**LETTER • OPEN ACCESS**

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

To cite this article: Laura Kiely *et al* 2020 *Environ. Res. Lett.* **15** 094054

View the article online for updates and enhancements.

Recent citations

- Large air quality and human health impacts due to Amazon forest and vegetation fires
Edward W Butt *et al*

# Environmental Research Letters

## LETTER

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

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

1 School of Earth and Environment, University of Leeds, Leeds, United Kingdom
2 CIRES, University of Colorado, Boulder, Colorado, United States of America
3 Ludwig-Maximilians University, Munich, Germany
4 Department of Chemistry, University of Malaya, Kuala Lumpur, Malaysia
5 Department of Earth Sciences and Environment, University Kebangsaan Malaysia, Bangi, Selangor, Malaysia
6 Faculty of Forestry, IPB University, Bogor, Indonesia
7 Computer Science Department, IPB University, Bogor, Indonesia

**E-mail:** eelk@leeds.ac.uk

## 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.

## 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 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, 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 $\mu$g 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.
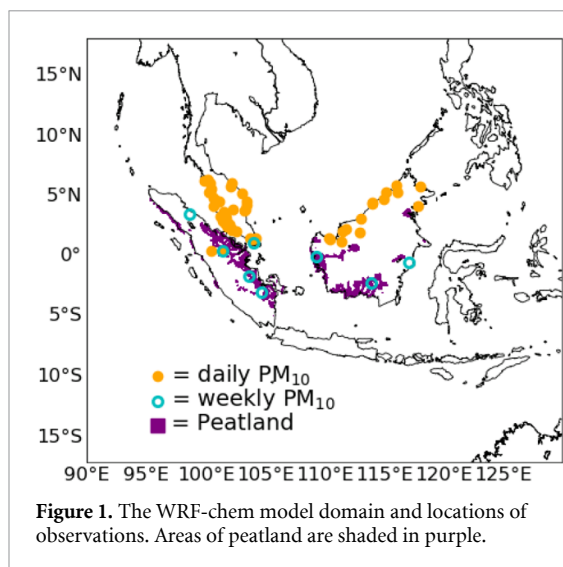
## 2. Methods

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.

### 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).

### 2.2. WRF-chem

WRF-chemv3.7.1 was used to simulate PM concentrations across Equatorial Asia (figure 1). The model has been run at 30 km resolution with 33 vertical levels, between the surface and 50 hPa. We used

**Figure 1.** The WRF-chem model domain and locations of observations. Areas of peatland are shaded in purple.

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 day using National Centre Environmental Prediction Global Forecast System (NCEP 2007). In between the meteorology was free running, to allow the 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 $\mu$m, 0.156–0.625 $\mu$m, 0.625–2.5 $\mu$m and 2.5–10 $\mu$m. 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 supplement (table S1 (available online at stacks.iop.org/ERL/15/094054/mmedia)).

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.

**2.3. Observations**
Hourly measurements of $PM_{10}$ (mass concentration of particulate matter < 10 $\mu$m 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 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 (supplementary methods).

**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).
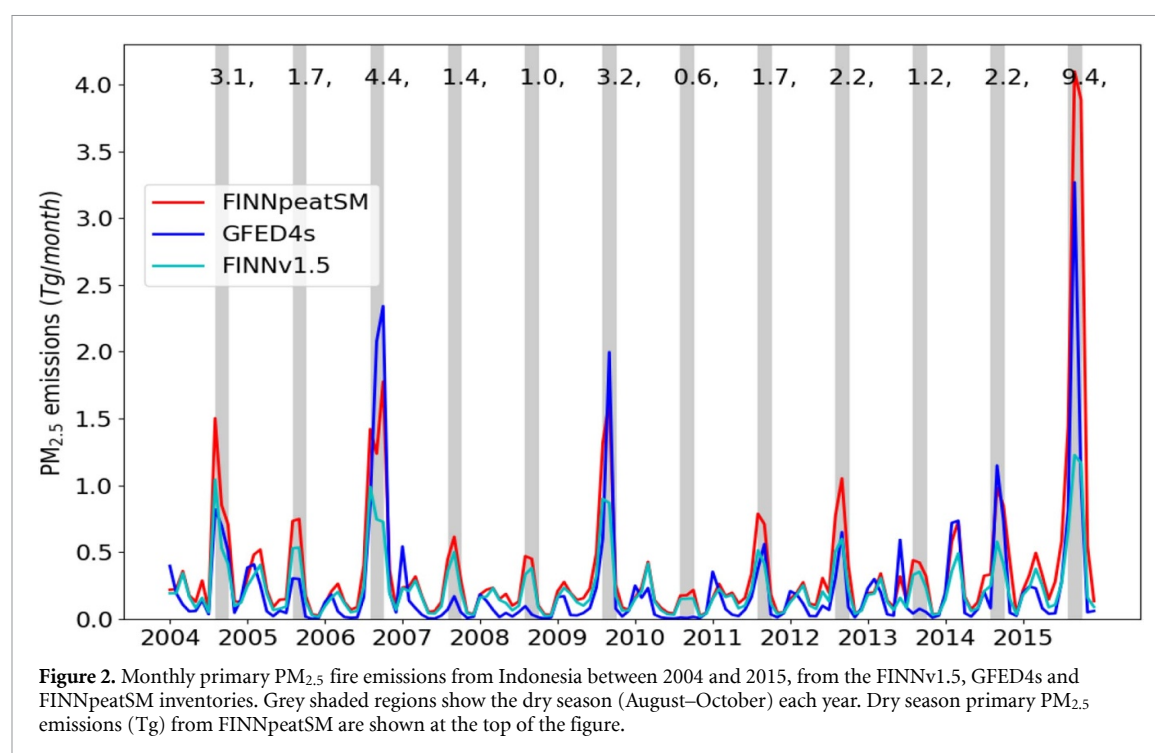
**2.5. Mortality**
The long term premature mortality was calculated using the simulated annual mean $PM_{2.5}$, with and without fire emissions. $PM_{2.5}$ from August from the simulation with no fires was used to represent January to July and November to December. Anthropogenic emissions in the tropics 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,

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

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

**Figure 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.

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. Results and discussion

### 3.1. Emissions

The greatest fire emissions occur between August and October each year, with a secondary peak in January to April (figure 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 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 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 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 supplementary results).

GFED4s uses MODIS burned area (Giglio *et al* 2013), whereas FINNpeatSM applies a 1 $km^2$ 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,

**Table 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 GFED4 s, 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%) | 10527 | 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 ± 18 250 (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 |
| | GFED4 s | 12 246 ± 8895 (51%) | 10.8 ± 4.8 | 186 ± 193 (52%) | 15 189 | 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 | |

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).

There is a strong correlation between the dry season emissions simulated by FINNpeatSM and GFED4s (r = 0.87–0.98 for different pollutants, supplementary results), although GFED4s emissions have greater interannual variability (figure S1), due to greater variability in peat burn depth (figure S2). 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 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).

### 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 S3). 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 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 supplementary results). The NMAEF and FB for the comparison of fires derived PM are also low for each year (NMAEF = 1.07, FB = −0.02; figure S4). 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
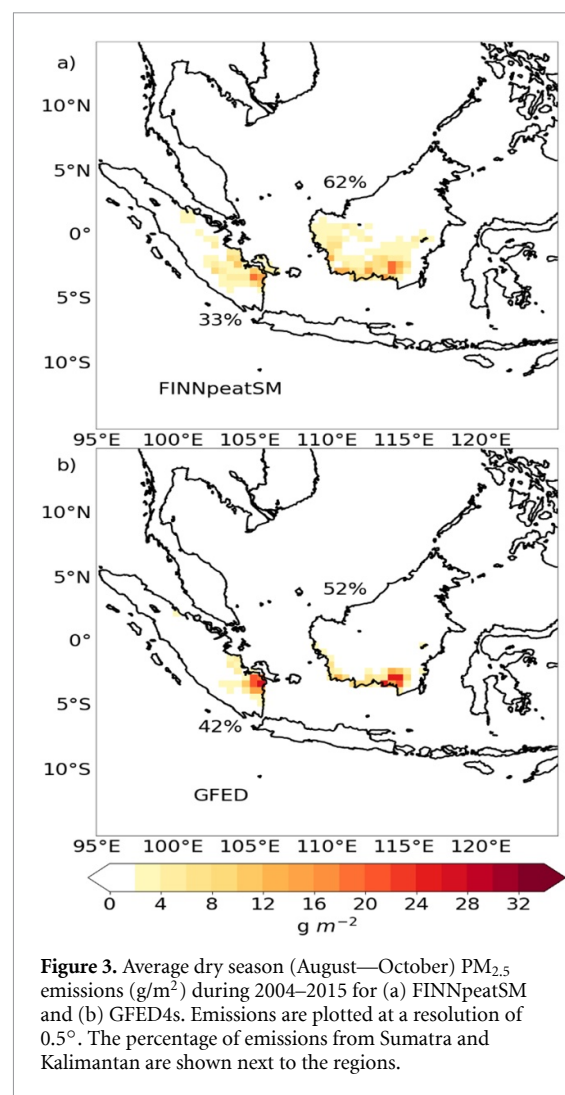


**Figure 3.** Average dry season (August—October) $PM_{2.5}$ emissions (g/m$^2$) during 2004–2015 for (a) FINNpeatSM and (b) GFED4s. Emissions are plotted at a resolution of 0.5°. The percentage of emissions from Sumatra and Kalimantan are shown next to the regions.

NMBF of −0.24 for comparison against $PM_{10}$ observations at two sites in 2015.

### 3.3. $PM_{2.5}$ exposure

Table 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 $\mu$g m$^{-3}$ in 2006 (compared to 8 $\mu$g m$^{-3}$ simulated by Koplitz *et al* (2016)) and 25.6 $\mu$g m$^{-3}$ in 2015 (compared to 19 $\mu$g m$^{-3}$ by Koplitz *et al* (2016)).

Fires increase exposure to $PM_{2.5}$ concentrations above the WHO recommended limit of 25 $\mu$g m$^{-3}$
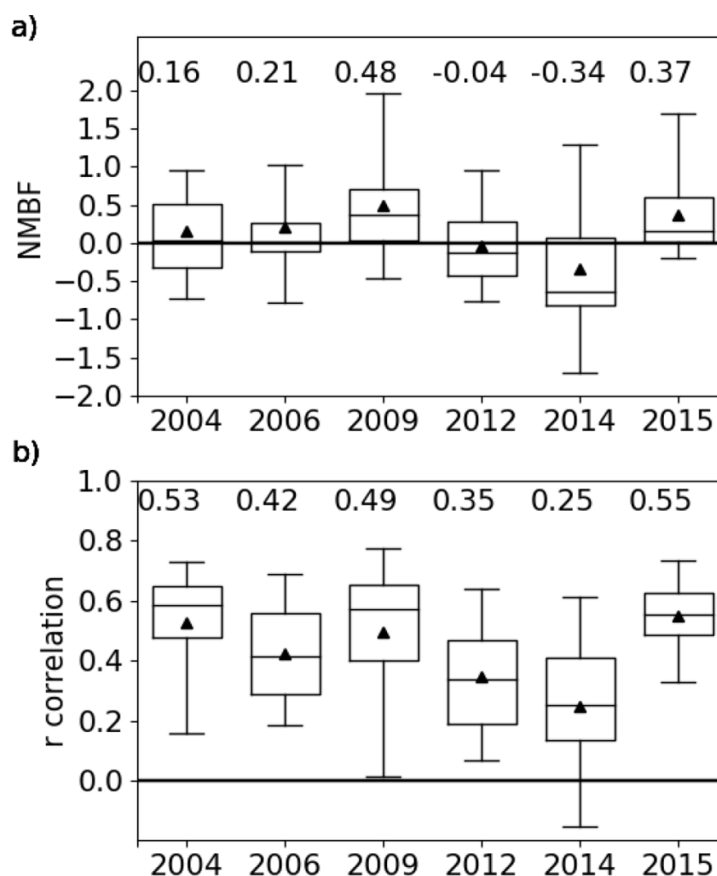
**Figure 4.** Box plot showing (a) the normalized mean bias factor (NMBF) and (b) the correlation coefficient (r) between simulated and measured fire-derived PM concentration. NMBF and r have been calculated at each of the sites in Malaysia and Indonesia. The box plots show the mean value as a triangle, 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).

**Table 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 $PM_{2.5} > 25$ $\mu$g 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 the supplement. The upper and lower estimates are shown in brackets.

| Year | Average $PM_{2.5}$ ($\mu$g m$^{-3}$) | Average population-weighted $PM_{2.5}$ ($\mu$g m$^{-3}$) | People exposed to $PM_{2.5} > 25$ $\mu$g 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 (12 562–20 191) | 392 761 (303 728–489 295) | 637 727 (456 836–856 074) |
| 2006 | 21.0 | 8.8 | 51.7 | 22 088 (17 145–27 427) | 532 655 (412 927–661 631) | 867 220 (622 619–1 161 097) |
| 2009 | 15.4 | 5.2 | 22.2 | 16 656 (12 868–20 768) | 404 715 (312 146–505 219) | 654 733 (468 340–879 776) |
| 2012 | 11.7 | 5.2 | 26.7 | 14 573 (11 287–18 132) | 353 026 (273 043–439 511) | 573, 084 (410 643–768 854) |
| 2014 | 11.7 | 4.7 | 27.9 | 13 705 (10 598–17 085) | 333 931 (257 964–416 406) | 541 086 (387 007–727 671) |
| 2015 | 65.8 | 25.6 | 66.5 | 44 041 (34 672–53 948) | 1 057 573 (832 357–1 294 657) | 1 725 203 (1 256 322–2 278 572) |

(World Health Organization 2005) (figure 5). In 2015 fires resulted in an average of 20 million people being exposed to a daily $PM_{2.5}$ concentration > 150 $\mu$g m$^{-3}$

(figure 5(a)), and 66.5 million people being exposed to daily $PM_{2.5}$ concentrations > 25 $\mu$g m$^{-3}$ for at least one in two days during August–October (figure 5(b)).
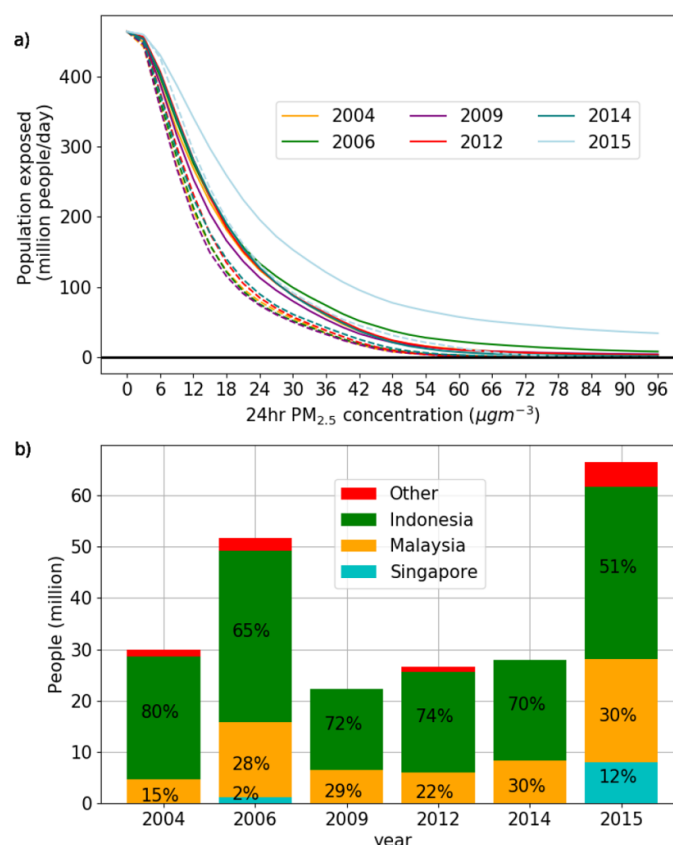
**Figure 5.** Population exposure to poor air quality. (a) The average population per day exposed to 24-hr PM$_{2.5}$ concentrations above levels shown on x axis, for simulation with fires (solid lines) and without fires (dashed lines). (b) The number of people exposed to 24-hr PM$_{2.5}$ concentrations over 25 μg m$^{-3}$ for at least half the days in August–October.
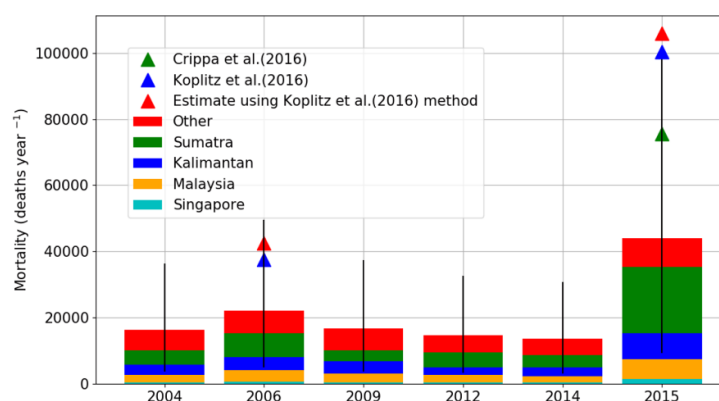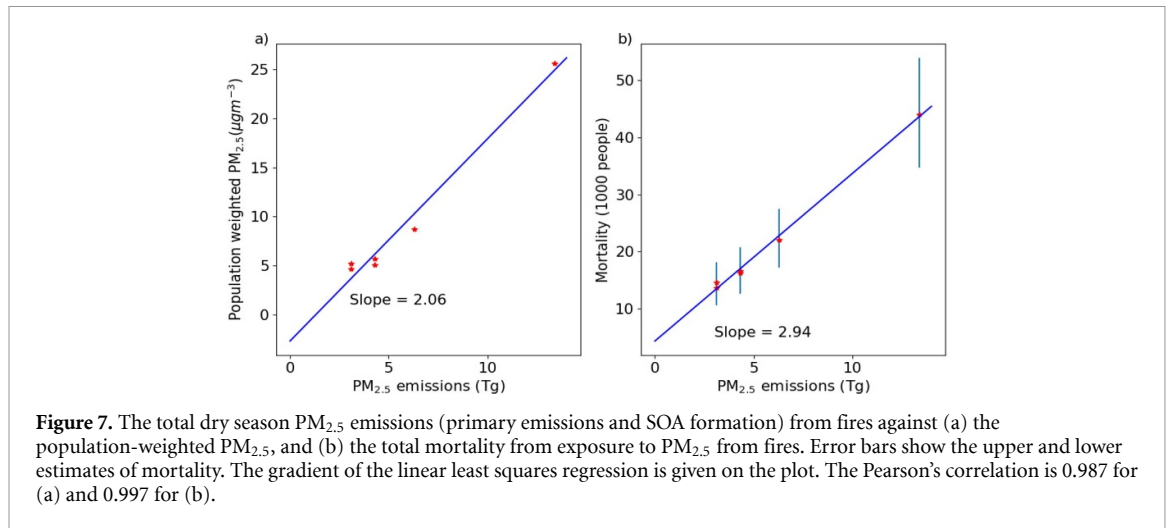


**Figure 6.** Excess premature mortality due to exposure to PM$_{2.5}$ from fires. The upper and lower 95% uncertainty interval for the total domain is shown as black lines. Triangles show comparison against previous studies as well as an estimate using our PM exposure combined with the health function used by Koplitz et al (2016).

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 5(b)). The majority of people exposed to poor air quality from fires live in Indonesia (51%–80% of people exposed) and Malaysia (15–30%).

### 3.4. Public health impacts

Table 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$_{2.5}$

**Figure 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).

from fires caused 44 000 excess deaths in 2015, less than 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 $\mu$g 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) also found that the majority of uncertainty in long term mortality estimates for Europe is related to the relative risk function. For China, Giani *et al* (2020) found that the uncertainty in the PM concentrations and the relative risk function contributed similarly to overall uncertainty, increasing the range of estimated mortality when both uncertainties were considered. Similar to this study, they found using a different relative risk function led to a much greater difference in estimated mortality, outside the 95% confidence interval. 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 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 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 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 $\mu$g m$^{-3}$, and excess annual premature mortality increases by 2940.

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), consistent south-easterly winds over South Kalimantan and Sumatra result in similar atmospheric transport patterns (Chang and Wang 2005, Heil *et al* 2007, Wang *et al* 2013, Lee *et al* 2017), and the same areas are exposed to poor air quality (figure S6). 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 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).

## 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 factors 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* 2016; 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 $\mu$g $m^{-3}$, 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).

## Data availability

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

## ORCID iDs

Dominick V Spracklen ⬤ https://orcid.org/0000-0002-7551-4597
Christine Wiedinmyer ⬤ https://orcid.org/0000-0001-9738-6592
Hari A Adrianto ⬤ https://orcid.org/0000-0001-8345-1867

## References

Adrianto H A, Spracklen D V and Arnold S R 2019 Relationship between Fire and Forest Cover Loss in Riau Province, Indonesia between 2001 and 2012 *Forests* **10** 889

Adrianto H A, Spracklen D V, Arnold S R, Sitanggang I S and Syaufina L 2020 Forest and Land Fires Are Mainly Associated with Deforestation in Riau Province, Indonesia, pp 1–12

Ballhorn U, Siegert F, Mason M and Limin S 2009 Derivation of burn scar depths and estimation of carbon emissions with LIDAR in Indonesian peatlands *Proc. Natl Acad. Sci. USA* **106** 21213–8

Burnett R *et al* 2018 Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter *Proc. Natl Acad. Sci. USA* **115** 9592–7

Cai W *et al* 2014 Increasing frequency of extreme El Niño events due to greenhouse warming *Nat. Clim. Change* **4** 111–6

Carmenta R, Zabala A, Daeli W and Phelps J 2017 Perceptions across scales of governance and the Indonesian peatland fires *Glob. Environ. Change* **46** 50–59

Cattau M E, Harrison M E, Shinyo I, Tungau S, Uriarte M and Defries R 2016 Sources of anthropogenic fire ignitions on the peat-swamp landscape in Kalimantan, Indonesia *Glob. Environ. Change* **39** 205–19

Center for International Earth Science Information Network and NASA Socioeconomic Data and Applications Center 2016 Gridded Population of the World, Version 4 (GPWv4): Population Count. Columbia University (https://doi.org/10.7927/H4JW8BX5)

Chang C P and Wang Z 2005 Annual Cycle of Southeast Asia — Maritime Continent Rainfall and the Asymmetric *J. Climate* **18** 287–301

Christian T J, Kleiss B, Yokelson R J, Holzinger R, Crutzen P J, Hao W M, Saharjo B H and Ward D E 2003 Comprehensive laboratory measurements of biomass-burning emissions: 1. Emissions from Indonesian, African, and other fuels *J. Geophys. Res.-Atmos.* **108** 4719

Cohen A J *et al* 2017 Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015 *The Lancet* **389** 1907–18

Crippa P, Castruccio S, Archer-Nicholls S, Lebron G B, Kuwata M, Thota A, Sumin S, Butt E, Wiedinmyer C and Spracklen D V 2016 Population exposure to hazardous air quality due to the 2015 fires in Equatorial Asia *Sci. Rep.* **6** 37074

Dorigo W *et al* 2017 ESA CCI Soil Moisture for improved Earth system understanding: state-of-the art and future directions *Remote Sens. Environ.* **203** 185–215

Emmanuel S C 2000 Impact to lung health of haze from forest fires: the Singapore experience *Respirology* **5** 175–82

Emmons L K *et al* 2010. Description and evaluation of the Model for Ozone and Related chemical Tracers, version 4 (MOZART-4) *Geoscientific Model Development* pp 43–67

Field R D *et al* 2016 Indonesian fire activity and smoke pollution in 2015 show persistent nonlinear sensitivity to El Niño-induced drought *Proc. Natl Acad. Sci. USA* **113** 9204–9

Field R D, Van Der Werf G R and Shen S S P 2009 Human amplification of drought-induced biomass burning in Indonesia since 1960 *Nat. Geosci.* **2** 185–8

Gaveau D L A *et al* 2014 Major atmospheric emissions from peat fires in Southeast Asia during non-drought years: evidence from the 2013 Sumatran fires *Sci. Rep.* **4** 4

Giani P, Anav A, Marco A D, Zhaozhong F and Crippa P 2020 Exploring sources of uncertainty in premature mortality estimates from fine particulate matter: the case of China *Environ. Res. Lett.* **15** 064027

Giglio L, Randerson J T and Van Der Werf G R 2013 Analysis of daily, monthly, and annual burned area using the fourth-generation global fire emissions database (GFED4) *J. Geophys. Res. Biogeosci.* **118** 317–28

Gruber A, Dorigo W A, Crow W and Wagner W 2017 Triple collocation-based merging of satellite soil moisture retrievals *IEEE Trans. Geosci. Remote Sens.* **55** 6780–92

Guenther A, Karl T, Harley P, Wiedinmyer C, Palmer P I and Geron C 2006 Estimates of global terrestrial isoprene emissions using MEGAN (Model of Emissions of Gases and Aerosols from Nature) *Atmos. Chem. Phys.* **6** 3181–210

Harrison M E *et al* 2019 Tropical forest and peatland conservation in Indonesia: challenges and directions *People Nat.* **2** 4–28

Hatch L E, Luo W, Pankow J F, Yokelson R J, Stockwell C E and Barsanti K C 2015 Identification and quantification of gaseous organic compounds emitted from biomass burning using two-dimensional gas chromatography-time-of-flight mass spectrometry *Atmos. Chem. Phys.* **15** 1865–99

Heil A, Langman B and Aldrian E 2007 Indonesian peat and vegetation fire emissions: study on factors influencing large-scale smoke haze pollution using a regional atmospheric chemistry model Indonesian peat and vegetation fire emissions: study on factors influencing large-scale smoke haze *Mitig. Adapt. Strateg. Glob. Chang.* **12** 113–33

Hodzic A and Knote C 2014 WRF-Chem 3.6.1: MOZART gas-phase chemistry with MOSAIC aerosols

Hu Y, Fernandez-Anez N, Smith T E L and Rein G 2018 Review of emissions from smouldering peat fires and their contribution to regional haze episodes *Int. J. Wildland Fire* **27** 293–312

Institute for Health Metrics and Evaluation 2019 *GBD Compare Data Visualization* (Seattle, WA: IHME, University of Washington)

Janssens-Maenhout G *et al* 2015 HTAP _ v2. 2 : a mosaic of regional and global emission grid maps for 2008 and 2010 to study hemispheric transport of air pollution *Atmos. Chem. Phys.* **15** 11411–32

Jayachandran S 2013 Air quality and early-life mortality evidence from Indonesia's Wildfire *J. Hum. Resour.* **44** 916–54

Jayarathne T *et al* 2018 Chemical characterization of fine particulate matter emitted by peat fires in Central Kalimantan, Indonesia, during the 2015 El Niño *Atmos. Chem. Phys.* **18** 2585–600

Jefferson U, Carmenta R, Daeli W and Phelps J 2020 Characterising policy responses to complex socio-ecological problems: 60 fire management interventions in Indonesian peatlands *Glob. Environ. Change* **60** 2019

Johnston F H, Henderson S B, Chen Y, Randerson J T, Marlier M, Defries R S, Kinney P, Bowman D M J S and Brauer M 2012 Estimated global mortality attributable to smoke from landscape fires *Environ. Health Perspect.* **120** 695–701

Kaiser J W *et al* 2012 Biomass burning emissions estimated with a global fire assimilation system based on observed fire radiative power *Biogeosciences* **9** 527–54

Kiely L *et al* 2019 New estimate of particulate emissions from Indonesian peat fires in 2015 *Atmos. Chem. Phys.* **19** 11105–21

Kim P S, Jacob D J, Mickley L J, Koplitz S N, Marlier M E, Defries R S, Myers S S, Chew B N and Mao Y H 2015 Sensitivity of population smoke exposure to fire locations in Equatorial Asia *Atmos. Environ.* **102** 11–17

Koplitz S N *et al* 2016 Public health impacts of the severe haze in Equatorial Asia in September-October 2015: demonstration of a new framework for informing fire management strategies to reduce downwind smoke exposure *Environ. Res. Lett.* **11** 094023

Kushta J, Pozzer A and Lelieveld J 2018 Uncertainties in estimates of mortality attributable to ambient PM2.5 in Europe *Environ. Res. Lett.* **13** 064029

Lee H H, Bar-Or R Z and Wang C 2017 Biomass burning aerosols and the low-visibility events in Southeast Asia *Atmos. Chem. Phys.* **17** 965–80

Liu T, Mickley L J, Marlier M E, Defries R S, Khan F, Talib M and Karambelas A 2020 Remote Sensing of Environment Diagnosing spatial biases and uncertainties in global fire emissions inventories : indonesia as regional case study *Remote Sens. Environ.* **237** 111557

Liu Y Y, Dorigo W A, Parinussa R M, de Jeu R A M, Wagner W, Mccabe M F, Evans J P and van Dijk A I J M 2012 Trend-preserving blending of passive and active microwave soil moisture retrievals *Remote Sens. Environ.* **123** 280–97 (Accessed 5 March 2019)

Lohberger S, Stängel M, Atwood E C and Siegert F 2017 Spatial evaluation of Indonesia's 2015 fire-affected area and estimated carbon emissions using Sentinel-1 *Glob. Change Biol.* **24** 644–54

Marlier M E, Defries R S, Kim P S, Gaveau D L A, Koplitz S N, Jacob D J, Mickley L J, Margono B A and Myers S S 2015 Regional air quality impacts of future fire emissions in Sumatra and Kalimantan *Environ. Res. Lett.* **10** 54010

Marlier M E, Defries R S, Voulgarakis A, Kinney P L, Randerson J T, Shindell D T, Chen Y and Faluvegi G 2012 El Niño and health risks from landscape fire emissions in southeast Asia *Nat. Clim. Change* **3** 131–6

Marlier M E *et al* 2019 Fires, smoke exposure, and public health: an integrative framework to maximize health benefits from peatland restoration *GeoHealth* **3** 178–80

Mead M I, Castruccio S, Latif M T, Nadzir M S M, Dominick D, Thota A and Crippa P 2018 Impact of the 2015 wildfires on Malaysian air quality and exposure: a comparative study of observed and modeled data *Environ. Res. Lett.* **13** 044023

Miettinen J, Shi C and Liew S C 2017 Fire distribution in peninsular malaysia, sumatra and borneo in 2015 with special emphasis on peatland fires *Environ Manage.* **60** 747–57

Nara H, Tanimoto H, Tohjima Y, Mukai H, Nojiri Y and Machida T 2017 Emission factors of $CO_2$, CO and $CH_4$ from Sumatran peatland fires in 2013 based on shipboard measurements *Tellus B: Chem. Phys. Meteorol.* **69** 1399047

NCEP 2007 NCEP Global Forecast System (GFS) Analyses and Forecasts (Available at: https://doi.org/10.5065/D65Q4TSG)

Page S E and Hooijer A 2016 In the line of fire: the peatlands of Southeast Asia *Philos. Trans. R. Soc. Lond. B: Biol. Sci.* **371** 20150176

Page S E, Rieley J O and Banks C J 2011 Global and regional importance of the tropical peatland carbon pool *Glob. Change Biol.* **17** 798–818

Page S E, Siegert F, Rieley J O, Boehm H D V, Jaya A and Limin S 2002 The amount of carbon released from peat and forest fires in Indonesia during 1997 *Nature* **420** 61–65

Pan X, Chin M, Ichoku C M and Field R D 2018 Connecting Indonesian fires and drought with the type of El Niño and phase of the indian ocean dipole during 1979–2016 *J. Geophys. Res. Atmos.* **123** 7974–88

Reddington C L, Spracklen D V, Artaxo P, Ridley D, Rizzo L V and Arana A 2016 Analysis of particulate emissions from tropical biomass burning using a global aerosol model and long-term surface observations *Atmos. Chem. Phys. Discuss.* **16** 11083–106

Reddington C L, Yoshioka M, Balasubramanian R, Ridley D, Toh Y Y, Arnold S R and Spracklen D V 2014 Contribution of vegetation and peat fires to particulate air pollution in Southeast Asia *Environ. Res. Lett.* **9** 094006

Roulston C, Paton-Walsh C, Smith T E L, Guérette A, Evers S, Yule C M, Rein G and Van der Werf G R 2018 Fine particle emissions from tropical peat fires decrease rapidly with time since ignition *J. Geophys. Res. Atmos.* **123** 5607–17

Sahani M, Ashikin N, Rozita W, Mahiyuddin W, Talib M, Hod R, Khan F, Mohd N and Chan C 2014 A case-crossover analysis of forest fire haze events and mortality in Malaysia *Atmos. Environ.* **96** 257–65

Sloan S, Locatelli B, Wooster M J and Gaveau D L A 2017 Fire activity in Borneo driven by industrial land conversion and drought during El Niño periods, 1982–2010 *Glob. Environ. Change* **47** 95–109

Spracklen D V *et al* 2011 Aerosol mass spectrometer constraint on the global secondary organic aerosol budget *Atmos. Chem. Phys.* **11** 12109–36

Stockwell C E *et al* 2016 Field measurements of trace gases and aerosols emitted by peat fires in Central Kalimantan, Indonesia, during the 2015 El Niño *Atmos. Chem. Phys.* **16** 11711–32

Tosca M G, Randerson J T and Zender C S 2013 Global impact of smoke aerosols from landscape fires on climate and the Hadley circulation *Atmos. Chem. Phys.* **13** 5227–41

Usup A, Hashimoto Y, Takahashi H and Hayasaka H 2004 Combustion and thermal characteristics of peat fire in tropical peatland in Central Kalimantan, Indonesia *Tropics* **14** 1–19

van der Werf G R *et al* 2008 Climate regulation of fire emissions and deforestation in equatorial Asia *Proc. Natl Acad. Sci. USA* **105** 20350–5

Van Der Werf G R, Randerson J T, Giglio L, Collatz G J, Mu M, Kasibhatla P S, Morton D C, Defries R S, Jin Y and Van Leeuwen T T 2010 Global fire emissions and the contribution of deforestation, savanna, forest, agricultural, and peat fires (1997–2009) *Atmos. Chem. Phys.* **10** 11707–35

van der Werf G R *et al* 2017 Global fire emissions estimates during 1997–2016 *Earth Syst. Sci. Data* **9** 697–720

Vongruang P, Wongwises P and Pimonsree S 2017 Assessment of fire emission inventories for simulating particulate matter in Upper Southeast Asia using WRF-CMAQ *Atmos. Pollut. Res.* **8** 921–9

Wang J, Ge C, Yang Z, Hyer E J, Reid J S, Chew B, Mahmud M, Zhang Y and Zhang M 2013 Mesoscale modeling of smoke transport over the Southeast Asian Maritime Continent : interplay of sea breeze, trade wind, typhoon, and topography *Atmos. Res.* **122** 486–503

Wiedinmyer C, Akagi S K, Yokelson R J, Emmons L K, Al-Saadi J A, Orlando J J and Soja A J 2011 The Fire INventory from NCAR (FINN) – a high resolution global model to estimate the emissions from open burning *Geosci. Model Dev. Discuss.* **3** 2439–76

Wijedasa L S, Sloan S, Page S E, Clements G R, Lupascu M and Evans T A 2018 Carbon emissions from South-East Asian peatlands will increase despite emission-reduction schemes *Glob. Change Biol.* **24** 4598–613

Wooster M *et al* 2018 New tropical peatland gas and particulate emissions factors indicate 2015 indonesian fires released far more particulate matter (but Less Methane) than current inventories imply *Remote Sens.* **10** 495

Wooster M J, Perry G L W and Zoumas A 2012 Fire, drought and El Niño relationships on Borneo (Southeast Asia) in the pre-MODIS era (1980-2000) *Biogeosciences* **9** 317–40

World Health Organization 2005 WHO Air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide: Global update 2005, pp 1–21

World Resources Institute 2017 World Resources Institute. 'Peat lands' (Accessed through Global Forest Watch on 17 April 2017) (Available at: www.globalforestwatch.org)

Wösten J H M, Clymans E, Page S E, Rieley J O and Limin S H 2008 Peat – water interrelationships in a tropical peatland ecosystem in Southeast Asia *Cantena* **73** 212–24

Yin Y *et al* 2016 Variability of fire carbon emissions in equatorial Asia and its nonlinear sensitivity to El Niño *Geophys. Res. Lett.* **43** 10472–9

Yu S, Eder B, Dennis R, Chu S-H and Schwartz S E 2006 New unbiased symmetric metrics for evaluation of air quality models *Atmos. Sci. Lett.* **7** 26–34

Zaveri R A, Easter R C, Fast J D and Peters L K 2008 Model for simulating aerosol interactions and chemistry (MOSAIC) *J. Geophys. Res.* **113** 1–29