fires have been quantitatively compared across multiple events. It is also the first study to use the social and economic impacts of fires to demonstrate the benefits of fire mitigation.

In this chapter the key findings across the three publications are outlined and the implications of these findings suggested. The limitations of the work are discussed, and recommendations for future work given. The research from the three publications is presented as one piece of work, separated into relevant findings rather than by publication.

5.1 Summary of key findings and implication

- **Indonesian dry season fires emitted 32 Tg of $PM_{2.5}$ and 4080 Tg of CO_2 between 2004 and 2015.**

  Indonesian fires emit substantial amounts of pollutants into the atmosphere, and are an important emissions source in the region. Over 2004 – 2015, $PM_{2.5}$ emissions from fires in Indonesia were greater than the amount emitted from other anthropogenic sources (Permadi et al., 2017), and CO_2 emissions from fires were similar to the amount emitted from Indonesian fossil fuel combustion (5000 Tg; The World Bank, 2020). The greatest dry season (August - October) fire emissions were in 2015, with 2-3 times the emissions of the next largest event, in 2006. Following this were the 2009 and 2004 fire events, which both had similar emissions of $PM_{2.5}$ and CO_2, and the 2012 and 2014 fires events. FINNpeatSM shows that these six fire events contributed 77% of the 32 Tg $PM_{2.5}$ emitted from dry season fires in 2004-2015.

  The 2004-2015 dry season $PM_{2.5}$ emissions in FINNpeatSM are around 50% greater than those in GFED4s (20.4 Tg), while the CO_2 emissions are 7% greater (3816 Tg in GFED4s). The large difference in $PM_{2.5}$ emissions is predominantly due to the peat $PM_{2.5}$ emissions factor, which for FINNpeatSM is from measurements of Indonesian peat burning, more than double the vegetation EF which is used in GFED4s. Comparing different metrics of FINNpeatSM and GFED4s, the average burned area is greater in FINNpeatSM while the average burn depth is smaller, leading to a similar dry matter consumption in some years. The contribution of peat fires to overall combustion is greater in GFED4s, due to the larger average burn depth of these fires. The average burn depth in GFED4s also has a greater interannual variability, leading to a greater interannual variability in emissions than FINNpeatSM. These differences between these inventories suggests that the dynamics of peat burning are still unclear. Improved understanding and quantification of peat burn depth would improve emission estimates.

  FINNpeatSM fire emissions have been shown to improve comparisons between modelled and observed PM and AOD in 2015 compared with FINN and GFED4s emissions, supporting the emissions estimates in FINNpeatSM. The comparisons suggest that current emissions inventories (FINN and GFED4s) underestimate PM emissions from peat combustion during the 2015 fire event, and when used in a model result in $PM_{2.5}$ concentrations which are biased low. This implies that studies using these emissions may have underestimated the impact of fire emissions on particulate air quality. Determining which inventory gives a better representation of peat fire dynamics, such as the burned area and depth, is difficult due to the compensating differences. These are discussed in section 5.2.2.

The total $PM_{2.5}$ and CO_2 emissions for each fire event are reasonably similar to those suggested by studies specifically evaluating Indonesian fires (Wooster et al., 2018; Jayarathne et al., 2018). These studies used field measurements to estimate total emissions from specific fire events for one or two species, and are likely a good estimate of total emissions from a fire event. However, they do not provide temporally or spatially varying emissions, and cannot be used to analyse atmospheric concentrations. Therefore creating an emissions inventory which agrees with these estimates is important.

- **Peat fires contribute a substantial amount to Indonesian fire emissions**. Overall 36% of the area burned is on peatlands, with 50% in 2015. The depth peat fires burn into the ground, combined with the large $PM_{2.5}$ EF from peat burning, means that peat fires contribute a substantial amount to the overall fire PM emissions. The contribution of peat burning (not including peatland surface vegetation) to $PM_{2.5}$ emissions in 2004-2015 is 45%. In years with increased drought and a large burn depth, such as 2015, peat burning contributed 68% of the $PM_{2.5}$ emissions, while in years with a low average burn depth, such as 2006, the contribution of peat burning to emissions (45%) is similar to the percentage of burning which occurred on peatland (46%). The burn depth is a particularly important variable for controlling the emissions from fires. Burned area was similar between the 2006 and 2015 fire events, yet the latter had over 3 times the $PM_{2.5}$ emissions, due to the large average burn depth.

  When using emissions inventories in an air quality model simulation, measured concentrations were substantially underestimated if emissions from peat fires were not included. Correctly calculating peat emissions is therefore important for understanding the full impact on Indonesian fires. Including soil moisture as a metric to estimate burn depth in the emissions calculation improves the correlation of simulated and observed PM concentrations, demonstrating the importance of soil moisture on peat fire emissions. This suggests that interventions to control soil moisture (e.g., rewetting peatlands through blocking drainage canals) may also help to control emissions from peat fires.

- **Indonesian fires expose millions to poor air quality for long periods and cause tens of thousands of premature mortalities**.

  Each fire event studied caused 22-67 million people to be exposed to PM concentrations above the WHO recommended limit for at least half the dry season, and resulted in 14,000 - 56,000 premature mortalities and 541,000 - 2,188,000 disability affected life years (DALY). This represents 4-16% of the average annual global estimated mortality from exposure to fire PM (Johnston et al., 2012). In total for the 6 years studied, long term exposure to poor air quality from fire resulted in 127,281 premature mortalities. Vegetation fires in the Amazon have been found to result in 7041 - 16,800 premature mortalities annually (Reddington et al., 2015; Butt et al., 2020), of a similar magnitude to the 2004-2014 Indonesian fires events, although less than for 2015.

  Years with greater emissions have a greater health impact, and for the 6 years studied the emission and health impacts have a strong linear relationship, with 2940 premature mortalities per Tg of PM emitted. Using this relationship to estimate mortalities, the total premature mortalities caused by dry season fires, including years not modelled, is 131,700, with 86% occurring in the 6 highest fire years. The relationship between emissions and health impacts implies that reducing emissions will directly reduce the mortality resulting from fires, providing incentive for efforts to prevent emissions. There are limitations to this assumption, however, discussed in section 5.2.3.

  The mortality from fires in 2015 and 2006 estimated in this thesis are substantially lower than found by Koplitz et al. (2016) and Crippa et al. (2016), due to the difference in relative risk used, discussed further in section 5.2.3.

There are no previous studies estimating mortality from fires in other years, and, to my knowledge, this thesis gives the first estimate of total mortality from fires over the period.

- **Indonesian fires in 2004-2015 had an economic cost of US$93.7 billion.** The economic cost of fires through damage to land cover, CO_2 emissions and long-term health impacts, the three largest contributing sectors to overall cost, has been calculated at US$93.7 billion for the 6 years studied. The largest cost was for the 2015 fires at US$28.8 billion, and in other years the total costs came to US$9.1 – 19.8 billion.

  These estimates focus on the three sectors which contribute the majority of overall cost, as found by The World Bank (2016). Using the FINNpeatSM inventory and estimates of long-term health effects, the costs attributable to fires in these three sectors have been shown to be greater than estimated by the World Bank for 2015. There are few studies analysing the economic impact of Indonesian fire events, despite the important implications it can have on policy. By reviewing the cost estimated by The World Bank (2016), and providing an alternate estimate of costs, the work in this thesis contributes to this largely uncertain area of research.

  Fires are predominantly used to clear land as they are considered the cheapest method. However, the cost benefit analysis done in Chapter 4 suggests that overall fires are not beneficial financially; the cost to land owners through damage to crops and plantations outweighs the savings made by using fire. This finding contradicts a widely accepted rationale for the use of fire. This implies that fire prevention can be a benefit to land owners, and the cost analysis should be used as an incentive in fire mitigation schemes. While land damage costs mostly effect land owners, the costs of health impacts and CO_2 emissions can be more widely felt, and incentivise government responsibility for fire prevention. Such policy requires funding, however, and the economic cost of fires provides a guideline on reasonable spending for fire prevention.

The economic cost of fires is one of the many impacts fires can have, and should be considered alongside the social and climate impacts. An economic framing has been used here for two reasons; to consider the impacts of fires in the same framework as the rationale for using fires is often given, and to show the cost of fire impacts compared against the cost of fire prevention methods. This is an important part of analysing the impacts of fires in the region. It is not a completely objective method for considering fires, however, as there are benefits and impacts of fire use which cannot be easily represented economically, for example, the importance of fire use as part of a traditional ceremony (Silvianingsih et al., 2020), or the adverse effects of fires on wildlife (Harrison et al., 2009). The economic position of fire should therefore be used alongside other approaches, such as those centred on well-being, when considering policy.

- **Peatland restoration is an effective method for reducing fires and emissions.**

  Restoring 2.49 Mha of peatland could have reduced $PM_{2.5}$ emissions by 3.9 Tg, CO_2 emissions by 343 Tg, premature mortality by 20,000, DALY by 774,000, and economic costs by US$8.6 billion for the 6 fire events studied. The largest reductions are in 2015, when peat fires made the largest contribution to emissions. This is a substantial reduction in emissions and health impacts, and the reduction in the cost of fires surpasses the cost of restoration, making peatland restoration a cost effective strategy for fire mitigation.

  The effectiveness varies, however, depending on the degree to which peatland is restored to and where the restoration takes place. Randomly allocating the areas for restoration results in half the reduction in emissions, compared with selecting areas most at risk from fires. A complete prevention of fires on peatland results in a substantially greater reduction in emissions compared with reducing the burn depth of fires through rewetting peatlands. A reduction in burn depth is the most likely outcome of peatland restoration, however, while fire prevention would likely also require other fire mitigation policies, such as a strict fire ban and schemes working with farmers to avoid the use of fire.

It has been suggested that a complete fire ban will negatively affect local livelihoods, and that burning outside of peatlands, or during non-drought times, should be allowed (Tacconi, 2016; Silvianingsih et al., 2020). However, in Chapter 3 it is shown that the emissions coming from non-peat fires are not insignificant, and on average contribute around half the total fire emissions. Furthermore, in Chapter 4 the comparison of restoration scenarios shows that with all peat fire emissions prevented there are significantly larger emissions than when no fires occur on restored land. These findings imply that a total prevention of fire should be aimed for, and the focus should be on mitigating the effects on livelihoods.

5.2 Limitations and uncertainties

The work in this thesis is predominantly limited by data availability, computing time, and uncertainties in knowledge. Here, these limitations have been addressed, and, where applicable, recommendations made for how the limitations could be navigated in the future.

5.2.1 Study domain and period

One limitation of the work throughout this thesis is that eastern Indonesia is not included in the study area. To include the whole of Indonesia would require a large domain, increasing the run time and computational expense of the model simulations. Large fires occurred in New Guinea in 2015, with 17% of the total burned area for Indonesia and 15-20% of the total CO emissions (Lohberger et al., 2017; Nechita-banda et al., 2018). However, the contribution in other years is likely smaller, as there is little evidence of significant forest clearing prior to this year (Margono et al., 2014). Fires in Kalimantan and Sumatra are also likely more important from an air quality perspective, as these areas are close to densely populated areas in Malaysia and Singapore. The contribution of fires in the region during the 2015 event, however, suggests that the region will likely be susceptible to fire again, and future work looking at fires in 2015 and later should include eastern Indonesia.

The largest Indonesian fire event on record was in 1997; however, this event has not been included in this study. The MODIS hotspot product, used to detect fires in the FINN emissions inventory, is only available from 2000 onwards, and therefore FINN emissions data does not exist for the 1997 event. Adapting methods employed in other studies to estimate fire occurrence prior to the MODIS period (Wooster et al., 2012; van Marle et al., 2017) would allow an estimate of emissions from the 1997 fires as well as a better understanding of when fires became an issue in this region. However, since one of the key objectives of this work was to use a consistent methodology to calculate emissions for different years, calculating the 1997 emissions using a different fire detection method was not considered.

The most recent fire event in Indonesia, which occurred in 2019, is also not included in this work. Data has only recently become available for this event, too late to be included in the multi-year emissions analysis. Published studies on the event are not yet available, but media sources from the time suggest that emissions were of a similar magnitude or lower than the 2015 event (CAMS, 2019; Bloomberg, 2019; Post, 2019), although this is still being confirmed. It is therefore likely that the impacts will be somewhere between those of the 2006 and 2015 fire events.

5.2.2 Emissions

One of the main limitations relates to the uncertainties which still remain in the calculation of emissions from fires. These emissions are used throughout this thesis, and uncertainties may carry through into other findings. There are complexities of peat burning which have not been included in the emissions calculation, such as the length of time peat fires can burn. The FINNpeatSM emissions inventory is consistent with other fire emissions inventories in that the total emissions from a fire are recorded on the day the fire is detected, when, in reality, peat fires can smoulder for weeks at a time. This added complexity has not been included as the exact length of time peat fires burn for is uncertain. It is likely dependent on the peat water table rising, which is difficult to determine. As the primary focus of the research in Chapters 2 – 4 has been on total emissions over a fire season, the daily variation in emissions is likely to be insignificant to the results. However, daily variations in PM concentrations could be important for calculating short-term health effects, or for air quality forecasting. Recent research from the field has suggested emissions factors (EF) from peat combustion which vary in time (Roulston et al., 2018), and these could be used in future work to make emissions inventories more realistic. The persistence of peat burning is not completely unaccounted for in FINNpeatSM, however, as emissions from repeat fires within the same season are included, meaning that if a smouldering peat fire re-surfaces and a fire hotspot is detected, it will be registered again as a new fire.

When calculating fire emissions, compensating differences between variables mean that combinations of smaller and larger values can result in the same emissions. For example, in some years, FINNpeatSM uses a smaller average burn depth than GFED4s but a larger area burned, resulting in a similar overall biomass consumed. Since there is a large uncertainty in both these variables, particularly around the assumptions made about the relationship between soil moisture and burn depth in both inventories, it is difficult to determine the optimum values to use. Evaluating emissions does not show clearly which inventory is correctly simulating these dynamics; increased field measurements of these metrics are needed to reduce the uncertainty. Although the compensating differences means there is not a large effect on overall emissions, the combination of burned area and burn depth does affect the fraction of biomass coming from peat. If this is being underestimated in FINNpeatSM, then the benefits found when peatland is rewetted could also be underestimated.

The data which is combined to calculate emissions contains many uncertainties. The EFs, burned area per hotspot and maximum burn depth used all come from only a few studies, and there can be large variations in the values suggested. For example, the EFs for $PM_{2.5}$ from peat burning varied by a factor of 5 for different fire plumes within one study (Jayarathne et al., 2018). Soil moisture data is scarce, as frequent cloud clover in the tropics makes satellite detection difficult. The soil moisture data used to create the FINNpeatSM emissions has required averaging to a course resolution to navigate gaps in the data, meaning that small scale variations in soil moisture are likely missed. From 2015 onwards, SMAP soil moisture data is available, which has better coverage than ESA, and it is recommended that peat fire emission calculations for years after 2015 make use of the SMAP soil moisture data. Uncertainties in the emissions inventory will carry through to the other work in this thesis.

Using a model to simulate PM concentrations and AOD with different fire emissions inventories, there is some mismatch in 2015 between the simulations and observations. The greatest simulated PM concentrations occur in September, while the greatest observed PM concentrations are in October. This could be due to uncertainties in the measurements, issues with the model, or uncertainties in the emissions. If the bias is coming from the emissions, it could be due to the assumptions made about the relationship between burn depth and soil moisture, or because emissions are all released on the day the fire is detected. There is a lower average soil moisture in October than September, and a more sensitive relationship between the burn depth and soil moisture could result in greater October emissions. Releasing emissions over time would also result in greater emissions towards the end of the fire season, although the strong temporal correlation between peaks in the simulated and observed PM suggest that the timing of emissions is good. An underestimation of fires in October could also be due to issues with fire detection, as smoke could prevent satellites from detecting hotspots. Work to analyse all these issues would further improve the emissions. Bias due to uncertainties in the model is considered in section 5.2.3.

The uncertainty in what might be causing differences between simulated and observed PM is a large limitation in using a model to confirm emissions. Multiple factors contribute to the concentration of a species in the atmosphere, including emissions from multiple sources, secondary formation, deposition and atmospheric transport. These components all have uncertainties, and it is difficult to determine what bias might be due to the emissions. However, using a model to simulate concentrations resulting from fires is one of the few ways to evaluate the fire emissions inventories. There are some ways to mitigate the uncertainty in this evaluation. Firstly, when comparing between simulations with different emissions inventories, model uncertainty is consistent between simulations, making the bias caused by uncertainties in the emissions inventory slightly clearer. Secondly, the correlation of peaks in simulated and observed PM can be a useful measure to evaluate fire emissions, as short peaks in atmospheric concentrations are likely due to fires rather than other sources. Finally, when evaluating fire emissions, comparisons of concentrations close to the fires can be more significant, as there is less impact of transport, deposition and atmospheric chemistry. Observation sites, however, are often located in cities, as that is where air quality measurements are most useful, while fires occur in more remote locations. Satellite AOD data has good spatial and temporal coverage, but is difficult to use in the tropics as cloud cover can affect the availability of measurements. Observations close to fires can also be important in analysing the dynamics of a plume. In Chapter 2, two different plume injection schemes have been used, however the difference this made to concentrations was largest close to the fires, and the available observations do not indicate which scheme may be more realistic.

5.2.3 PM concentrations and health impacts

Computational limitations mean that the model simulations done for this thesis have been restricted to the dry seasons of 6 years, although emissions have been calculated for the entire 2004-2015 period. This leaves a gap in the understanding of fire impacts in years with low emissions, or outside of the dry season, although the impacts are likely to be small. Evaluating fire emissions during periods of low fire has increased difficulty, as uncertainty from other emissions sources will be more influential on simulated concentrations. Therefore, although the gaps in understanding are acknowledged, there is a low priority for studying low emissions periods in more detail, at least from an air quality perspective. In the future, fires outside of the dry season may become more significant. In this case it is worth noting that emissions at other times of the year may be transported differently, and the relationship between emissions and air quality exposure could be different, as discussed in more detail later in this section.

In the previous section the differences between simulated and observed PM in 2015 are discussed in terms of what they could mean for the emissions. However, the overestimation of PM concentrations in Singapore and Malaysia in September, and underestimation in October, could also be due to issues with transport or deposition in the model. Observation sites in cities are useful for evaluating the concentrations which are used to calculate exposure and health impacts The simulations of each fire event have been compared with these observations, and, although there can be a larger bias on individual days, on average the bias for each event is small. Since the simulated PM concentrations are converted to an annual average in order to estimate health impacts, day to day bias will have a small impact on these estimates. One limitation in evaluating the model is that the available PM measurements are predominantly PM_{10}, while the health impact calculations use $PM_{2.5}$ concentrations.

The estimated health impacts from fires have a high uncertainty associated with them, and are difficult to evaluate, as multiple factors can contribute to real-life data. They are strongly dependent on the sensitivity of the relative risk function used, which may not be suitable to regions with a high background PM concentration (Chapter 1). The risk functions are also often from studies of anthropogenic air pollution, which may have a different toxicity to fire emissions (Chapter 1). As more data is becoming available on the impacts of fire smoke on health, future studies could use fire smoke specific relative risk. To estimate the health impacts caused by fires, the health impacts from exposure to simulated concentrations are found with and without fires in the model. Due to the non-linearity of the relative risk used to estimate health impacts, the health impacts have a higher sensitivity to uncertainty in PM concentrations when the concentrations are low, i.e. for the simulation with no fire. Therefore, uncertainties in the removal of PM and emissions from sources other than fire can affect the estimated health impacts from fire. The model setup can also effect these concentrations, for example by changing the meteorology re-initialisation period (see appendix A). However, this difference is substantially less than that caused by using a different relative risk function.

The health impacts estimated in Chapter 3 are limited to the health effects for adults. Studies have linked fire haze with poor health in children (Jayachandran, 2013; Sahani et al., 2014; Kim et al., 2015), although the exact risk is uncertain. Another limitation is that only the health impact of PM exposure has been included, when many other species emitted from fires may also be dangerous to health. The total health impacts of fires on the entire population are likely to be larger than those estimated in Chapter 3.

There is also uncertainty in which health impact calculations best describe exposure to fire emissions. Poor air quality events can last weeks to months, between the typical scales for short and long term health effects, the former of which covers events lasting a few days and the latter of which covers annual exposure. The health estimates in this thesis are for long-term exposure, following the methodology from other studies (Johnston et al., 2012; Koplitz et al., 2016). Long-term exposure to poor air quality has a greater effect on health than short-term exposure (World Health Organization, 2005), and the health impacts of short term exposure to fire PM are likely to be less. Indeed, Crippa et al. (2016) estimate both long and short term health impacts resulting from fires, and find the long term mortality to be around 6 times the short term mortality.

Only outdoor exposure to PM has been considered in this work, and the estimated health impacts therefore do not show the total health burden from $PM_{2.5}$ exposure. Indoor exposure can also have a large impact on health, but estimating this impact requires knowledge of living conditions and indoor air quality measurements. Indoor air quality is likely to be worse in rural areas due to the cooking fuels used (Massey et al., 2009). It has been shown that during light, medium and severe haze events in Singapore, indoor $PM_{2.5}$ concentrations are similar to outdoor concentrations, suggesting that the outdoor exposure may be a good approximation for indoor exposure during fire periods (Sharma and Balasubramanian, 2018).

A linear relationship between emissions (and secondary formation) of PM and the subsequent health impacts of fires has been found and used to approximate the health impact of dry season fires in years not simulated by the model (Chapter 3). While this relationship has been shown to hold for the years studied, it is important to acknowledge that this is only 6 data points, and the relationship may not be robust. This is particularly true for large fire events, as the 2015 fires are the only example in this study of an event with more than 5 Tg emitted. However, there are reasons why a linear relationship is likely. Health impacts depend on the exposure to PM concentrations, which depends on the magnitude of emissions, transport, atmospheric chemistry, deposition and population. In Indonesia the dry season meteorology is consistent between years, therefore transport and deposition of PM, and the population exposed, are likely to also be consistent, leaving the health impacts dependent on the emissions and secondary formation of PM. One thing to note is that for fires outside of the dry season the relationship may change significantly, as PM is transported to different locations with different populations. Also, at high extremes in emissions this relationship will logically not be linear, as health impacts are limited by the population, while emissions are not. However, it is uncertain where this limit is. In Chapter 4 it is shown that using this linear relationship to estimate the reduction in mortalities and DALYs that would have occurred in 2015 if emissions had been reduced due to peatland restoration, the results are very similar to when estimated using the simulated $PM_{2.5}$ concentration and health impact calculations, confirming the linear relationship. Analysis of more fire events is needed to increase confidence in the relationship, particularly for events with large emissions.

5.2.4 Economic cost

One limitation when calculating the economic cost of fires is that the impacts of fires are numerous, and it is not possible to model them all. The three sectors with the greatest costs have been included in the work in Chapter 4. These are damages to land cover, CO_2 emissions and health impacts. Other costs could come from loss of tourism and trade, school closures, transport and industry delays, infrastructure damage, and fire suppression (World Bank, 2016). There are also suggestions of costs relating to other impacts which are harder to quantify. For example reductions in crop productivity due to haze (Tacconi, 2016).

Land use data availability is also a strong limitation when calculating the costs. The land use and land cover maps are only for one year, and this may not match the year the fire occurred. Even within a year, land cover may have been established before or after a fire event. Ascertaining accurate land cover maps is difficult and unlikely to be done more frequently. This means that the wrong land cover damages could be applied to the fire. One factor which does partially mitigate this concern, however, is that oil palm crops are in place for 20-30 years, and so are unlikely to change on time scales covering a few years. Also, the total economic value of oil palm and forest are similar, so uncertainty in land cover is unlikely to affect the costs significantly, unless the land was between uses at the time of a fire. Tacconi (2002) suggests that only accidental fires should count towards costs for damaged land cover, as intentional fires have an economic rationale (De Mendonça et al., 2004). However determining accidental fire in Indonesia is difficult. The costs relating the emissions of CO_2 and $PM_{2.5}$ are applicable for any land use.

5.2.5 Peatland restoration impacts

A lack of data on how restoration effects fires results in uncertainty, and assumptions have been made on fire reduction. A range of fire reduction scenarios have been used to give an idea of the uncertainty. The exact location of peatland restoration is also unclear from records, and therefore two scenarios have been compared. In one the highest emitting peatland areas between 2015 and 2004 are restored, and in another peatland has been chosen at random. The real locations are more likely to be similar to the former scenario, as the peatland being restored is degraded, which is often linked with high fire occurrence in previous years.

To simplify the restoration scenario, the effects of restoration have been applied to areas in squares of 488 km^2. Some of these squares contain a mixture of peatland and non-peatland, which means that of the 2.49 Mha restored, it is actually 2.25 Mha of peatland restored, with the remaining 0.24 Mha consisting of non-peatland at the edges of peatland. This is a marginal amount and is unlikely to greatly affect the simulated benefits, which are already the product of several assumptions.

One further limitation in the work on the effects of peatland restoration is that only past fire events have been studied. Predicting future fires is difficult and not something that has been considered in this work. Many added complexities would need to be considered, for example how fire use and fire conditions might change in the future, and any potential feedback loops.

5.3 Future Work

In section 5.2 it has been recommended that further measurements of peat fires, including the length of burn time, burned area and burn depth, are needed to better constrain emissions inventories. Also, observations of $PM_{2.5}$ concentrations close to fire locations are needed to better evaluate model simulations and emissions. The complexities included when calculating peat fire emissions could also be increased.

Uncertainty and simplifications in the representation of atmospheric processes within the model lead to model uncertainty, which could be explored in future work. This uncertainty can be estimated by finding the sensitivity of the model output to perturbation of different model parameters. For a complex model this requires thousands of simulations, often not possible due to computing restraints. An emulator uses statistical techniques such as a Gaussian process to estimate model output across multiple parameter variations, based on a small number of simulations (Lee et al., 2011). This technique could be used to estimate the uncertainty in the simulations used in this thesis.

Future studies leading on from this work could provide a better evaluation of the total impacts of Indonesian fires, by investigating the climate and meteorology impacts of fires. Literature shows that emissions of greenhouse gasses effect the climate (IPCC, 2014), but the impact of Indonesian fires is uncertain. The FINNpeatSM emissions inventory could be used to quantify the contribution of Indonesian fires, particularly under future scenarios of increased drought and fire mitigation policy. Emissions of PM can alter the radiation budget and interact with clouds, which effects regional wind and rainfall, and global weather systems; however, the changes to the meteorology are uncertain (Tosca et al., 2010; Tosca et al., 2013; Reid et al., 2013). Meteorological impacts, such as a reduction in rain, may also result in further fire costs through effects to crop production and water availability. Fire emissions can also effect global background atmospheric concentrations, and can reach remote parts of the atmosphere, contributing to radiative forcing (Davison et al., 2004; Schill et al., 2020). FINNpeatSM emissions and the WRF-chem model could be used to investigate these impacts.

Fires also change the land-atmosphere dynamic by changing the land cover. This can affect radiation, evapotranspiration, and surface roughness, causing further changes in wind and rainfall (McAlpine et al., 2018). How these changes interact with the changes due to fire has not been well studied, and could be important for recognising the full impacts of fire and land use change in the region.

Changes to meteorology due to fires can result in positive feedbacks. Smoke from fires likely reduces rainfall in the region (Tosca et al., 2010; Tosca et al., 2013; Lee et al., 2018), which in turn makes fires more likely and emissions greater. Deforestation also is likely to increase temperatures (Baker and Spracklen, 2019), reduce rainfall and increase wind speeds in the tropics, increasing the risk of fire (Hoffmann et al., 2003). Work to understand these feedbacks is important for understanding and predicting future fire.

The carbon emissions calculated in this thesis are from combustion only, but fires can result in further emissions years after the fire has stopped. Fires in the tropics result in increased tree mortality and large amounts of carbon can be emitted as this vegetation decays (Silva et al., 2020). In Indonesia, fires can also degrade peatlands, resulting in increased carbon emissions from peat mineralisation (Page and Hooijer, 2016). The total carbon emissions caused by fires is therefore likely larger than that from combustion only, and estimating total emissions could should show an increased environmental impact of fires.

Other future work is to include global peat fire emissions in FINN. This would require research into the dynamics and emissions of peat fires in different environments. Recent discoveries, such as the magnitude of peatlands in the Congo (Dargie et al., 2017), show that knowledge of tropical peatlands is still growing. While these peatlands remain relatively undisturbed, they are at risk of future land use change and drought, which could make them susceptible to fire (Dargie et al., 2017). Outside of the tropics, there are large areas of peatland in boreal regions across North America, Europe, Asia and the Arctic (Xu et al., 2018). Peat fires in these regions can be large, and are predicted to increase in the future under a changing climate (Flannigan et al., 2005; Turquety et al., 2007; Shvidenko et al., 2011; Mccarty et al., 2020; Graham et al., 2020). Including emissions from these fires in fire emissions inventories is therefore important. Emissions from peat fires in the Arctic, in particular, are poorly understood, and work is needed to better constrain these (Mccarty et al., 2020).

In the future, Indonesian peatlands are increasingly likely to be at risk of fire, with large environmental, social and global impacts. Fire risk is closely linked to land use change and climate, and fire predictions are based on how these factors might change in the future. Drought conditions and El Nino events are expected to be more common in Indonesia with climate change (Herawati and Santoso, 2011; Cai et al., 2014). Future land use change is variable depending on land management scenarios, but expected to increase under a business as usual scenario (Marlier et al., 2014; Marlier et al., 2015; Wijedasa et al., 2018), as an increase in palm oil production is encouraged (Koh and Ghazoul, 2010). Alternative future land use scenarios which have been considered see high deforestation with oil palm prioritised, or reduced deforestation under a sustainable development plan which conserves forest and protects peatlands (Marlier et al., 2014; Marlier et al., 2015). Spessa et al. (2015), show that that fire events can be forecasted reasonably well months in advance, using seasonal rainfall forecasts and accounting for forest clearance. However, predicting when fire events will occur in future years is difficult. Modelling future fire events could show the future benefits of fire mitigation projects.

Previous studies have suggested that protected areas in Indonesia may not be efficient in preventing land use change and fire (Curran et al., 2004; Spracklen et al., 2015). It has been shown in Chapter 4, however, that protected areas can reduce fires, although the effect is variable between protected area types. There are many types of protected area in Indonesia and the reasons for these differences is uncertain. It could be down to size, location, accessibility or management style. Research into why the amount of fires in protected areas is so variable would be useful to help protected areas better protect against fire.

Fire prevention in Indonesia is complex, as many local communities rely on fire (Silvianingsih et al., 2020). Studies have shown that there are barriers to fire mitigation policies and initiatives (Jefferson et al., 2020), but scientific findings may help to reduce these barriers, if they are included in future policy planning. Carmenta et al. (2020) suggest that local support for initiatives is vital to their success. One method of focussing interests on the benefits of fire prevention is to demonstrate the air quality and health impacts of fires, using local air quality monitoring (Carmenta et al., 2020). The health impacts per km^2 of land burned suggested in Chapter 3 could be used for this purpose. The cost benefit analysis in Chapter 4, which suggests fire may not be economically beneficial to land owners could also be used as an incentive for fire mitigation. Further work is needed to include these findings in policy. Future work is also needed to assess the long term effects of fire mitigation initiatives on fire use.

5.4 Conclusion

Indonesian fire events have large emissions and severe social and economic impacts. However, they are still poorly understood in global emissions inventories, due to uncertainties in modelling peat fire emissions. The combination of anthropogenic and meteorological drivers make the future of these fires difficult to predict, but it is clear that a better understanding of the emissions and impacts is needed in order to prevent future events.

The work in this thesis provides a better understanding of the dynamics of Indonesian peat fires, and of the various impacts. It has been shown that both EFs specific to Indonesian peat combustion, and a peat burn depth variable with soil moisture, are important when calculating the emissions from these fires. The air quality and economic impacts of the fires have been estimated, with the former showing that fire impacts are considerable, and the latter providing evidence against the economic rationale behind fire use in Indonesia. The variation in emissions and impacts between multiple fire events has been considered, and the total impact of over a decade of fire events has been estimated. The improved understanding of peat fire emissions and impacts have been combined to show the benefit of peatland restoration.

This work contributes to the growing knowledge of Indonesian fire events. It will aid future research by providing an improved emissions inventory for Indonesian peat burning. It will also aid future policy by demonstrating the substantial and wide spread impacts of fires, and the numerous potential benefits of fire mitigation.

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Appendix A Model Description

Atmospheric models simulate the chemical and physical processes which are taking place in the atmosphere. These processes are often approximated, and the complexity needed depends on the required model output and use, and on computational requirements. The work in this thesis uses model simulations to determine the effect of fires on particulate concentrations in the atmosphere, and choosing a suitable model requires consideration of how the important mechanisms controlling atmospheric concentrations are simulated. This work uses the Weather Research and Forecasting model with chemistry (WRF-chem v3.7.2). In this section the model options used have been described and the suitability for the work evaluated.

To simulate concentrations of chemical species in the atmosphere, the controlling factors are the emissions, transport, chemical processes and deposition. The transport is controlled by physical processes in the atmosphere, which, in models, are described using equations of conservation of air mass, momentum, heat and water. The chemical processes are described by the mass conservation of chemical species.

A.1 WRF-chem

WRF-chem is an extension of the WRF model, with a chemistry component added to allow the simulation of atmospheric chemical processes alongside the physics. WRF is a numerical weather prediction system, developed at the National Center for Atmospheric Research (NCAR), designed to be used for both forecasting and research. WRF consists of a pre-processing system (WPS), which defines the simulation domain and interpolates inputted terrestrial and meteorological data, and the Advanced Research WRF (ARW) model, which solves the governing equations (NCAR, 2016). ARW is an Eulerian model and uses time splitting integration techniques to solve the fully-compressible nonhydrostatic equations of motion.

WRF-chem is an online fully coupled model, meaning that the chemistry and meteorology components can interact. The two components use the same transport scheme, grid and timestep (Grell et al., 2005). Interaction is important for modelling atmospheric aerosol, as in the atmosphere aerosol can affect the meteorology, and the meteorology effects the movement and removal of aerosol. Coupling means that chemistry and meteorology have to be simulated every time the model is run, increasing the run time.

Emissions, transport, chemical processes and deposition, the controlling factors for atmospheric concentrations, are all included in WRF-chem. Emissions are either inputted into the model or calculated online. WRF-chem is capable of simulating resolved and non-resolved transport, gas and aerosol interactions, and dry and wet deposition, through a combination of physics and chemistry schemes (Grell et al., 2005). There is a choice for the physics, gas phase chemistry, photolysis, and aerosol schemes, and a choice of emissions to be inputted into the model (Peckham et al., 2015). Not all schemes will work together and the set-up options chosen can be important. The WRF-chem schemes used in this work are shown in **Table A.1** and explained in detail in sections A.2-A.5. This set-up has been used previously to study PM and air quality (Conibear et al., 2018; Reddington et al., 2019; Graham et al., 2020).

The simulations in this work have been run at 30 km resolution over 140×140 grid points. The domain is centred at 0° N and 110° E, and covers the area 17° S– 18° N and 90–130◦ E (Figure A.1). A Mercator projection has been used for the simulation since the domain is at the Equator. The simulation contains 33 vertical levels, between the surface and 10 hPa. WRF has a hydrostatic pressure vertical co-ordinate which follows the surface terrain (NCAR, 2016). The resolution used is suitable for air quality modelling, as the spatial and vertical resolution of models has been shown to make little difference to mortality estimates due to air pollution exposure, and models at 36 km resolution are only slightly biased compared with models at 12 km resolution (Punger and West, 2013; Kushta et al., 2018). WRF-chem has been used previously in studies on air quality impacts of fires in several regions including the Amazon (Archer-Nicholls et al., 2015; Butt et al., 2020), the US (Chen et al., 2014), China (Reddington et al., 2019) and Indonesia (Wang et al., 2013; Ge et al., 2014; Aouizerats et al., 2015; Crippa et al., 2016; Putriningrum et al., 2017; Lee et al., 2018; Mead et al., 2018). Evaluations against

Table A.1: Setup options used in WRF-chem simulations.

Chemistry		
Chemistry scheme	MOZART + MOZAIC 4 bins	Zaveri et al. (2008) Emmons et al. (2010)
Photolysis	Madronich F-TUV	Tie (2003)
Domain		
Vertical levels	33 vertical levels with 4 soil levels	
Resolution	30 km	
Timestep	120 seconds	
Physics		
Microphysics	Thompson graupel scheme	Thompson et al. (2008)
Longwave	RRTMG scheme	Mlawer et al. (1997)
Shortwaves	RRTMG scheme	Pincus et al. (2003)
Surface layer physics	MYNN	Nakanishi and Niino (2006)
Land/water surface	NOAH	Ek et al. (2003)
Boundary layer scheme	MYNN 2.5	
Cumulus scheme	Grell 3D	Grell and Deveny (2002) Grell and Freitas (2014)
Urban physics	Single-layer, UCM	

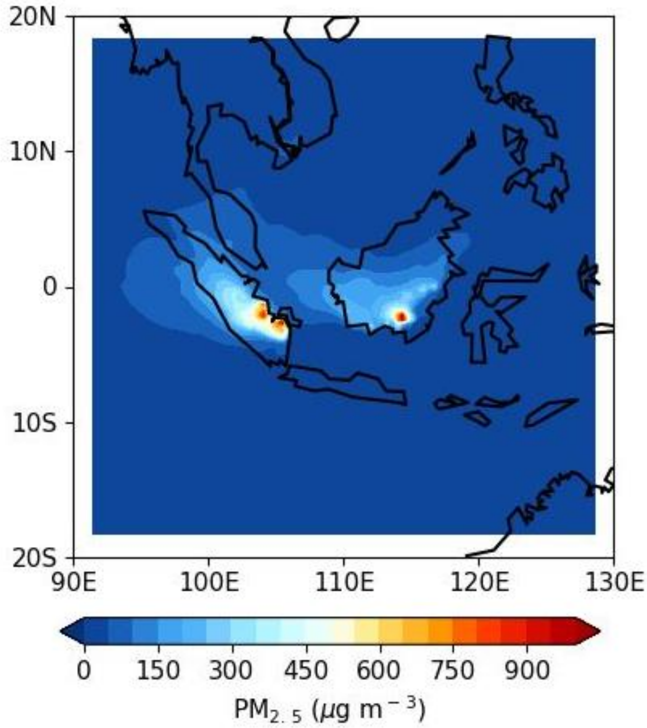

Figure A.1: Simulated $PM_{2.5}$ averaged over August - October 2015, showing the domain used for WRF-chem simulations.

observations in Indonesia, Malaysia and Singapore have shown that WRF-chem can simulate PM in the region reasonably well (Aouizerats et al., 2015; Crippa et al., 2016; Lee et al., 2018; Mead et al., 2018).

WRFotron has been used to run the WRF-chem simulations. WRFotron is a suite of tools which automate the running of WRF-chem with re-initialised meteorology. WRFotron runs pre-processor files, converting inputted emissions and meteorological data into WRF-chem input, runs the WRF-chem model, and formats the output files.

A.2 Physics in WRF-chem

The physics in WRF-chem is controlled by 6 schemes; microphysics, cumulus physics, long and shortwave radiation, planetary boundary layer, surface layer physics and a land/water surface scheme. These schemes interact with each other to simulate meteorology, physical processes and sub-grid scale transport within the model. The meteorology in the model effects the chemical concentrations by transporting gasses and aerosols away from a source, and through wet deposition. The complex meteorology over Indonesia can be difficult to simulate in models (Reid et al., 2013).

The microphysics scheme creates sub-grid scale transport and provides atmospheric heat and moisture. It is also responsible for providing the non-convective rainfall. In the simulations for this study the Thompson bulk microphysics scheme has been used (Thompson et al., 2008). This is a 6 class microphysics scheme which is double moment for rain and ice. Condensed water is partitioned into cloud liquid, cloud ice, rain, snow, and graupel. This scheme is coupled with the RRTMG radiation scheme so that the same cloud properties are used in the radiation scheme as the microphysics (Thompson et al., 2016). The Thompson physics scheme has been shown to be suitable for simulating cloud development over Indonesia (Sari et al., 2018).

Convective clouds and rainfall are simulated in the cumulus parameterisation, needed when WRF-chem is run at a resolution greater than 10 km. Here, the GRELL 3D scheme (Grell and Deveny, 2002), which is recommended for use with MOZART-MOSAIC chemistry (Section A.3; Hodzic and Knote, 2014), has been chosen. The model sensitivity to parameterisation assumptions has been improved using data assimilation and ensemble techniques. The GRELL 3D scheme is the only cumulus physics scheme with cloud chemistry. This scheme has been used previously in WRF-chem to study Indonesian fires (Wang et al., 2013; Putriningrum et al., 2017).

The long and shortwave radiation schemes compute upward and downward radiation fluxes for clear and cloudy skies, and control the warming and cooling of the atmosphere. These need to interact with clouds and aerosols. We have used the RRTMG scheme for longwave and shortwave radiation, which is a modified version of the RRTM radiative transfer model. RRTMG has been made for use in models as it uses fewer points in a spectral band, providing better efficiency with minimal loss of accuracy compared with RRTM (Iacono et al., 2008). RRTMG is also able to represent partial cloud where RRTM is restricted to clear sky or full cloud calculations. RRTMG shares the same basic physics and absorption coefficients as RRTM. The molecular absorbers included are water vapour, carbon dioxide, ozone, methane, nitrous oxide, oxygen, nitrogen and the halocarbons in the longwave and water vapour, carbon dioxide, ozone, methane and oxygen in the shortwave. The longwave and shortwave RRTMG schemes are consistent with each other. The RRTMG radiation schemes are commonly used in studies looking at biomass burning (Putriningrum et al., 2017; Mead et al., 2018; Lee et al., 2018).

Fluxes within the planetary boundary layer (PBL) are covered by the PBL scheme, MYNN2.5. The scheme takes fluxes from the surface and simulates mixing in the PBL. MYNN2.5 is an improved Mellor-Yamada model with condensation physics, a set of equations which simplify the full turbulent flow model (Nakanishi and Niino, 2006). MYNN2.5 improves on turbulence in the Mellor-Yamada model, and on the underestimation of the mixed layer depth. The MYNN scheme is also used for the surface layer physics in WRF-chem. These schemes have been used previously looking at biomass burning in south-east Asia (Lee et al., 2017; Lee et al., 2018).

The surface physics scheme covers heat and moisture fluxes from the soil and canopy into the PBL scheme, and the emissions and albedo which go into the radiation scheme. It also provides the surface roughness parameters which feed into surface eddies. The surface scheme provides a lower boundary condition for WRF-chem. The Noah land surface model from NCAR has been used in these simulations. Noah has 4 soil levels and also provides moisture information from the canopy. It can be used in conjunction with an urban physics model to simulate building energy. Noah allows multiple categories of land surface within a grid cell. Noah has been commonly used in WRF-chem simulations over Indonesia (Wang et al., 2013; Ge et al., 2014; Lee et al., 2017; Mead et al., 2018).

A.3 Chemistry in WRF-Chem

Chemical processes in WRF-chem are controlled by the chemistry scheme. This covers the mixing, deposition, scavenging and chemical transformation of trace gasses and aerosols, all simulated simultaneously with the meteorology (Grell et al., 2005). The photolysis rates for chemical reactions are provided by a photolysis scheme.

The MOZART-MOSAIC chemistry scheme has been used in the simulations in this thesis (option 201; Hodzic and Knote, 2014). This is based on the MOZART scheme for gas-phase chemistry (Emmons et al., 2010), and the MOSAIC scheme for aerosol chemistry (Zaveri et al., 2008). MOZART chemistry includes 85 gas phase species and 12 aerosol compounds, and includes 196 chemical reactions. This has been extended for MOZART-MOSAIC to include treatment aromatics, HONO and C_2H_2 (Hodzic and Knote, 2014), which are all emitted during peatland fires (Akagi et al., 2011; Hatch et al., 2015).

MOSAIC includes all major aerosol species important for anthropogenic and biomass burning emissions (Zaveri et al., 2008). Aerosol interactions are based on the aerosol size (Chapman et al., 2009), and MOSAIC is a sectional aerosol scheme with the aerosols separated into 4 bin sizes: 0.039-0.156 μm, 0.156 – 0.625 μm, 0.625 – 2.5 μm and 2.5 – 10 μm. These bins allow $PM_{2.5}$ and PM_{10} to be simulated separately. These sizes are for the dry particle diameter, meaning that particles do not move between bins with water uptake or loss, only through chemical and physical processes (Zaveri et al., 2008). MOSAIC is less computationally expensive than other aerosol models, while remaining accurate (Zaveri et al., 2008), and commonly used in biomass burning studies using WRF-chem (Aouizerats et al., 2015; Archer-Nicholls et al., 2015; Putriningrum et al., 2017; Mead et al., 2018).

Cloud aerosol interactions are uncertain (Boucher et al., 2013; Reid et al., 2013) and have competing effects (Rosenfeld et al., 2008), making them complex to model. Direct aerosol feedback works with MOZART-MOSAIC, however indirect aerosol feedback does not (Hodzic and Knote, 2014). Indirect aerosol feedback does work with MOZART-MOSAIC with aqueous chemistry (option 202), however this option has not been chosen for this study due to the increased run time.

Organic aerosols (OA) can be emitted directly into the atmosphere, referred to as primary organic aerosols (POA), or can be formed in the atmosphere via chemical reactions, known as secondary organic aerosols (SOA). The role of SOA in fire plumes is uncertain. Some field studies have found negligible amounts of SOA forming in smoke plumes (Jolleys et al., 2012; Brito et al., 2014), while laboratory studies often find it could be significant (Ortega et al., 2013). For Indonesian fires, Aouizerats et al. (2015) suggest that SOA formation is low, however, Hatch et al. (2015) found that Indonesian peat produced significant amounts of SOA when burned. The SOA scheme in MOZART-MOSAIC is based on Hodzic and Jimenez (2011), which gives a simplified parameterization of SOA in polluted air and smoke, based on the work of Spracklen et al. (2011). An SOA precursor is emitted as a fraction of the CO emissions, and reacts with OH to produce SOA. This method has a lower computational cost than a simulation using a volatility basis set, as there is no need to track a lot of aerosol variables (Hodzic and Jimenez, 2011). This scheme produces reasonable concentrations of SOA from anthropogenic and biomass burning emissions (Hodzic and Knote, 2014). In the simulations for this study, the SOA precursor from biomass burning was 4% of the emitted CO. The SOA scheme in MOZART-MOSAIC has been updated with increased isoprene oxidation (Knote et al., 2014), and with a new glyoxal SOA scheme (Hodzic and Knote, 2014; Knote et al., 2014). Both isoprene and glyoxal could be present in plumes from Indonesian fires (Stockwell et al., 2016; Budisulistiorini et al., 2018).

The washout of gases and aerosols by both convective precipitation (Grell and Deveny, 2002) and by grid-scale precipitation (Neu and Prather, 2012) is calculated in the MOZART-MOSAIC scheme (Hodzic and Knote, 2014). Dry deposition of gasses and aerosols is parameterized in WRF-chem using a deposition velocity based on concentrations at the surface and a surface resistance (Grell et al., 2005; Hodzic and Knote, 2014).

The photolysis scheme controls the photolysis rates for chemical reactions, and interacts with the cloud properties and aerosols. The fast Tropospheric Ultraviolet-Visible (fTUV; Tie, 2003) scheme has been used in this set-up, as recommended by Hodzic and Knote (2014) to work with MOZART-MOSAIC chemistry. The fTUV scheme is a simplified version of the TUV scheme provided by NCAR, which calculates spectral irradiance, spectral actinic flux, and photolysis rates for the wavelengths between 121 and 750 nm. fTUV has the same processes as TUV but uses fewer wavelength bins, meaning that it is 8 times faster than TUV while the difference in photolysis rates is minimal (Tie, 2003).

A.4 Emissions

Emissions of chemical species from anthropogenic, biogenic and biomass burning sources are either simulated in WRF-chem, or inputted from emissions inventories.

Anthropogenic emissions used for this study are from EDGAR-HTAP, a global dataset constructed from regional emissions (Janssens-Maenhout et al., 2012). It is available at 0.1° resolution for 2008 and 2010. Data is from seven categories (aircraft, shipping, power, industry, ground transport and agriculture) covering all emissions related to anthropogenic sources, with the exception of biomass burning. Species covered are CH_4, CO, SO_2, NO_x, NMVOC, NH_3, PM_{10}, $PM_{2.5}$, BC and OC. For Indonesia, emissions are from the Regional Emissions inventory in Asia (REAS) with gaps filled by EDGARv4.1 (Janssens-Maenhout et al., 2012). Yearly emissions are converted to monthly using a seasonal cycle dependent on location; for Indonesia, in the tropics, no seasonal variation is applied.

Biogenic emissions used in WRF-chem are from the Model of Emissions of Gasses and Aerosols from Nature (MEGAN), which has global coverage at 1 km resolution (Guenther et al., 2006). The emission are calculated online in WRF-chem by applying an emissions factor, an emissions activity factor and a factor accounting for production and loss in a canopy, to leaf area index maps. The emissions factors, leaf area index, and plant type fractions are inputted into WRF-chem. The emissions activity factor accounts for any changes in conditions, e.g. due to meteorology.

Dust emissions are calculated within the WRF-chem simulation using the land cover type and meteorology data (Peckham et al., 2015). Option 13 has been used, which is a version of the Air Force Weather Agency (AFWA) dust scheme, modified for use with MOSAIC aerosol scheme. The AFWA scheme uses a friction velocity, surface roughness and moisture variables to provide a bulk dust flux.

The biomass burning emissions inventories used change for each study done in this thesis, and are detailed in each chapter. They are all based on FINN emissions, and are inputted into the model at the start of each simulation. FINN combines fire hotspot detection with land cover type and emissions factors to produce emissions data for each fire. The emissions are at a 1 km^2 resolution and are available as a total emissions for each day, which are converted into an emissions rate within the model. In FINN, PM_{10} includes $PM_{2.5}$, and $PM_{2.5}$ includes OC and BC. In WRF-chem, $PM_{2.5}$ and PM_{10} are not treated as aerosol species, and so the $PM_{2.5}$ mass is separated into OC, BC and other inorganics (OIN), and the PM_{10} mass without the $PM_{2.5}$ mass is considered as OIN in the relevant bin sizes. Fire emissions are inputted into the model using a plume-rise calculation (Peckham et al., 2015), which is explained in more detail in section A.6.

A.5 Initial and boundary condition

At the beginning of a simulation, the chemistry and meteorology need to be defined to give initial conditions. While the simulation is running boundary conditions are needed to provide interaction with meteorology and chemistry happening outside the domain. To move away from the initial conditions, a 14 day spin up of the chemistry and a 24 hour spin up of the meteorology is used before each WRF-chem simulation. The domain for the WRF-chem simulations is larger than the study area used, to minimise the influence of the boundary conditions.

The initial and boundary chemistry is specified using data from MOZART-4, a global chemical transport model which includes 85 gas-phase species, 12 bulk aerosol compounds, 39 photolysis and 157 gas-phase reactions (Emmons et al., 2010). It is run at 1.9° by 2.5° resolution with 56 vertical levels. Transport in the MOZART-4 simulations is driven by meteorology from from NASA GMAO GEOS-5 model. Biogenic emissions are from MEGAN, anthropogenic emissions from ARCTAS and fire emissions from FINNv1. MOZART data is available for 2007 onwards, so for the simulations of fires in 2004 and 2006, an average of MOZART between 2007 and 2015 has been used for the initial and boundary conditions.

The initial and boundary conditions for meteorology are specified using GFS analysis data. This is based on NCEP model forecasts, run at 28 km resolution. From 2007 GFS analysis is available at 0.5° and from 2004 at 1° resolution, available every three hours. There is data for the surface, and at 26 other pressure levels. Available parameters include pressure, temperature, sea surface temperature, relative humidity, wind components, and vertical motion. Any gaps in the GFS data are filled using FNL data, available at 1° resolution every 6 hours. FNL data is based on the same forecast simulations but contains around 10% more observational data than GFS analysis. The meteorology is re-initialised with a 24 hour spin-up for this data at set periods, and is free running in between. Having the meteorology free running, rather than nudged, allows the chemistry and meteorology to interact, and allows for changes to the meteorology when emissions change, while re-initialising prevents too much drift in the simulation.

A.6 Fire injection

When fires burn a combination of heat convection and smoke related eddies causes emissions to be lofted vertically into the air and enter the atmosphere though a vertical plume (Freitas et al., 2007). The top height of the plume is dependent on both the atmospheric stability and the heat flux from the fire. This vertical transport happens at a sub-grid scale and a parameterisation is needed to simulate the height at which the emissions should enter the model. Air masses at different heights are transported differently, and so the injection height of emissions can be an important factor in simulating concentrations. The injection height of fire emissions in WRF-chem is based on a one dimensional plumerise model (Freitas et al., 2007) which is embedded into the WRF-chem column. This model takes environmental factors such as atmospheric stability from WRF-chem and balances with the buoyancy created by the fire to create a lower and upper injection height, which the emissions from flaming combustion are injected between.

This plumerise model is designed for vegetation fires, which have different properties to peat fires. Peat fires are known for having a large smouldering component, one of the characteristics of which is that smoke remains closer to the ground (Rein, 2016). Although only the flaming components of smoke should be considered in the plumerise algorithm, this relies on data about the fraction of emissions from flaming and smouldering combustion. The FINN emissions inventory does not contain this information, and emissions are therefore arbitrarily separated equally between the two components, irrelevant to the type of burning.

The injection height of fire emissions when using the plumerise code has previously been found to be too high for fires in the Amazon (Archer-Nicholls et al., 2015) and for Indonesia (Lee et al., 2017). If emissions are injected above the boundary layer in the model they are unlikely to mix down, and the simulated surface concentrations will be underestimated.

As an alternative to the plumerise method of emissions injection, two injection scenarios have been considered in the simulations for this work. For the first, all emissions are released into the bottom level of the model, and for the second, half of the emissions are released into the bottom level of the model and half are injected evenly throughout the boundary layer. The average boundary layer height for a WRF-chem simulation is shown in Figure A.2, with an average boundary layer top height around 750 m over land. Tosca et al. (2011) found that average plume top heights for smoke from fires in Borneo were around 700 m, and the plume height was rarely more than 500 m above the boundary layer height.

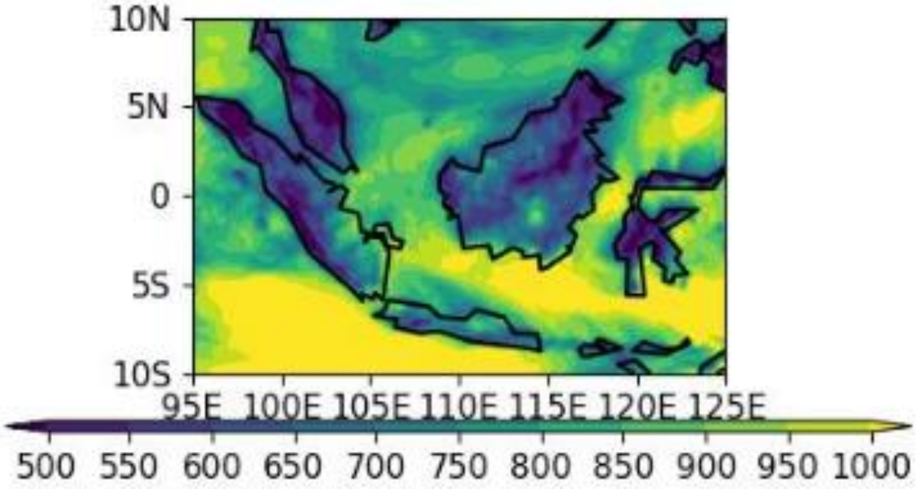

Figure A.2: Average boundary layer height for October in a WRF-chem simulation. Over land the top of the boundary layer ranges from around 500 m – 900 m.

The differences these two alternative schemes make to the simulated PM concentrations are shown in Chapter 2, alongside a discussions on which scheme best represents smoke plumes in Indonesia. The model simulations used in Chapters 3 and 4 use the scheme where half of the emissions are released into the bottom level of the model and half are injected evenly throughout the boundary layer.

A.7 Re-initialising meteorology

Using WRFotron to run WRF-chem simulations, the meteorology is periodically re-initialised using GFS data. For the WRF-chem simulations of the 2015 fires in the first and second papers in this thesis, the meteorology was re-initialised at the start of each month. For the simulations of other years, and for the simulations of the 2015 fires in the third paper, the meteorology was re-initialised twice each month, at the beginning and on the 16^{th} (15^{th} for September). This change was recommended to reduce drift in the simulated meteorology. Meteorology in the model affects the transport and removal of PM in the atmosphere, and the effect that changing the re-initialisation period had on the simulated $PM_{2.5}$ concentrations and mortality estimates have been investigated. In this section the simulations with meteorology re-initialised once a month are referred to as simulation1, and the simulations with meteorology re-initialised every 15 or 16 days are referred to as simulation2. Both simulation1 and simulation2 were run with and without fire emissions included in the model. The mortality estimates are done using the methods explained in Chapter 3.

Re-initialising meteorology more frequently leads to a reduction in $PM_{2.5}$. The average August-October simulated $PM_{2.5}$ for the region when fires are included in the model is reduced by 6% for simulation2 compared with simulation1. For the simulations with no fires included, the average $PM_{2.5}$ is reduced by 18% (Table A.2). When compared with observations (see Chapter 3 for a description of observations) there is very little difference between the comparison metrics for simulation1 and simulation2 (Figure A.3), and so it is not possible to determine which set-up leads to a more realistic representation of particulate pollution from fires. More extensive measurements of particulate pollution are needed to evaluate models and inform model design and setup.

The relative risk functions used to calculate the health impacts have increased sensitivity at low $PM_{2.5}$ concentrations. This means that the estimated health impacts are more sensitive to changes in the no fire simulation, when $PM_{2.5}$ concentrations are lower. The no fire simulations are also more strongly affected by the change in re-initialisation period, and the difference in mortality between simulation1 and simulation2 without fires (51,894 less deaths) is larger than the difference in mortality between the two simulations with fire (40,116 less deaths). This results in the mortality from fires increasing between simulation1 and simulation2 despite the overall mortality decreasing.

The difference in mortality from fires between simulation1 and simulation2 is greatest over Java (Figure A.4). This island is not largely affected by fire $PM_{2.5}$, as smoke from Kalimantan and Sumatra is transported North-West, meaning that the mortality estimate for Java has a strong sensitivity to the no fire simulation. There is also a large population in West Java, leading to a high number of people being affected.

Table A.2: Air quality and health impacts from simulation1 (meteorology re-initialised every month) and simulation2 (meteorology re-initialised every 15-16 days).

	Simulation 1	Simulation 2
Av PM2.5 (µg m^{-3})	92.43	87.14
Av PM2.5 no fires (µg m^{-3})	13.58	11.11
Av PM2.5 from fires (µg m^{-3})	78.84	76.04
Mortality (deaths)	369,294	329,178
Mortality no fires (deaths)	325,253	273,359
Mortality from fires (deaths)	44,041	55,819

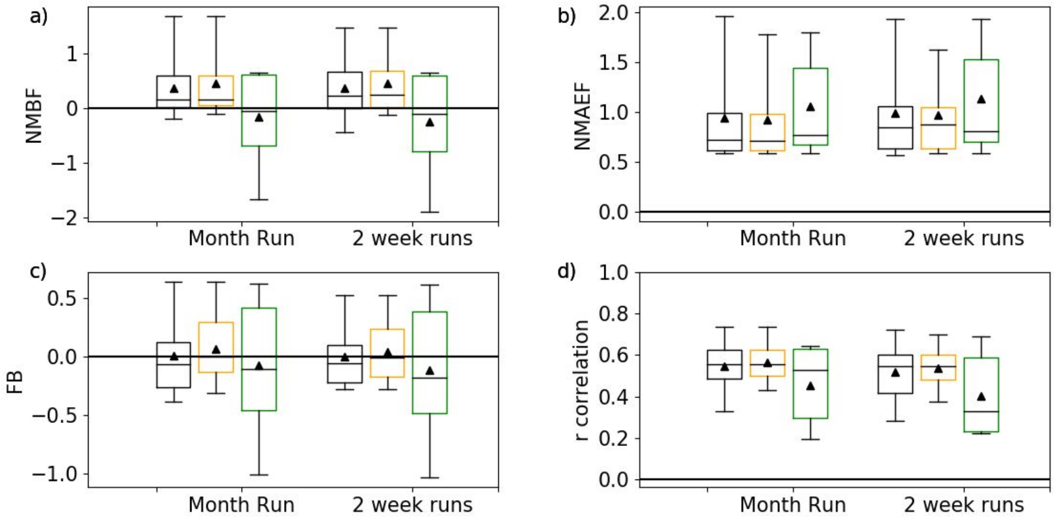

Figure A.3: The (a) normalised mean bias factor (NMBF), (b) normalised mean absolute error factor (NMAEF), (c) fractional bias (FB) and (d) r correlation for simulated and observed PM_{10} and $PM_{2.5}$ at each site. The Black box shows the comparison for all sites, the orang box for daily comparisons and the green box for weekly comparisons. The box plots show the mean value as a triangle, the median as the middle of the box, the box showing the upper and lower quartiles and the whiskers showing the range of values without outliers. All comparisons are for PM from fire.

In simulation1 (used in Chapter 3), the total change in mortality resulting from fires in 2015 was 44,041. Changing the length of the period between meteorology being re-initialised causes an increase in mortality from fires, to 55,819 (used in Chapter 4). The estimated health impacts from the 2015 fires given in Chapter 3 are therefore a conservative estimate. The difference caused by the change in model re-initialisation period is still well below the difference caused by using a more sensitive relative risk function, which estimated 106,000 mortalities resulting from fires (Chapter 3).

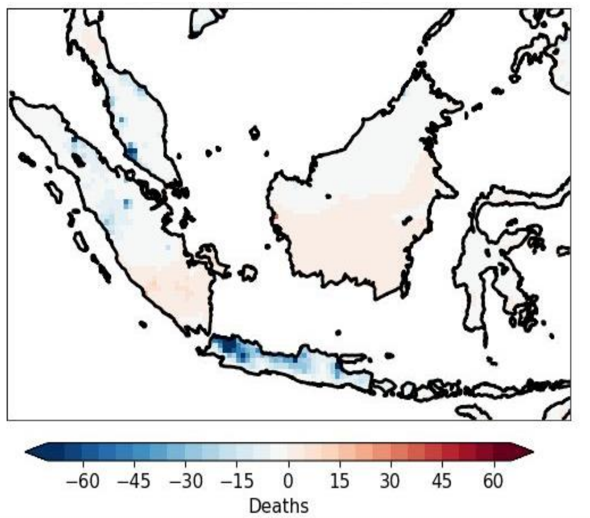

Figure A.4: The difference in total mortality from fires between simulation1 and simulation2. Positive (red) means simulation 1 has higher values, and negative (blue) means simualtion2 has higher values.

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Appendix B Supplement for Chapter 2

This appendix contains the supplementary material for Chapter 2. It includes the supplementary tables and plots which are referred to and analysed in Chapter 2.

Table B.1: Chemistry and Physics options used in WRF-chem

Physics options		
Microphysics	Thompson	(Thompson et al., 2008)
Longwave/Shortwave radiation	RRTMG	(Iacono et al., 2008)
Land Surface Physics	NOAH	
Planetary Boundary layer	MYNN 2.5	(Nakanishi and Niino, 2006)
Cumulus parameterizations	GRELL 3D	(Grell and Deveny, 2002)
Chemistry Options		
Gas-phase chemistry	MOZART	(Emmons et al., 2010)
Aerosols	MOSAIC	(Zaveri et al., 2008)
Anthropogenic Emissions	EDGAR-HTAP2	(Janssens-Maenhout et al., 2015)
Biogenic Emissions	MEGAN	(Guenther et al., 2006)

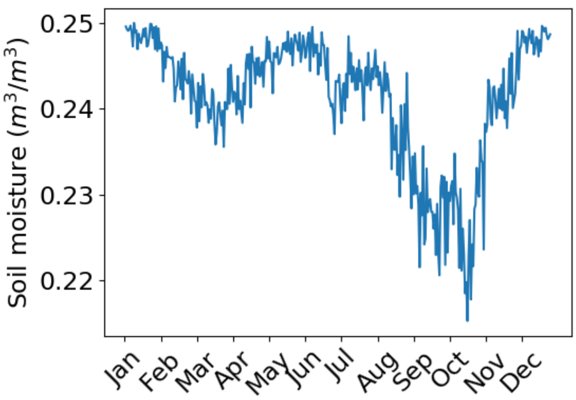

Figure B.1: Daily average soil moisture for peat across the study area (95-120°E and 10°S-10°N) for 2015.

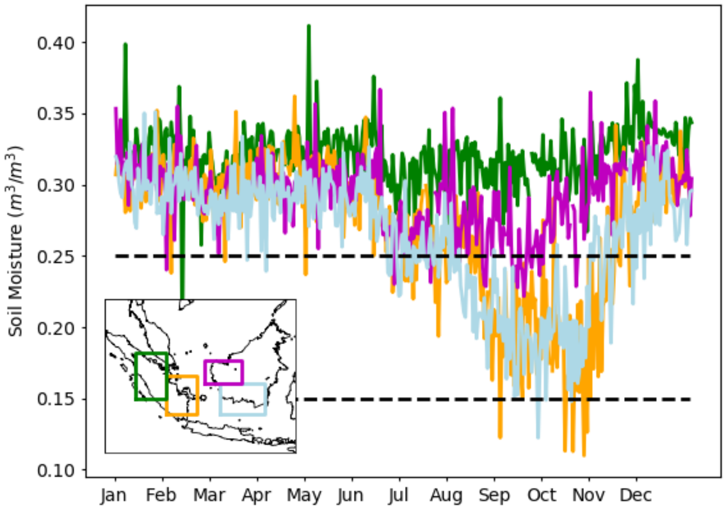

Figure B.2: Soil moisture over high fire peatland regions (blue and orange) and low fire regions (green and purple). The regions are shown inset. The upper and lower soil moisture limits are shown by the dotted lines.

Equation S1

Fractional bias, FB, is defined by

$$FB = \frac{1}{N}\sum \frac{(M_i - O_i)}{(M_i + O_i)/2}$$

where N is the number of pairs of modelled (M) and observed (O) values.

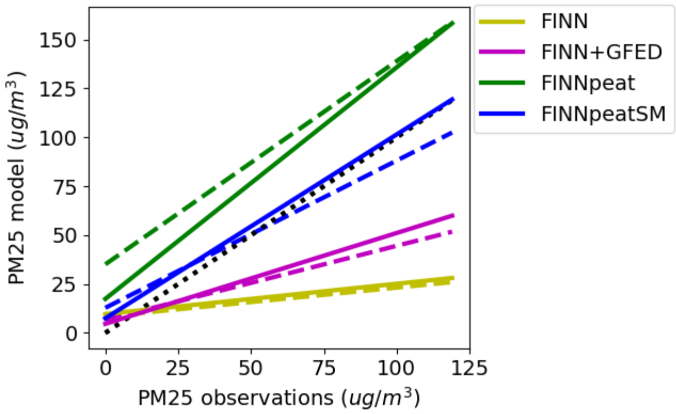

Figure B.3: **24 hour mean $PM_{2.5}$ from observations in Singapore and model simulations with different fire emissions datasets and injection options. Solid lines are simulations with surface injections, dashed lines and simulations with boundary layer injection. 1:1 relationship shown by black dotted line. The fractional bias for each comparison is (for model runs with surface injection and boundary layer injection respectively), -1.01 and -1.05 for FINN, -0.64 and -0.71 for FINN+GFED, 0.09 and 0.14 for FINNpeat, -0.17 and -0.26 for FINNpeatSM. The r correlation coefficient for each comparison (for model runs with surface injection and boundary layer injection respectively), is 0.48 and 0.64 for FINN, 0.73 and 0.69 for FINN+GFED, 0.56 and 0.38 for FINNpeat, and 0.60 and 0.53 for FINNpeatSM.**

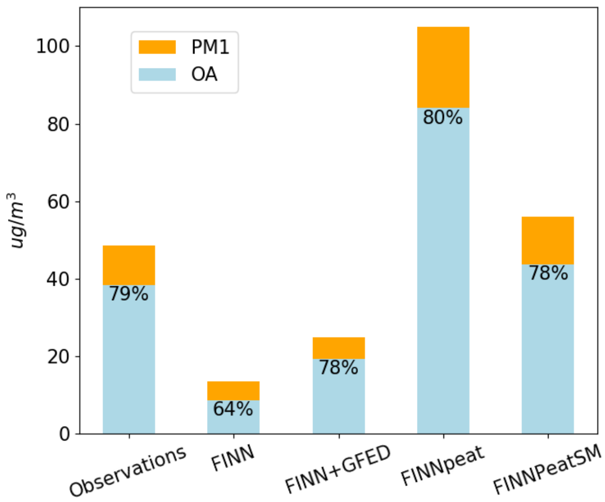

Figure B.4: Average PM_1 and OA in Singapore for October 10th- 31st, for observations and WRF-chem runs with the boundary layer injection option and different fire emissions datasets. The percentage contribution of OA to PM_1 is shown on each bar. PM_1 observations are made up of Cl, NH_4, NO_3, SO_4, OA. PM_1 from the model is NH_4, NO_3, SO_4, OA.

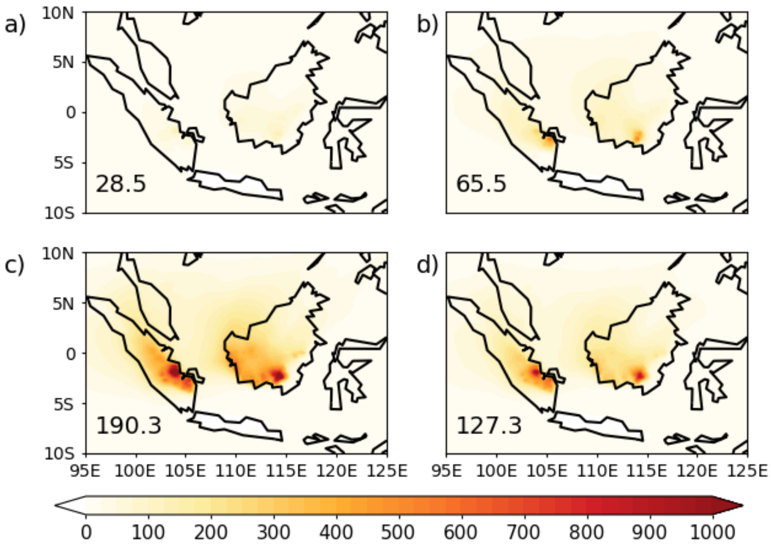

Figure B.5: Mean model surface $PM_{2.5}$ concentration (µg m^{-3}) from fires for Sep-Oct 2015 with the boundary layer injection and (a) FINN emissions, (b) FINN+GFEDpeat, (c) FINNpeat and (d) FINNpeatSM . On each plot is the surface $PM_{2.5}$ from fires averaged over Sumatra and Kalimantan **for September and October.**

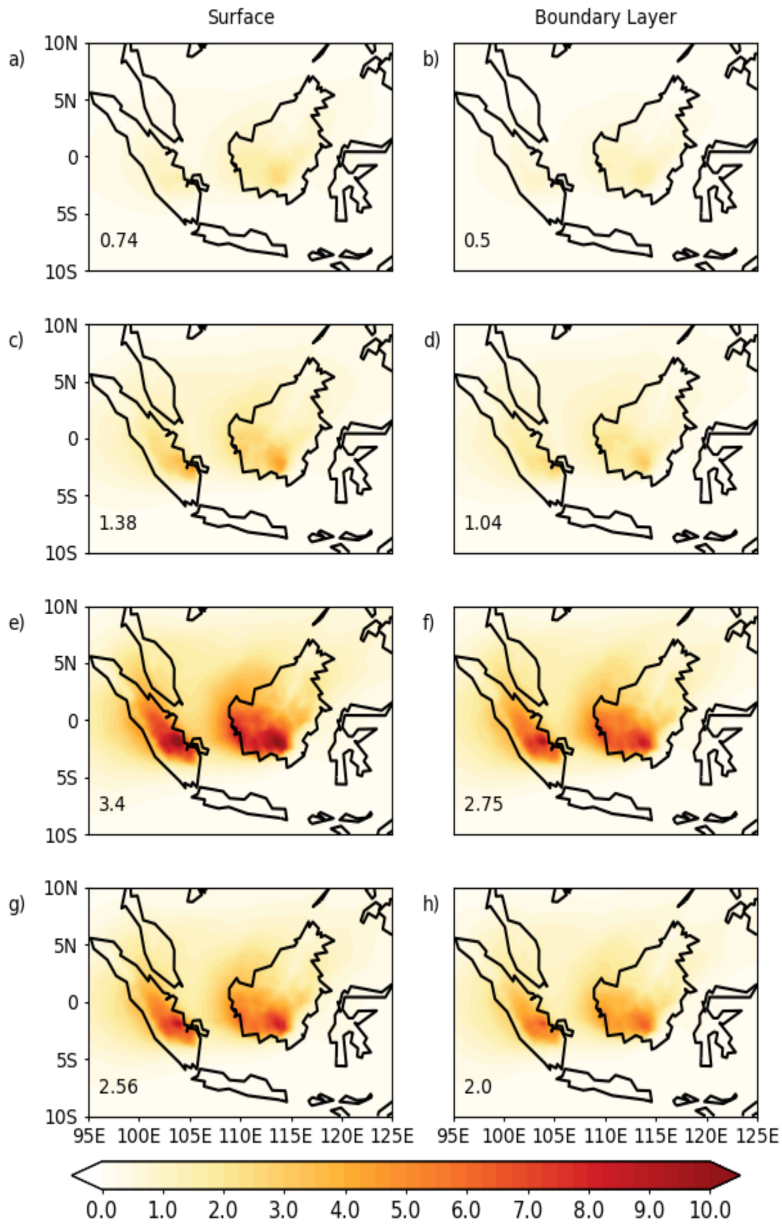

Figure B.6: Mean AOD from fires for Sep-Oct 2015 with the surface (a,c,e,g) and boundary layer injection (b,d,f,h) and FINN emissions (a-b), FINN+GFEDpeat (c-d), FINNpeat (e-f) and FINNpeatSM (g-h). On each plot is the average AOD from fires for Sumatra and Kalimantan during September and October.

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Appendix C Supplement to Chapter 3

This appendix contains the supplementary material for Chapter 3. Model evaluation metrics and health impact metrics are defined, and details are shown for the model setup and observation data used. Analysis of the emissions and model evaluation is given in greater detail than provided in Chapter 3.

C.1 Supplementary Methods

Fractional bias, normalized mean bias factor and normalized mean absolute error factor

The fractional bias been calculated by,

$$FB = \frac{1}{N}\sum \frac{(M_i - O_i)}{(M_i + O_i)/2}$$

where N is the number of pairs of modelled (M) and observed (O) values.

The normalized mean bias factor has been calculated by,

$$NMBF = \frac{\sum (M_i - O_i)}{\sum O_i}, \quad if\ \bar{M} \geq \bar{O}, \quad \text{and}$$

$$NMBF = \frac{\sum (M_i - O_i)}{\sum M_i}, \quad if\ \bar{M} < \bar{O}$$

and the normalized mean absolute error factor by,

$$NMAEF = \frac{\sum |M_i - O_i|}{\sum O_i}, \quad if\ \bar{M} \geq \bar{O}, \quad \text{and}$$

$$NMAEF = \frac{\sum |M_i - O_i|}{\sum M_i}, \quad if\ \bar{M} < \bar{O}$$

where M_i and O_i are pairs of modelled and observed values.

Calculation of year of life lost (YLL), years lived with disability (YLD) and disability affected life years (DALY)

The YLL and YLD are calculated similarly to the mortality:

$$YLL = PI_{YLL}\,(RR_c - 1)/RR_c$$

$$YLD = PI_{YLD}\,(RR_c - 1)/RR_c$$

where P is the population, I_{YLL} and I_{YLD} are the corresponding baseline mortality rate (deaths year^{-1}), taken from GBD2017 (Institute for Health Metrics and Evaluation, 2019). RR_c is the relative risk at $PM_{2.5}$ concentration, c (μg m^{-3}), from the GEMM (Burnett et al., 2018).

DALY are calculated as

$$DALY = YLL + YLD$$

Table C.1: WRF-Chem options

Physics options		Reference
Microphysics	Thompson	(Thompson et al., 2008)
Longwave/Shortwave radiation	RRTMG	(Iacono et al., 2008)
Land Surface Physics	NOAH	
Planetary Boundary layer	MYNN 2.5	(Nakanishi and Niino, 2006)
Cumulus parameterizations	GRELL 3D	(Grell and Deveny, 2002)
Chemistry Options		
Gas-phase chemistry	MOZART	(Emmons et al., 2010)
Aerosols	MOSAIC	(Zaveri et al., 2008)
Anthropogenic Emissions	EDGAR-HTAP2	(Janssens-Maenhout et al., 2015)
Biogenic Emissions	MEGAN	(Guenther et al., 2006)

Table C.2: Observations of PM used to evaluate the model

Data	Location	Time Period	Frequency of data	Method	Reference / Source
PM_{10}	Pekanbaru, Indonesia 0.52°N, 101.43°E	1 Jan 2010 – 31 Dec 2015	30 mins	Measured using a Met One BAM 1020, Real-Time Portable Beta Attenuation Mass Monitor (BAM-1020)	
PM_{10}	Bukit Kototabang, Indonesia	2004-2010			
PM_{10}	52 locations across Malaysia	2004 – 2015	1 hr	Measured using a Met One BAM 1020, Real-Time Portable Beta Attenuation Mass Monitor (BAM-1020)	(Mead et al., 2018)
PM_{10}	6 sites in Kalimantan and Sumatra	2014-2015	1 week		
$PM_{2.5}$	5 sites in Singapore	2014-2015	1 hr	Thermo Scientific™ 5030 SHARP monitor	National Environment Agency for Singapore

C.2 Supplementary Results

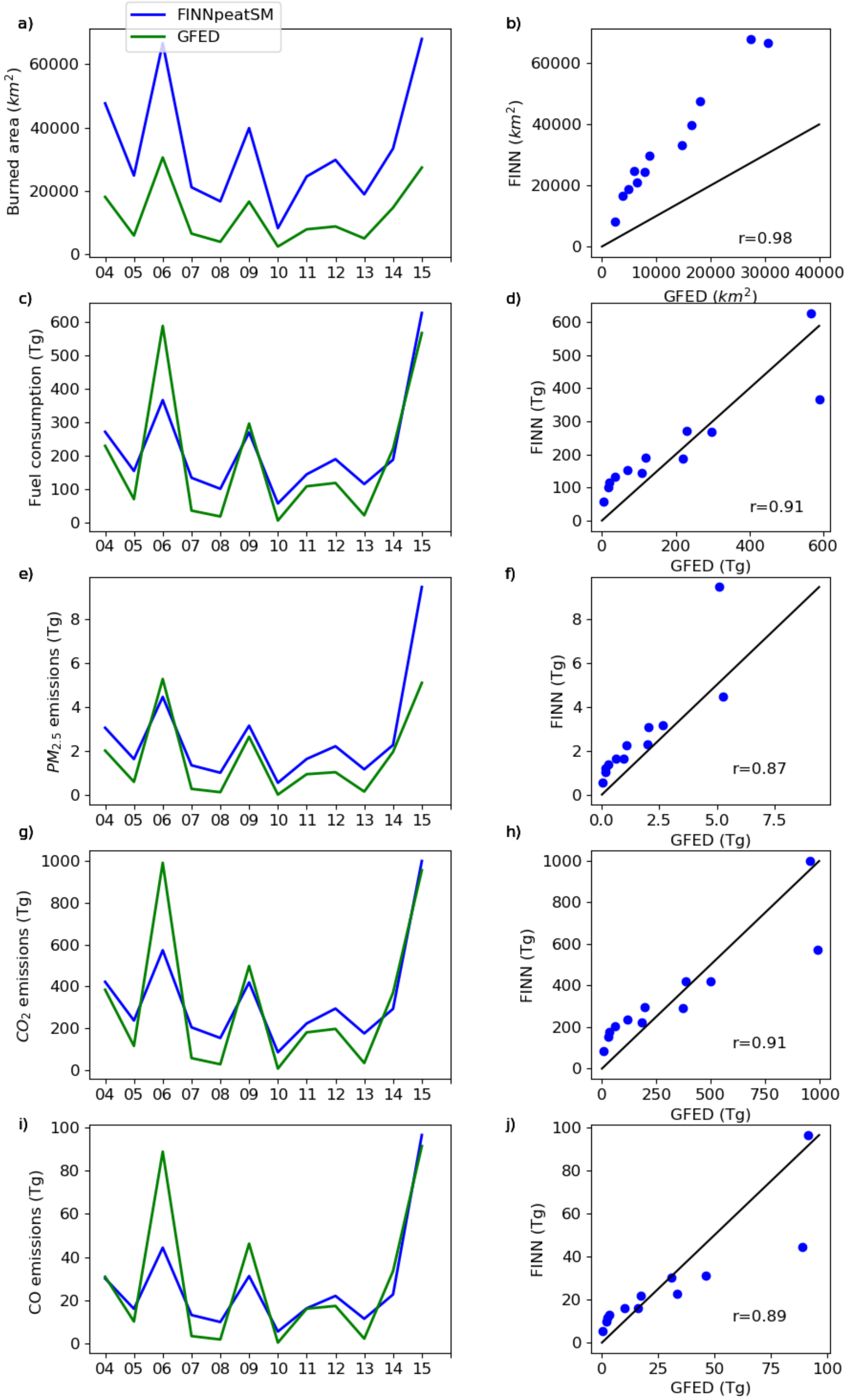

Figure C.1: Total burned area (a, b), fuel consumption (c, d) and emissions of CO (e, f), CO2 (g, h) and PM2.5 (i, j) for Aug-Oct of each year 2004 – 2015 for FINNpeatSM and GFED4s, shown as a timeline (a, c, e, g, i) and plotted against each other (b, d, f, h, j). The correlation coefficient, r, is shown on each plot.

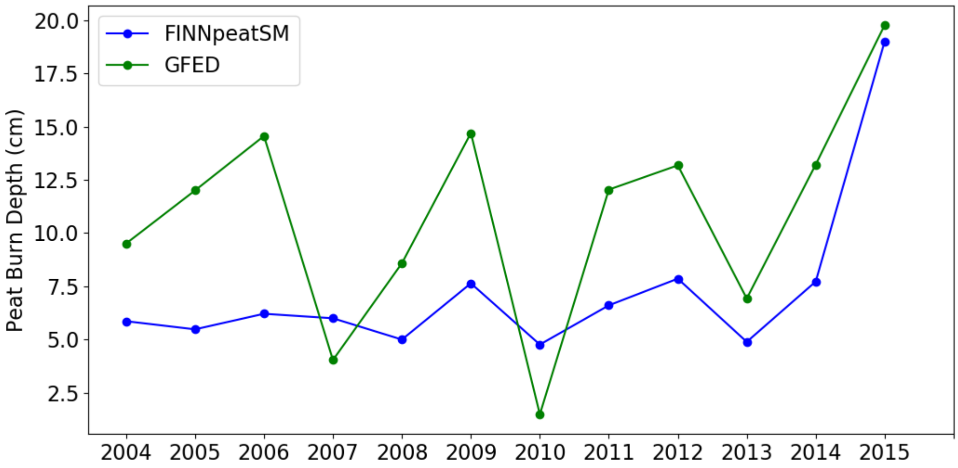

Figure C.2: The average burn depth for fires in August-October for each year for FINNpeatSM and GFED4s. The burn depth for GFED4s is calculated using a peat density of 0.11 g cm-3.

In low fire years GFED has lower emissions of CO and CO_2 compared to FINNpeatSM, and in high fire years the emissions are greater. Emissions of $PM_{2.5}$ are greater in FINNpeatSM in almost all years, due to the higher peat emissions factor used.

Although all emissions from FINNpeatSM were largest in 2015, CO_2 emissions scale similarly to dry matter while CO emissions are disproportionately larger. This is due to the higher percentage of peat combustion in 2015, as the EFs for CO and PM are larger for peat (243.5 g kg^{-1} and 22.3 g kg^{-1}) than for vegetation (92 g kg^{-1} and 9.1 g kg^{-1}). The total emissions of primary $PM_{2.5}$, CO and the resulting SOA therefore depend on the percentage of peat burned, as well as the overall dry matter (Table 1).

For 2015, Wooster et al. (2018) estimated 9.1±3.2 Tg of primary $PM_{2.5}$ emissions from fires in Sumatra and Kalimantan in September and October, based on 358 Tg of dry matter consumed. For the same period, $PM_{2.5}$ emissions from FINNpeatSM are 7.33 Tg, with 465 Tg dry matter consumed. Huijnen et al. (2016) found that during September and October 2015, 692 Tg of CO_2 and 84 Tg of CO was emitted by fires in Indonesia. Over the same period, FINNpeatSM estimate similar amounts; 781 Tg of CO_2 and 78 Tg of CO. Annual CO emissions for 2015 fires been estimated as 96 Tg (Huijnen et al., 2016), 112 Tg (Yin et al., 2016) and 113-138 Tg (Nechita-banda et al., 2018). For July to November 2015, Heymann et al. (2017) estimated fires emitted 748±209 Tg CO2, lower than in GFED4s or FINNpeatSM.

Lohberger et al. (2017) estimated that fires in 2015 burned 37 860 km^2, greater than estimated by GFED4s (27 300 km^2) but less than in FINNpeatSM (68 000 km^2).Chang and Song (2010) use two burned area products to estimate fires in 2006 burned 2410-3630 km^2, substantially lower than both our (66 700 km^2) and GFED4s (30 500 km^2) burned area. Using this burned area, they estimate that fires emitted around 8-10 Tg CO in 2006, also lower than our estimate by a factor of 4. Per unit area burned, Chang and Song (2010), found 2754 – 3319 g m^{-2} CO emitted, higher than FINNpeatSM and GFED4s (Table 1). This is likely due to the deeper burn depth they used, of 51 cm.

The comparison of daily PM_{10} from fires confirms that the simulations perform well against observations. The average NMBF varies between -0.26 to 0.48 across years, the average FB is between -0.15 and 0.15, and the NMAEF is between 0.95 and 1.26 (Table C.3). For the sites with weekly averaged concentrations, in 2015, simulated fire-derived PM_{10} is unbiased (FB = -0.08, NMBF = -0.17, NMAEF = 1.07) while in 2014, a year with smaller fire emissions, the model underestimates fire-derived PM_{10} (FB = -0.56, NMBF = -1.22, NMAEF= 1.46) (Figure C.4). In years with lower fire emissions, such as 2014, uncertainty in the background PM concentrations will have a greater effect on the comparison between model and observations. Observations of $PM_{2.5}$ from Singapore are available for 2014 and 2015. Simulated fire derived $PM_{2.5}$ shows a reasonable comparison in these years with NMBF and r correlation values of 0.04 and 0.45 respectively for 2014, and 0.54 and 0.43 respectively for 2015; within the range across sites for the PM_{10} comparison in each year (Figure C.4). Including fires in the simulation improves the comparison with all observations (Figure C.3).

The model is able to reasonably simulate PM concentrations from fires, both close to the fire emissions and in regions that are 100s to 1000s km away from the fires. There is no clear spatial pattern to the model bias when comparing all source PM_{10} although the comparison of fire-derived PM_{10} shows the model tends to underestimate PM_{10} around Singapore and the Malaysian peninsula, and overestimate elsewhere (Figure C.5). The southern Malaysian peninsula is densely populated including a number of cities (e.g. Singapore, Kuala Lumpur) and the underestimation of fire-derived PM in these area may be due to uncertainties in determining the background concentrations at the measurement sites. The range the model bias across sites is also likely partially due to difficulties in simulating small scale transport within cities at 30 km resolution.

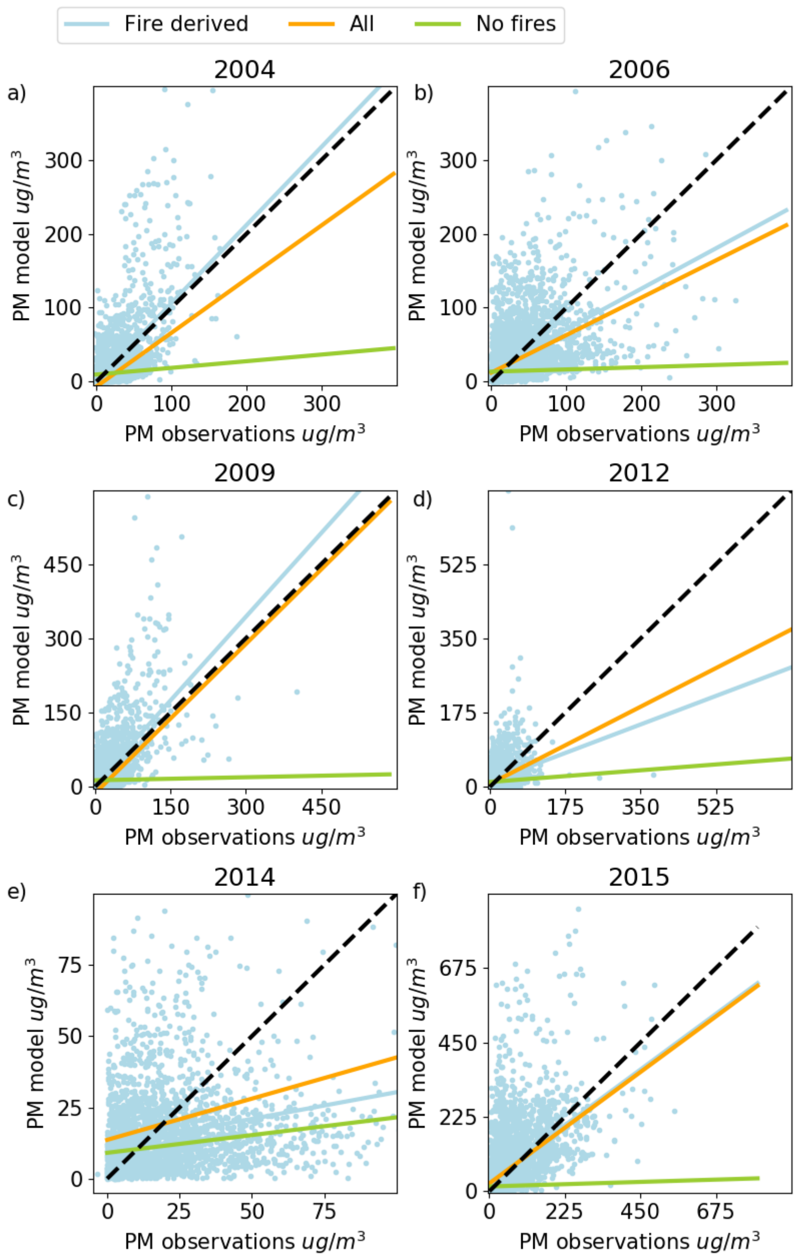

Figure C.3*:* **Simulated 24 hour mean PM10 and PM2.5 plotted against 24 hour mean observations across all locations (dots), with the linear trend shown as a solid line, and the 1:1 line shown as a dashed black line. The comparison of fire derived PM is shown in blue, all-sources PM in orange and the simulations with no fires in green. Each year is shown on a separate plot. For each plot a) - f): for fire derived PM the FB is -0.03, 0.03, 0.15, -0.14, -0.09, -0.07 respectively, and the Pearson's correlation is 0.53, 0.42, 0.49, 0.35, 0.25, 0.55; for all source PM_{10} the FB is -0.62, -0.46, -0.50, -0.51, -0.53, -0.16 respectively, and the Pearson's correlation is 0.63, 0.48, 0.55, 0.41, 0.40, 0.57; for the no fire simulation the FB is -1.13, -1.15, -1.04, -1.01, -0.99, -1.18 respectively, and the Pearson's correlation is 0.36, 0.27, 0.30, 0.30, 0.33, 0.13.**

Table C.3: Normalized mean bias factor (NMBF), normalized mean absolute error factor (NMAEF) and fractional bias (FB) for the comparison between daily simulated and observed fire derived PM_{10} for each year (see methods).

	PM_{10}		
Year	NMBF	NMAEF	FB
2004	0.16	0.10	-0.03
2006	0.21	1.04	0.03
2009	0.48	1.14	0.15
2012	-0.04	1.05	-0.14
2014	-0.26	1.26	-0.09
2015	0.45	0.93	-0.07

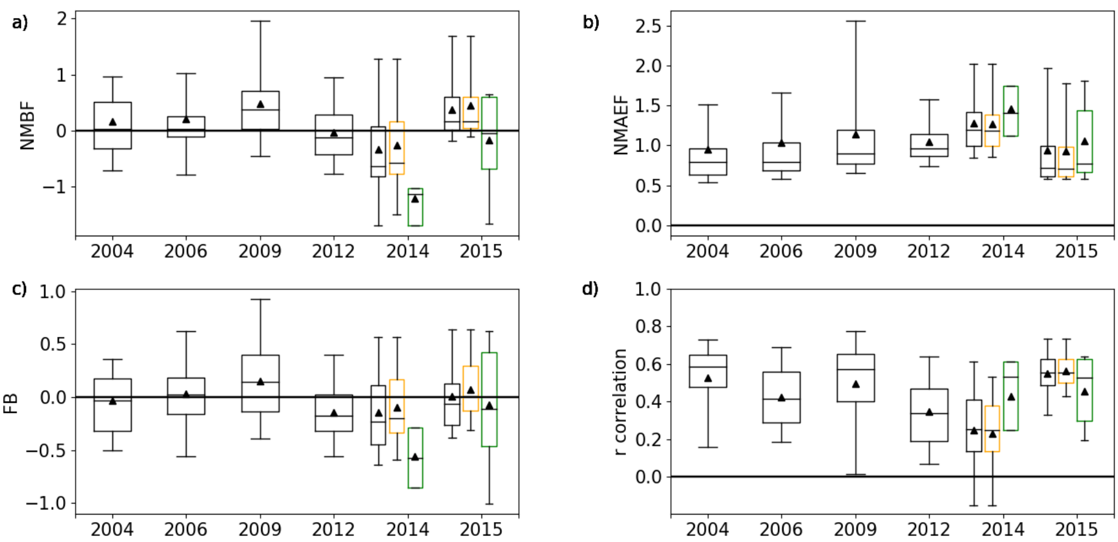

Figure C.4: Box plots showing a) the normalised mean bias factor (NMBF), b) the normalised mean absolute error factor (NMAEF), c) the fractional bias (FB), and d) the correlation coefficient (r) between simulated and measured fire-derived PM concentration at each observation site. For 2014 and 2015 the comparisons of daily measurements are shown in orange, the comparison of weekly measurements shown in green, and all measurements are shown in black. The box plots show the mean value as a triangle, the median as the middle of the box, the box showing the upper and lower quartiles and the whiskers showing the range of values without outliers. Measured fire-derived PM_{10} is estimated at each site by subtracting measured PM_{10} from periods without fire (see Methods).

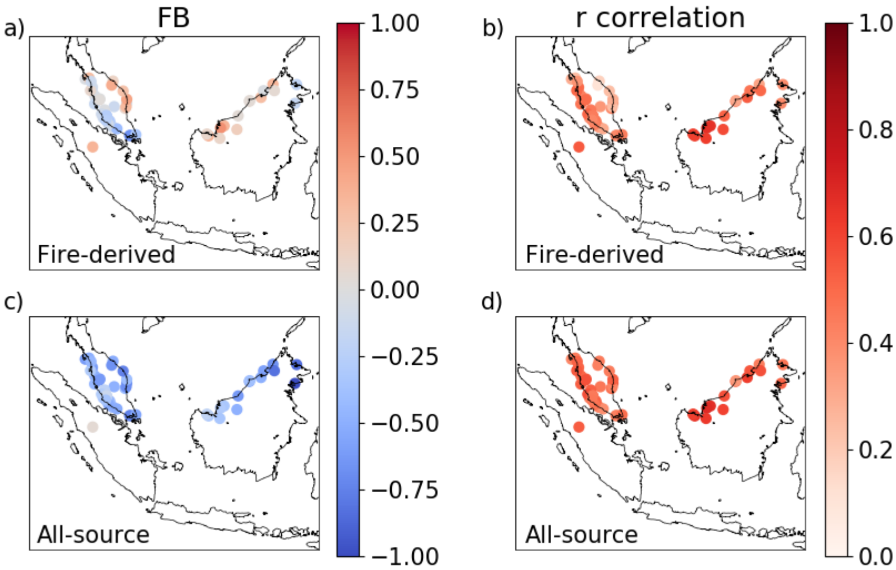

Figure C.5*:* The average fractional bias (FB) and correlation coefficient (r) for comparisons of fire-derived PM_{10} (a-b) and all source PM_{10} (c-d) at each measurement site over all the years, at the location of each site.

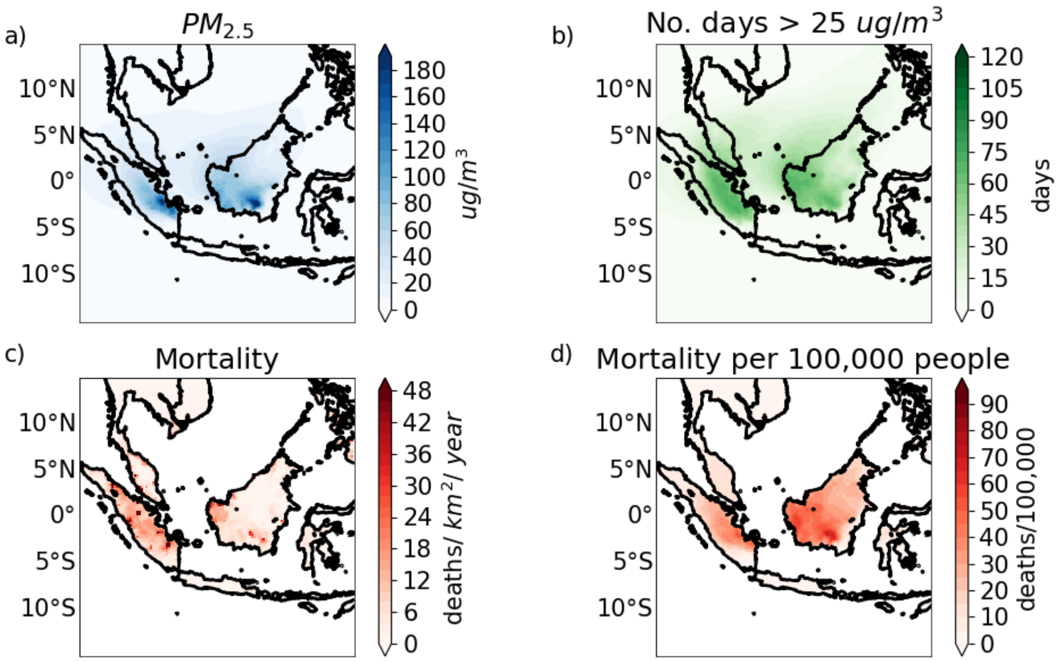

Figure C.6: Simulated a) PM2.5 concentration, b) number of days with PM2.5 > 25 ug/m3, c) long term premature excess mortality, d) long term premature excess mortality per 100,000 people. Results shown for an average of 2004, 2006, 2009, 2012, 2014, and 2015.

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Appendix D Supplement to Chapter 4

This appendix contains the supplementary material for Chapter 4, including supplementary tables, plots and analysis as referred to in Chapter 4.

D.1 Costs included in analysis

Table D.1: Costs included in this study

Category		**Included in cost**	**Cost**	**Source**
CO_2 emissions		Closing price of CO_2 in EU Emissions trading system	\$11.8 tCO_2^{-1}	Business Insider (2020)
Long term health impacts	DALY from $PM_{2.5}$ exposure	The economic loss of a DALY caused by non-communicable diseases.	\$4710 $DALY^{-1}$	World Economic Forum (2015) Mboi et al. (2018)
Damage to Land cover	Oil palm	NPV of oil palm	\$6500 ha^{-1}	Sofiyuddin et al. (2012)
	Crops	NPV of rice and maize	\$700 ha^{-1}	Sofiyuddin et al. (2012)
	Wood fibre	NPV of Acacia plantations	\$1040 ha^{-1}	Sofiyuddin et al. (2012)
	Rubber	NPV of rubber plantations	\$2000 ha^{-1}	Sofiyuddin et al. (2012)
	Logging	NPV of logging concessions	\$6114 ha^{-1}	Sofiyuddin et al. (2012)
	Forest	Improved water supply Reduced flooding risk Increased biodiversity Increased tourism to forests	\$6093 ha^{-1}	Beukering et al. (2003)

D.2 Fire reduction in different PA types

Table D.2 shows the ratios of normalised burned area within and outside of protected areas. A value < 1 implies that there is less burned area per km^2 inside the protected areas than outside, a value > 1 suggests that there is more burned area per km^2. Some protected area types, such as Nature Reserves or Grand Forest Parks, seem to be less effective in reducing fires than others, such as National Parks. Of the 22 protected areas which contain peatland in Sumatra, 8 are Wildlife reserves and 12 are National Parks with only 1 Grand Forest Park and 1 Nature Recreation Park. In all years the burned area ratio is greater than 1 for the Grand Forest Park, suggesting that the protection against fires is low for this park. Table D.3 shows the ratio of average soil moisture inside and outside of protected areas. The soil moisture is greater inside protected areas, where there are no drainage canals. Again, the difference is greatest for National Parks.

Grand Forest parks in Sumatra are 86 km^2 on average and Nature Reserves in Kalimantan are 469 km^2. In contrast National Parks are much larger, on average 2826 km^2 in Sumatra and 4700 km^2 in Kalimantan. Table D.4 shows the burned area ratios for protected areas of all categories over 1000 km^2 are mostly lower than for all protected areas over 100 km^2, showing that size is likely one factor in the level of protection from fire. This could be because large protected areas are less likely to be influenced by deforestation and drainage happening outside of the protected area. It is also possible that larger protected areas are more remote and are less effected by runaway fires from other land types.

Not all smaller protected areas have high burned area, however. Wildlife reserves are on average around 350 km^2, and these have substantially lower burned area ratios than Nature reserves. The differences here could be due to location or due to how well the protected area is managed. This could also explain the differences seen between protected areas in Sumatra and Kalimantan.

Table D.2: The average ratio of burned area per km^2 on peatland within a protected areas to burned area per km^2 on peatland within 0.25° of the protected area for different years, split for different types of protected area and for Sumatra and Kalimantan. The average ratio for non-peatland is also shown for National Parks.

	2004		2006		2009		2012		2014		2015	
	Suma	Kali	Suma	Kali	Suma	Kali	Suma	Kali	Suma	Kali	Suma	Kali
National Parks	0.28	0.30	3.69	0.41	0.60	0.21	0.37	0.33	0.58	0.23	1.17	0.63
(Non-peat)	0.90	0.16	0.35	0.22	0.89	0.12	0.53	0.06	0.81	0.09	0.68	0.43
Grand Forest Park	1.39	-	2.45	-	1.97	-	1.35	-	1.54	-	2.47	-
Nature Recreation Park	-	-	0.54	0.80	0.55	-	0.37	4.07	0.71	2.35	0.68	4.09
Nature Reserve	-	1.15	-	0.92	-	1.97	-	1.37	-	1.33	-	0.93
Wildlife Reserve	0.71	0.34	0.29	0.54	0.19	0.56	0.82	0.32	0.16	0.12	0.28	0.58
Undesignated	-	2.18	-	0.89	-	1.55	-	0.98	-	1.09	-	2.00

Table D.3: The average ratio of average soil moisture on peatland inside a protected are to average soil moisture in peatland outside a protected area (within 0.25° of the protected area) for August, September and October 2015. The average ratio is shown for protected areas in Sumatra and Kalimantan separately, and for all protected areas and National parks only.

	August		September		October	
	Suma	Kali	Suma	Kali	Suma	Kali
National Parks	1.34	1.48	1.41	1.57	1.35	1.49
All protected areas	1.12	1.35	1.13	1.44	1.11	1.33

Table D.4: The average ratio of burned area per km^2 on peatland within a protected areas to burned area per km^2 on peatland within 0.25° of the protected area for different years and for Sumatra and Kalimantan. The average over all protected areas over 100 km^2 and for all protected areas over 1000 km^2 is shown.

PA type	2004		2006		2009		2012		2014		2015	
	Suma	Kali	Suma	Kali	Suma	Kali	Suma	Kali	Suma	Kali	Suma	Kali
>100 km^2	0.58	0.54	1.89	0.74	0.75	0.68	0.72	0.74	0.65	0.71	0.86	1.23
>1000 km^2	0.25	0.39	0.18	0.56	1.00	0.32	0.48	0.41	1.02	0.33	0.96	0.82

D.3 Contribution of Non-Indonesian Fires to health impacts

The simulated $PM_{2.5}$ used to estimate health impacts of fires is from all fire emissions in the study area, not only from Indonesian fire emissions. For 2015 Indonesian fires produced 97% of the total PM2.5 emissions in the study area, with the remaining coming from fires in Malaysia, Brunei and mainland South-East Asia. In other years non-Indonesian fires contributed 4-7% of total $PM_{2.5}$ emissions.

For 2015 we have also found the $PM_{2.5}$ concentrations and health impacts resulting from Indonesian fires only. These non-Indonesian fires resulted in 1900 mortalities (3% of the mortalities from all fires) and 76,500 DALYs (3% of DALYs from all fires). For the mortalities in Singapore non-Indonesian fires resulted in 4% of the mortality and DALYs caused by all fires. For Indonesian and Malaysian mortalities it was 3%. In other years the health impact contributions are likely to be similar.

The costs resulting from CO_2 emissions and damage to land cover are calculated from Indonesian fires only, while the costs relating to health impacts are from all fires. These non-Indonesian fires could be contributing 3-7% to the health impacts.

D.4 Estimating DALYs

In Kiely et al. (2020) it is shown that the $PM_{2.5}$ exposure and premature mortality caused by fires has a strong linear relationship with the total $PM_{2.5}$ emissions and resulting secondary organic aerosol (SOA). In Figure D.1 we show that this linear relationship also holds for DALYs from the study. Using 0.16 million DALYs per Tg $PM_{2.5}$ and SOA, we estimate the reduction in DALYs resulting from peatland restoration, shown in Table D.5. For 2015 the reduction in $PM_{2.5}$ emissions and resulting SOA after 2.49Mha of peatland have been restored is 2.99 Tg. With the relationship in Figure D.1, this suggests a reduction of 0.48 million DALYs. Using the simulated $PM_{2.5}$ for 2015 with peatland restoration, and the health impact equations, the total DALYs estimated to result from fires in 2015 after 2.49 Mha of peatland has been restored is 1.72 million giving a reduction of 0.47 million DALYs, close to the estimate using the $PM_{2.5}$ emissions relationship (1.71 million).

In order to separate these DALYs into the countries effected, we use the percentage of total DALYs from Indonesia, Malaysia and Singapore from Kiely et al. (2020). 54%, 55%, 47%, 52%, 55% and 58% of the total DALYs come from Indonesia in 2004, 2006, 2009, 2012, 2014 and 2015 respectively. From Malaysia it is 13%-16% for these years and for Singapore is 3.1% - 4.0%.

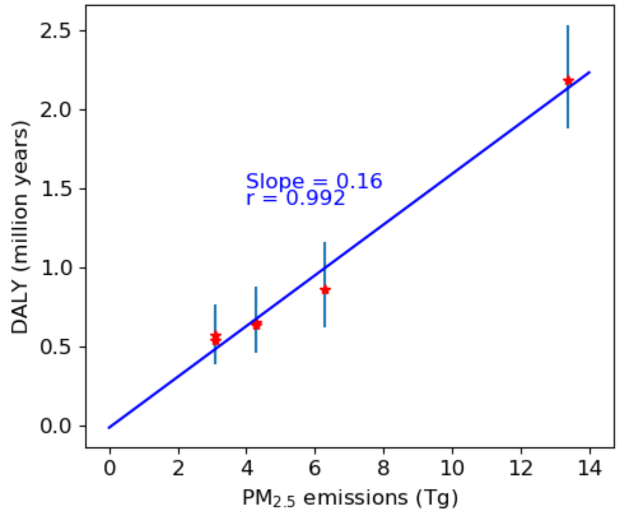

Figure D.1: The DALYs resulting from August – October fires in 2004, 2006, 2009, 2012, 2014 and 2015, plotted against the total August-October $PM_{2.5}$ emissions and resulting SOA from that year. The upper and lower 95% uncertainty interval is shown for the DALYs. A line of best fit is shown with the gradient of the line and the r correlation shown on the plot.

Table D.5: The reduction in $PM_{2.5}$ and SOA from restoring 2.49 Mha to the level of National Parks, and the DALYs and premature mortality before and after this restoration. Health impacts before restoration are calculated from the simulated $PM_{2.5}$ concentrations and health impact equations, and the reduction in health impacts is calculated using the relationship of 0.16 million DALYs per Tg fire emissions.

Year	Reduction in $PM_{2.5}$ and SOA (Tg)	DALY without restoration	DALY after restoration (using 0.16 DALYs per Tg reduced PM)	Mortality without restoration	Mortality after restoration (using 4110 deaths per Tg reduced PM)
2004	0.41	637,727	572,127	16,219	14,533
2006	0.11	867,220	849,620	22,088	21,635
2009	0.59	654,733	560,973	16,656	14,231
2012	0.33	573,084	520,124	14,573	13,216
2014	0.41	541,086	475,166	13,705	12,019
2015	2.99	2,187,614	1,709,374	55,819	43,530

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