**Global impact of landscape fire emissions on surface level PM2.5 concentrations, air quality exposure and population mortality**

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**Abstract**

Airborne fine particulate matter (PM2.5) represents the greatest ambient air pollution risk to health. Wildfires and managed burns, together referred to hereafter as ‘landscape’ fires, are a significant PM2.5 source in many regions worldwide, able to affect air quality in areas far away from the fires themselves.  We use 0.125°, 3 hourly outputs (2016-2019) from the Copernicus Atmospheric Monitoring System (CAMS) to investigate patterns of global population exposure to ambient surface level PM2.5, and specifically to the contribution coming from landscape fires. We calculate both the air quality impacts and annual average mortality at the level of the nation state, and our analysis highlights both the burden of poor air quality and the significance of landscape fire sources in developing nations in particular. We find 143 countries to have an average population weighted (PW) total PM2.5 surface level concentration exceeding the 10 µg.m-3 guideline recommended by WHO, with 67.2 million people annually exposed to PM2.5 levels classed as ‘hazardous’ (> 250.5 µg.m-3) according to the US Environmental Protection Agency (EPA) air quality index (AQI). Landscape fires alone result in 44 million people annually being exposed to air quality considered unhealthy (PM2.5> 55 µg.m-3), and 4 million to that considered ‘hazardous’ to health (> 250.5 µg.m-3). Populations in central and west Africa and south and south east Asia are most affected by the landscape fire smoke, and eight countries exceed the WHO annual mean 10 µg.m-3guideline from this source only - with the contribution from fires highest in Laos (61% of the total PM2.5), Democratic Republic of Congo (45%) and Sierra Leone (44%). Combining published dose-response functions with these landscape-fire PM2.5 contributions, we estimate that 677,745 premature deaths annually result from exposure to landscape fire smoke, with almost 39% of these in children under five. This mortality represents between 8 and 21% of the estimated 3.2 to 8.9 million people dying annually from outdoor air pollution exposure, highlighting landscape fires as a significant contributor. Our results indicate that environmental programmes aimed at lessening the use of fire in land clearance and agricultural residue management in developing nations would very likely result in significant co-benefits for health.

**1. Introduction**

Despite clean air being long identified as necessary for good public health and well-being, outdoor (ambient) air pollution remains the world’s greatest environmental health risk (WHO, 2016). Outdoor air pollution in many developing nations is a growing problem, greater even than indoor air pollution whose influence is forecast to decrease over the coming decades as people transition away from burning solid fuels for cooking and heating (Li et al., 2020; Chafe et al., 2010). Outdoor air pollution comes from a variety of anthropogenic and natural sources, with estimates of annual average mortality (premature deaths) resulting from total ambient PM2.5 and O3 exposure varying from around 3.2 to 8.9 million (Giannadaki et al., 2017; WHO, 2016, Lelieveld et al., 2015; Burnett et al. 2018), with adverse health effects felt by hundreds of millions more (WHO, 2016). Populations in Asia seem most affected in terms of mortality (Lelieveld et al., 2015), and in 2010 70% of global total excess deaths due to outdoor air pollution were reported as being in Asia (Giannadaki et al., 2017).

Ambient air pollution comprises gases such as tropospheric ozone (O3), nitrogen dioxide (NO2), volatile organic compounds (VOCs), carbon monoxide (CO), and sulphur dioxide (SO2), along with particulate matter (PM) size fractions such as PM10 and PM2.5. The finer PM2.5 particles represent the greatest ambient air pollution risk to health (WHO, 2006), and in 2010 anthropogenic sources such as residential combustion and industrial processes accounted for 59% of global total PM2.5 emissions (Klimont et al., 2017). In certain countries however, large amounts of PM2.5 are produced by landscape fires, many of which are ignited deliberately for land clearance or land management purposes – for example for clearing forest for agriculture or when removing agricultural residues after harvest (Reddington et al., 2015; Zhang et al., 2017; Cusworth et al., 2018). In many developing countries, such landscape fires may actually represent the single largest PM2.5 source (Colbeck and Lazaridis, 2010), and in many cases buoyant fire plumes can help the smoke travel far away from the source region, sometimes becoming transboundary in nature to significantly affect air quality in neighbouring nations (e.g. Ikeda and Tanimoto, 2015; Demoah et al., 2004). The extreme impacts that can result from such transboundary transport of biomass burning emissions is perhaps best highlighted by the regional ‘haze’ episodes that occur sporadically in southeast Asia, which are largely related to fires in degraded tropical peat swamps that have become far more flammable due to forest clearance and swampland drainage (Kiely et al., 2019; Reddington et al., 2014; Wooster et al., 2018). Certain (model-based) estimates of the regional PM2.5 exposure of populations during such episodes suggest the possibility of many tens of thousands of additional deaths resulting from the most extreme events (Crippa et al., 2016). Here we extend this type of health impact study across the globe, using outputs from a state-of-the-art global atmospheric composition modelling and monitoring system - the Copernicus Atmospheric Monitoring Service (CAMS).

A number of approaches exist for quantifying air quality and its effect on population health. Surface monitoring stations provide probably the most accurate and also highest temporal resolution air quality measurements, enabling the impact of long-term ambient exposure to air pollutants to be quantified (e.g. Miller *et al*., 2007; Samet *et al*., 2000). However, the density of the surface station network maybe relatively sparse, particularly in least developed and developing countries. Brauer *et al*. (2019) highlight the expense involved in developing surface air quality stations in India, comparable to that found the USA and China and estimated as having annual running costs of US $212 (540) million for 1600 (4000) stations. To obtain more complete spatial coverage, surface station measures have been spatially interpolated (Beelen *et al.*, 2008; Ahmed et al., 2018) and combined with satellite data and sometimes also with the outputs of atmospheric modelling (Brauer *et al*., 2016; Shaddick *et al.,* 2018). Whilst benefitting from the high temporal resolution of the surface station network data, these methods are still constrained by the network density, and the integration/calibration required to relate satellite and surface observations is non-trivial, particularly since the satellite data often provide column integrated values (e.g. of aerosol optical depth) whereas the station network provides surface values (Li et al., 2015). Computational developments have seen increased application of atmospheric chemical transport models, such as Weather Research and Forecasting (WRF) - Community Multiscale Air Quality Modeling System (CMAQ; Appel *et al*., 2017). These models can linked to emissions inventories (anthropogenic and fire emissions etc) and to enable the quantification of different emissions sources to overall air quality (e.g. Reddington et al., 2015; Lelieveld et al., 2015). The models also provide complete spatial coverage and can do so at a comparatively high spatial resolution, but they are computationally intensive which often limits their application to regional scales and\or shorter timeframes (e.g. Zhang et al., 2014; Baldassarre et al., 2015; Appel et al., 2010; Wong et al., 2012). In this study we use the model outputs from the CAMS global model, which runs on a very high performance supercomputer and which are available globally at moderate spatial (0.125°) and temporal (3 hourly) resolution. We use CAMS outputs to understand the global surface-level ambient atmosphere PM2.5 concentrations, the influence of landscape (comprising wildfire and managed burns) fire emissions on these and on the levels of air quality that result, and the degree to which premature mortality results from exposure to the fire emitted PM. Our work builds on methodologies previously employed by Johnston et al. (2012) to estimate global mortality due to landscape fire PM2.5 emissions, but we use outputs from the more recent CAMS system and study more recent years, quantifying the air quality and health impacts globally but also at the scale of the nation state. Whilst we focus on exposure to PM2.5 emitted by landscape fires, we also assess population exposure to all source PM2.5 in order to put the landscape fire source properly in context.

**2. Models and Datasets**

**2.1 The Copernicus Atmospheric Monitoring Service (CAMS)**

The CAMS is supported by the Copernicus Programme of the European Union (EU), and has six focus areas providing near continuous monitoring of Earth’s atmosphere at regional and global scales using a combination of satellite data, *in situ* observations and atmospheric modelling, the latter primarily conducted using the Integrated Forecasting System (IFS) of the European Centre for Medium Range Weather Forecasting (ECMWF). The IFS is a state-of-the-art global data assimilation, modelling and forecasting system providing atmospheric composition data (aerosols, greenhouse gases, reactive gases) at 6 hourly intervals and forecasts at 3 hourly intervals for a maximum forward look of 5 days. The current IFS cycle operates with 137 vertical levels from the surface up to 0.01 hPa at a nominal horizontal resolution of ~40 km. Modelled data outputs can be resampled up to 0.125° resolution using the Meteorological Interpolation and Regridding scheme (MIR, Malardel et al., 2016). We are here primarily concerned with the surface-level PM2.5 abundances, which include contributions from fine and coarse nitrate and ammonium aerosols, sea salt covering three size distributions (0.03-0.5 µm, 0.5- 5 µm, 5- 20 µm), dust (0.03-0.55 µm, 0.55-0.9 µm, 0.9-20 µm), and sulphate, organic matter (OM) and black carbon (BC) aerosols emitted from both anthropogenic and natural sources. Biomass burning emissions are confined to the BC and OM components, and in no part of this study do we include the fine and coarse nitrate and ammonium aerosols since they were only recently introduced into the IFS (July 2019).

The specific aerosol model used within the IFS (IFS Cycle 45R1; 06/2018) is detailed in Remy et al. (2018) and only a brief overview is provided here. PM2.5 is calculated using aerosol mass mixing ratios (kg.kg-1) of the different components, following Remy *et al.* (2020):

[1]

where and are dust aerosols (0.03-0.55 µm and 0.55-0.9 µm), and are sea salt aerosols (0.03-0.5 µm and 0.5-5.0 µm), is sulphate aerosol, and are the organic matter and black carbon aerosols (both hydrophobic and hydrophilic)and is the air density calculated via:

[2]

where for a given model level, is the pressure (hPa), is the temperature (K) and is the specific gas constant (287.058, J.Kg K).

Anthropogenic aerosols come from the MACCity and CAMS-GLOB-ANT emissions inventories (Granier et al., 2011; 2019), and cover transportation, energy, industries, ships, residential, solvents, and agricultural activities. These in turn are based on an extension of the historical emissions from the atmospheric chemistry and climate model intercomparision project (ACCMIP). Landscape fire emissions come from the Global Fire Assimilation System (GFASv1.2; Kaiser et al., 2012), which is driven by satellite-derived fire radiative power (FRP) estimates made at the location of actively burning fires. At present these global FRP data come from observations made multiple times per day by the MODIS instruments operating onboard the Terra and Aqua polar-orbiting satellites (Giglio *et al.*, 2016). Small scale field experiments (e.g. Wooster *et al.,* 2005; Kremens *et al.,* 2012) found a strong relationship between the rate of thermal radiation emission by fires (i.e. the FRP) and the rate of fuel consumption. This relationship has been exploited to estimate fuel consumption from spaceborne data (e.g. Roberts *et al*., 2018; Li *et al*., 2019; Andela *et al*., 2016), and in GFAS the FRP density (W.m2; calculated by normalising the FRP by the grid cell area, m2) is the metric used to do this. Following the approach of Wooster *et al.* (2005), FRP density is used to calculate the rate of dry matter (DM) fuel consumption (kg.s-1.m-2), which when multiplied by the appropriate emissions factors provides trace gas emissions rate estimates. In total, 51 parameters are provided by GFAS, including surface flux (kg.m2.s-1) estimates of 41 species contained within the landscape fire smoke (both aerosols and trace gases). GFAS-derived biomass burning emissions used in the CAMS model outputs employed herein were released at the surface up until July 2019, after which CAMS uses a plume injection height formulation based also on the fires FRP and local meteorology to prescribe the placement of the emissions above the surface (Sofiev *et al*., 2012). However, though the plumes from large very intensely burning landscape fires maybe lofted high into the atmosphere and very occasionally even the stratosphere (Val Martin et al., 2010), such events represent a very small minority of total landscape fire plumes (Val Martin., 2018).

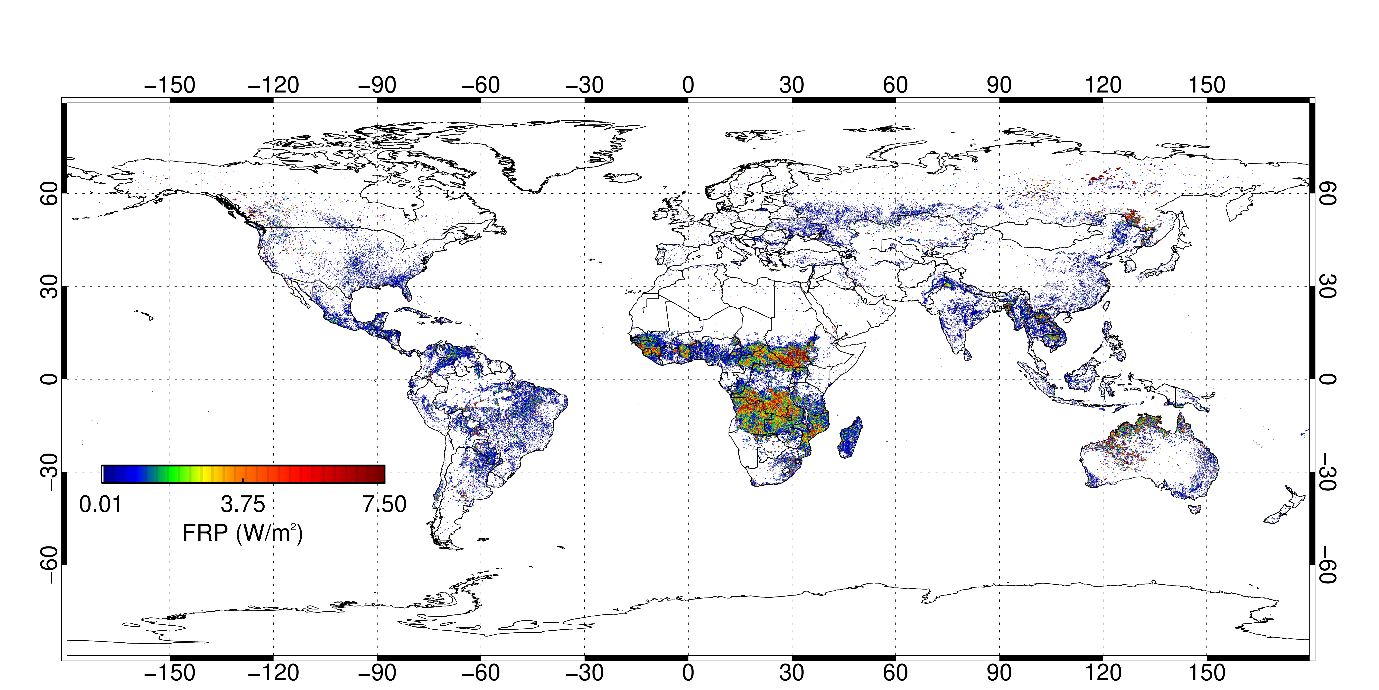
Figure 1a shows the global mean annual average surface level PM2.5 concentration output from CAMS at a grid cell size of 0.125°, calculated over the period 2016 to 2019. Figure 1b shows the FRP-derived measure of fire activity (the total MODIS-measured FRP areal density calculated at the same grid cell size and for the same period as Figure 1a). Whilst some areas show high surface level PM2.5 concentrations and relatively low fire activity (e.g. a few industrial regions of Southern Africa and parts of East Asia), there exist many more areas where elevated values of both metrics point to a potential relationship between mean PM2.5 concentrations and landscape fires. This is explored further in Figure 2, which shows a reasonably strong positive correlation between daily mean surface level PM2.5 and fire activity, with a Pearson correlation coefficient (R) of between 0.86 and 0.92, for continents outside of Africa and Oceania where dust and sea salt sources are very significant. Whilst in the other continents the PM2.5 particles also come from a variety of sources, the relations shown in Figure 2 provide evidence that landscape fire emissions maybe driving a significant fraction of their surface level PM2.5 variability. It seems likely that maybe the case in parts of Africa as well (notwithstanding the dust sources) since, despite the fuel loads in savannas and grasslands often being lower than those found in e.g. forested landscapes (Van Leeuwen et al., 2014), it is the continent where the largest area of landscape burning occurs (Giglio et al., 2010, Figure S1 in the supplementary material). Elucidating the link between landscape fires and air pollution in the form of PM2.5, and using this to estimate the air quality and health impacts of landscape fire activity, is the key aim of our work. For comparison, Figure S2 shows the mean annual (2016-19) average daily total PM2.5 concentration and the daily total GFAS FRP density (*W.m-2*) on a continental basis (excluding Antarctica).

(a)

Diagram

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b)



*Figure 1:**Globally mapped outputs (0.125°) from the Copernicus Atmosphere Monitoring Service (CAMS) calculated over the period 2016-2019, along with in (a) the location of air quality monitoring stations used herein. (a) Daily mean PM2.5 surface level concentration (µg.m-3), (b) GFAS Fire Radiative Power (FRP) areal density (W.m-2) (Kaiser et al., 2012), derived using MODIS FRP data from the MODIS active fire product (MCDML14; Giglio et al., 2016). Panels in (a) include as black dots the location of each of the in-situ surface air quality monitoring stations whose use is described in Section 3. These stations are respectively part of the US EPAs ‘AirNOW’ US Embassy network (22 sites), the Indian Central Pollution Control Board [CPCB]), the US EPAs ‘AirNOW’ North America network (442 sites), and the Purple Air network (84 sites). Green crosses mark the locations of the AirNOW and Purple Air sites* *at Werribee, New Delhi, Rio Branco and UC Davis whose data are shown in detail in Figure 3.*

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*Figure 2: Relationships between 2016-19 daily mean surface level PM2.5 concentration and the corresponding total daily FRP density (W.m-2) for all continents excluding Antarctica. Colours indicate day of year (DOY).* Each point represents data from one *CAMS 0.125° grid cell, with the OLS linear best fit to the data from all cells in each continent included.*

**2.2 Additional Datasets**

In addition to the CAMS data themselves, a series of *in situ* surface level PM2.5 concentrations were also deployed here to help evaluate the modelled CAMS values, both generally and at times of landscape fires. These *in situ* data come primarily from the US Environmental Protection Agency’s (EPA) AirNOW network (<https://www.epa.gov/outdoor-air-quality-data>), which in 2019 has access to 9143 sites - 90% of which provide hourly data. We selected data from 442 sites in California, Oregon, Washington State, Colorado, Kansas, Alabama, Florida, Georgia, Louisiana, Mississippi, Texas and Idaho (Figure 1) as they are located in areas of sometimes highly significant fire activity in agricultural and forested regions (McCarty et al., 2007; Korontzi et al., 2008; Dennison et al., 2014), as well as from stations located at 12 US Embassy and Consulates distributed across South America, Africa and Asia. These data are complemented by PM2.5 observations at 84 sites from the Purple Air network (https://www.purpleair.com/) for 2019. The Purple Air station data occasionally contain spurious signals (values > 2000 µg.m-3) which were removed from the analysis. We supplemented these global data with that from ten stations operated by the Indian governments Ministry of Environment and Forests Central Pollution Control Board (CPCB), India being a country where crop residue burning, widely varying anthropogenic emissions, and the monsoon bring air quality conditions that vary widely in space and time (Dey et al., 2012; Jethva et al., 2019; Sembhi et al., 2020). Combined, the surface station data enable the assessment of CAMS PM2.5 estimates in regions that experience high and low PM2.5 concentrations due to anthropogenic and/or landscape fire emissions. The location of each air quality measurement station used in this study is marked in Figure 1a. We also used global population data, again mapped to the CAMS 0.125° spatial grid, taken from the age and gender stratified global population dataset of 2018 developed by the WorldPop Project ([www.worldpop.org/](https://www.worldpop.org/); Tatem, 2017).

**3. Assessing CAMS Surface Level PM2.5 Data QUALITY**

Before outlining the results of the comparison between the CAMS and *in situ* PM2.5 concentration data, four globally distributed sites are selected which are influenced by anthropogenic and/or landscape fire emissions to varying extents by way of example. Figure 3 presents results for sites located at Werribee (2019), south-east Australia (37.89° S, 144.64° W), New Delhi (2019), India (28.61° N, 77.20° W), Rio Branco (2019), Brazil (9.89° S, 67.86° E) and UC Davis (2018) (California, 38.54° N, -121.74° W).

The air quality in Werribee and New Delhi is influenced by emissions from anthropogenic activities and landscape fires which occur between November and March around Werribee (Dennekamp et al., 2015) and in April/May and October/November around Delhi (Lui et al., 2018). New Delhi has a strong PM2.5 annual cycle with the highest concentrations seen in the northern hemisphere winter months whilst PM2.5 concentration in Werribee tends to be more stable throughout the year although increases in winter occur due to domestic heating (Bennett et al., 2007). The CAMS data capture both the dynamics and magnitude of the *in-situ* measures at the Werribee site (R=0.54), with a low bias (1.73 µg.m-3) albeit a higher RMSE (6.02 µg.m-3). Over Delhi, CAMS captures the temporal dynamics of the surface PM2.5 concentrations very well, and though the bias of -11.5 µg.m-3 is relatively high, a large part of this is attributable to the intense PM2.5 concentration maxima seen in the point-based *in situ* measurements around DOY 40.

The air quality in Rio Branco is affected by landscape fire emissions during the fire season between August and October. The comparison shows that, the CAMS overestimates PM2.5 at the start of the year but captures the trend and concentrations during the fire season with a moderate bias (3.6 µg.m-3) and RMSE (12.7 µg.m-3) and good correlation (R = 0.71). Davis (California) is a semi-rural area influenced by anthropogenic emissions which are <10 µg.m-3 for much of the year. The CAMS estimates are typically a little higher than the *in situ* measurements resulting in a bias of 8.9 µg.m-3, this site is subject to occasional influences from Californian fires. Around DOY 205 (24th July) and 313 (7th November) noticeable PM2.5 concentration increases related to landscape burning are evident in the modelled and *in situ* data. Comparison to the *in situ* data shows that CAMS captures the timing and surface level PM2.5 concentration increases resulting from the Camp (Brewer and Clements, 2020) and Montecedo fires extremely well, demonstrating excellent performance of the CAMS system in this fire-affected region.

Diagram

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*Figure 3: Daily mean modelled (CAMS) and measured (in situ) surface level ambient atmospheric PM2.5 concentration for locations containing Purple Air and AirNOW stations in Werribee [2019], New Delhi [2019], Rio Branco [2019] and UC Davis [2018].* *For the UC Davis station, the effect of smoke coming from the extreme Camp fire of November 2018 is clearly seen.*

Christophe *et al.* (2019) have already evaluated CAMS-generated surface level PM2.5 concentration data between March and May 2019, comparing them to *in situ* records from 160 ‘background sites’ across Europe and North America. They found CAMS estimates to be on average around 54% higher than the *in situ* measures in North America, but 17% lower in Europe. In Table 1 we present the statistical summary of our comparisons between the mean monthly CAMS-derived surface level PM2.5 concentration and those from the globally distributed set of *in situ* stations mapped in Figure 1a (548 stations in total). Since there is considerable variation between years, we present data for 2016, 2017, 2018 and 2019 separately in Table 1. We present both the mean bias and the Modified Normalised Mean Bias (MNMB, Wagner et al., 2015), the latter being robust to outliers and taking a value between 2 and -2, with values close to zero being optimum:

[3]

where is the number of observations, is the model estimate at step and is the *in situ* observation.

The average annual MNMB ranges between 0.56 and -0.38 – indicating that the CAMS data over (under) estimates by 56% (38%) depending on the year, and overall overestimates PM2.5 on average by 24%. Over North America the MNMB in 2018 (0.48) is slightly higher than that (0.32) found by Remy et al., (2019) over the same region using a larger number of sites (>1000). Greater underestimation is seen at the Embassy and Consulate sites in 2016 and the cause is unclear, but could be related to the fact that it was only in June of this earliest year of our study that CAMS began using the MACCity inventory (Remy et al., 2019), previously relying on the Emission Database for Global Atmospheric Research (EDGAR, Olivier et al., 1994). Reddington et al. (2019) compared WRF-CHEM-derived PM2.5 surface level concentrations and *in situ* data at sites in south and south-east Asia, finding a similar level of correspondence (R=0.55) to that found here for sites in the same region. Reddington et al. (2019) also quantified model performance and found WRF-CHEM-derived surface level PM2.5 marginally overestimated (MNMB =0.09, equivalent to overestimation by a factor of 1.09) but with regional variations over for example China (MNMB =0.33) and underestimation (e.g. Bhutan, MNMB = −0.63). In our work we find the ‘all year’ MNMB for sites in Asia and SE Asia to be 0.2, indicating CAMS overestimation by on average 20%. Of course, it is not possible for CAMS to characterise the local scale effects and potentially heterogeneous PM2.5 surface level concentrations found around specific *in situ* stations (Wagner et al., 2015). Our comparison between the CAMS outputs and the surface station PM2.5 measures aims to illustrate the correspondence between these data over the time period of our study (2016-2019). Our comparison builds on that of the European and North American focused study of Remy et al. (2019), adding further North American sites (total of 442) covering areas (e.g. southern states) and where air quality is affected by less common US fire types - such as agricultural burning – and including data from the global Purple Air network (84 in total) located in areas experiencing a wider range of landscape fires that are found in North America and Europe alone (e.g. tropical peatlands and topical forest, as well as temperate forest and agricultural areas). Together with the US Embassy sites, many of these locations experience PM2.5 concentrations far higher than typically is found in the sites focused on by Remy et al. (2019). Overall we agree with Remy et al. (2019) that the CAMS performance shows reasonable skill in forecasting surface level PM2.5 concentrations given the difficulties in comparing a point-based (in situ) and area-averaged (modelled) values, especially in areas of high concentration variability and given the constraints of the CAMS aerosol scheme (e.g. that it does not explicitly represent internal mixing and coagulation; Remy et al., 2019).

*Table 1:* *Summary statistics detailing the degree of correspondence between the mean monthly modelled (CAMS) and measured (in situ) surface level PM2.5 concentrations from the AirNOW, Central Pollution Control Board and Purple Air quality monitoring stations of Figure 1. The values in brackets in the Purple Air comparison are those from the data without outliers removed. MNMB ranges between -2 and +2, with values closer to zero indicating better agreement.*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Correlation (R)** | **Average RMSE (µg/m3)** | **Average Bias (µg/m3)** | **Modified normalised mean bias (MNMB)** | **Number of Sites** |
| **AirNOW USA** | | | | | |
| 2016 | 0.49 | 10.6 | 4.1 | 0.24 | 394 |
| 2017 | 0.52 | 13.1 | 5.3 | 0.27 | 439 |
| 2018 | 0.65 | 8.9 | 5.7 | 0.47 | 442 |
| 2019 | 0.40 | 5.1 | 2.8 | 0.3 | 426 |
| **AirNOW Embassy’s** | | | | | |
| 2016 | 0.58 | 37.3 | -20.1 | -0.38 | 19 |
| 2017 | 0.37 | 54.6 | 18.6 | 0.19 | 22 |
| 2018 | 0.45 | 76.3 | 31.7 | 0.39 | 20 |
| 2019 | 0.61 | 44.0 | 14.2 | 0.25 | 24 |
| **Central Pollution Control Board** | | | | | |
| 2017 | 0.66 | 85.8 | 42.5 | 0.31 | 5 |
| 2018 | 0.78 | 90.4 | 69.3 | 0.56 | 8 |
| **Purple Air** | | | | | |
| 2019 | 0.58 (0.56) | 13.2 (22.6) | 0.12 (-3.7) | 0.07 (0.06) | 84 |

**4. AIR QUALITY INDICIES (AQI) AND GLOBAL PM2.5 POPULATION EXPOSURE**

**4.1 All-Source AQI AND PM2.5 Exposure Estimates**

Figure 1amaps CAMS-derived annual mean surface level PM2.5 concentrations, calculated from data covering 2016 to 2019. The continents showing the highest concentrations are Africa (35.7 µg.m-3), Asia (36.2 µg.m-3) and North America (13.5 µg.m-3), each exceeding the annual mean of 10 µg.m-3 recommended by the World Health Organisation (WHO, 2016). Rather than reporting absolute concentrations however, levels of air pollution are often expressed to the public via air quality indices (AQIs) (EPA, 2009). These are generally based on a range of pollutants, such as O3, PM2.5, PM10, CO, SO2 and NO2 averaged over a set period (e.g. 24-hr means). The US EPA’s Air Quality Index (AQI) is one of the most commonly used AQI’s, originally named the Pollutant Standards Index (PSI, Ott and Hunt, 1976). It has breakpoint concentrations for the different AQ classes which are lower than those used in indices applied elsewhere. In India for example the AQI often used (IND-AQI; Sahu and Kota, 2016) defines ‘good’ and ‘severe’ air quality as having an average PM2.5 concentration between 0-30 and >250 µg.m-3 respectively. Care must be taken when interpreting AQI values therefore, and herein in we also report the PM2.5 concentration range corresponding to the AQI category. The AQI is designed to provide a consistent metric to characterise the degree of health impact coming from O3, PM2.5, PM10, CO, SO2, NO2 via a piece-wise linear function (Plaia and Ruggieri, 2010):

[4]

where is the air quality index, is the pollutant concentration (ppm, ppv or µg.m-3 depending on the pollutant), is the pollutant concentration breakpoint that is ≥ , is the pollutant concentration breakpoint that is ≤ , is the index breakpoint corresponding to and is the index breakpoint corresponding to .

The AQI takes a range between 0-500 in six breakpoints (shown it Table S1) that describe the air quality classes of good, moderate, unhealthy for sensitive groups, unhealthy, very unhealthy, and hazardous (which occupies two ranges). The AQI representing PM2.5 is based on 24-hour mean values, with 0-12 µg.m-3 classed as ‘good and 250-500 µg.m-3 as ‘hazardous’. To best use measures of ambient air pollution within studies of health effects, we use the per country population weighted PM2.5 metric of Gui et al. (2019):

[5]

where is the population weighted PM2.5 in country , is the daily PM2.5, is the population in country affected by PM2.5 on day and is the total country population derived from the WorldPop dataset for 2018.

Figure 4a presents the mean (2016-19) population weighted PM2.5 per country, highlighting the significant impact poor air quality has on developing nations. Many populations in northern Africa and the Middle East are exposed to annual average PM2.5 concentrations well above the WHO annual guideline, largely due to dust aerosols. Populations in South and South-east Asia are exposed to poor air quality as a result of numerous sources, but the anthropogenic component often dominates (Reddington et al., 2019). Figure 5a highlights this by showing the 15 countries that are impacted to the greatest extent by ‘hazardous’ air quality (PM2.5 >250 µg.m-3). Anthropogenic emissions provide the largest contribution to this poor air quality, including India and China (Crippa et al. 2018), but natural PM2.5 emissions sources (e.g. dust) also play a key role. When assessed against the WHO’s annual mean guideline of 10 µg.m-3, 90%, 92%, 75%, 69% and 48% of countries in Africa, Asia, South America, North America and Europe respectively exceeding this limit.

(a)

A close up of a map

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(b)

A close up of a map

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*Figure 4: (a) Population weighted mean annual surface level PM2.5 concentration for individual nations, as derived from CAMS. (b) Same as (a) but now only including PM2.5 coming from landscape fires as calculated in Section 5. Both are derived from data over the period 2016-19.*

The daily AQI values were then used to calculate the percentage of the national population exposed to different levels of air quality on a mean (2016-19) annual basis. When assessed in terms of the percentage of their national populations (Figure 5b), the severely dust affected countries of Kuwait, Mauritania and Western Sahara have the greatest percentage of people exposed to hazardous air quality. On average, 45% of the people in these countries are exposed to air quality considered ‘unhealthy’ (PM2.5 >55.5 µg.m-3) or worse.

a)

A screenshot of a cell phone

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b)

A screenshot of a cell phone

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*Figure 5. Countries whose populations have the greatest exposure to harmful levels of ambient atmospheric PM2.5 according to our analysis and the* US EPA’s Air Quality Index (AQI) *definitions of PM2.5 exposure (Table S1). (a) Top 15 countries having the greatest numbers of people exposed to hazardous air quality, and (b) top 15 countries with the greatest percentages of their populations exposed to hazardous air quality. Note that the x-axis is reverse logarithmic in (a).*

**5. Landscape Fire PM2.5 Contributions and Derived AQI**

To isolate the impact of landscape fire emitted PM2.5 on regional air quality, and to estimate population exposure to this air pollution source, we needed to remove the influence of non-fire PM2.5 sources on the data shown in Section 4. This is not simply a matter of looking at the fire emissions in a grid cell compared to the emissions of other sources, because emissions can be transported to affect areas well away from their source region (e.g. Colarco et al., 2004; Dirksen et al., 2009; Kaskaoutis et al., 2014; Saarnio et al., 2010). Instead the calculation could be based on re-running the CAMS models without the landscape fire emissions source included, and differencing the resulting concentrations from those including all sources. However, this approach is typically constrained to regional scales or seasonal time periods due to the high computational costs involved (Crippa et al., 2016; Reddington et al., 2014; Lee et al., 2018; Sembhi et al., 2020). Instead we used an approach similar to that implemented by Cusworth et al. (2018) when estimating the baseline (non-fire) contribution to PM2.5 surface level concentrations in Delhi. Our strategy involved identifying periods when CAMS grid cells were affected by smoke from landscape fires (‘the fire affected season’), and then estimating and subtracting the anthropogenically generated PM2.5 contribution from the concentration data of these grid cells to enable isolation of the landscape fire contribution. The anthropogenically generated PM2.5 contribution was estimated based on the mean surface level concentration seen in the month immediately prior to and subsequent to the ‘fire affected season’, interpolating between these to provide the values to subtract from the overall PM2.5 concentration of each ‘fire affected’ month. The basis for calculating the mean background PM2.5 concentration using the months immediately prior and after the ‘fire affected season’ is to account for seasonal variation in anthropogenic emissions. All calculations were performed using the PM2.5 surface concentrations coming out of Equation [1] but limited to the BC and OM fractions only, since these are sourced only from landscape fires and anthropogenic (e.g. industrial) sources.

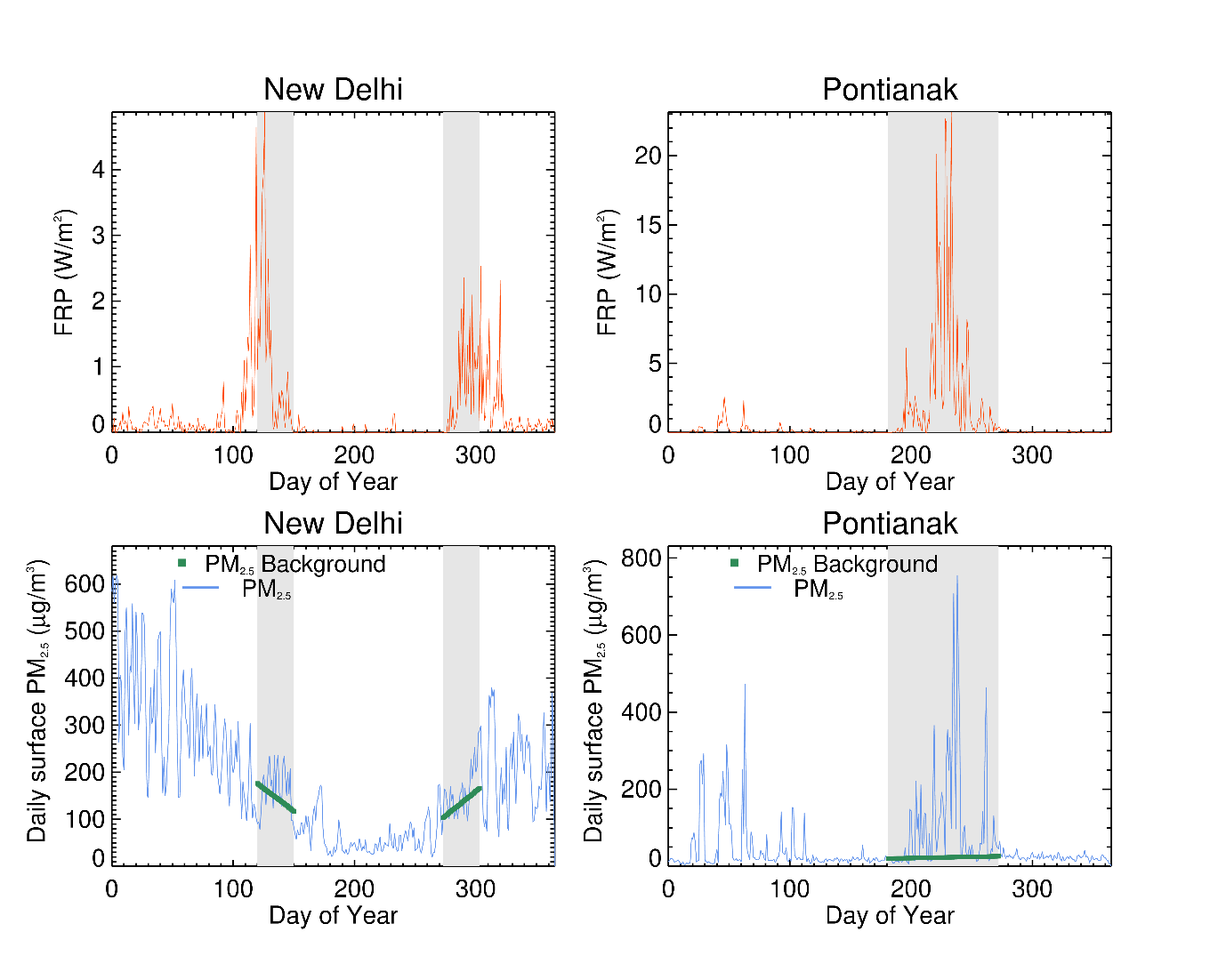
Months where the air quality of each 0.125° grid cell is considered ‘fire affected’ were selected based on levels of fire activity in both it and the immediately surrounding grid cells. An additional daily classification was based on levels of fire activity observed in both the grid cell and in the wider 20 × 20 grid cells surrounding it. For any day where the total FRP aerial density within this latter window was greater than 0.5 W.m-2 (see Figure 1b) the central grid cell was classified as potentially affected by landscape fire smoke. Months where this ‘potentially fire affected’ classification occurred for more than 30% of days led to those months being classed as part of the ‘fire affected season’. Globally, regions were identified as fire affected for generally between 2 and 7 months of the year, although some regions (e.g. southern Brazil and northern Australia) it was as high as 10 months. The months immediately prior to and subsequent to those that represented the ‘fire affected season’ were then used to estimate the background (non-fire) atmospheric concentration of PM2.5. Fires sometimes still occurred in the surrounding grid cells in these months – just not enough for the month to be identified as part of the fire season. To reduce the potential for such potentially smoke affected days being used in the calculation of ‘background’ PM2.5, the FRP aerial density and the 2m U and V wind vectors from the surrounding grid cells containing fires were used to identify ‘fire unaffected’ days for the grid cell. From these ‘fire unaffected’ days in the month immediately prior to and subsequent to the ‘fire affected’ season, the mean grid cell surface level PM2.5 concentration was taken as an estimate of the anthropogenically generated (non-fire) PM2.5 concentration. These two concentrations were then interpolated between to identify the anthropogenically generated (non-fire) background PM2.5 concentration for each month of the ‘fire affected season’. Subtraction of these monthly ‘background’ values from the total PM2.5 concentration for each month finally enabled the PM2.5 concentration contributions of landscape fires for each month of the ‘fire affected season’ to be isolated.

Fire affected regions were classified on a monthly basis, matching the temporal frequency of the underlying anthropogenic emissions inventories (MACCity and CAMS-ANTH) whose contribution to the overall (OM+BC) PM2.5 surface concentration of a region we were attempting to identify - such that the biomass burning contribution could then be isolated. We used an FRP density threshold to select these regions, and as this threshold was increased from 0.1 (low fire activity) to 2.0 W.m-2 (highly significant fire activity) the mean number of days a region was identified as being fire affected decreased from 132 to 74 globally. Constraining fire affected areas to those with reasonably significant fire activity (FRP density >0.5 W.m-2) identified regions where on average 94 days were fire affected. Identifying a month as being part of the fire season when it has 30% of days being fire affected results in 42%, 31% and 17% of land surface grid cells being classed as such during the year using FRP density thresholds of 0.1, 0.5 and 2.0 W.m-2 respectively (Figure S3). The window size defines the spatial extent over which fire activity is assessed and population exposure determined. The window size (21 x 21 grid cells) used here covers a NS and EW distance of ~ 150 km, which is smaller than the 200 km used by Liu et al. (2018) but greater than the mean smoke plume length (26 ± 20km) found over North America using Multi-angle Imaging Spectroradiometer (MISR) imagery (Val Martin et al., 2010). We assessed the sensitivity to window size using three different window sizes (11 x 11, 21 x 21 and 31 x 31), equating to between 78 and 221 km distance. As window size increases, the number of days classed annually as fire affected increased from 74 to 116, whilst the number of land surface grid cells classed being fire affected increased from 14% to 45%.

We conducted a further sensitivity analysis related to the population weighted (PW) PM2.5 calculation, as this metric characterises both the spatial variation and magnitude of surface PM2.5 concentrations. Mean continental PW PM2.5 decreases by a factor of three between use of the FRP density threshold of 0.1 W.m-2 and 2.0 W.m-2, due to the reduced inclusion of areas of low fire activity. With our selected threshold of 0.5 W.m-2, mean continental PW PM2.5 is 1.4× lower than with 0.1 W.m-2. Larger national PW PM2.5 differences are seen when changing between FRP density thresholds of 0.1 and 0.5 W.m-2 are found in Pakistan (21.1 µg.m-3), India (6.8 µg.m-3) and China (5.3 µg.m-3), areas where smaller and lower intensity fires associated with agricultural burning are often dominant (Zhang et al., 2017). Increasing the threshold to 2.0 µg.m-3 results in far less change (2.1, 1.0 and 0.1 µg.m-3 in Pakistan, India and China respectively). A sensitivity analysis to the number of days required for a month to be defined as being part of the fire season was conducted using percentage thresholds of 10, 30, 50, 70 and 90% respectively, together with our selected FRP density threshold of 0.5 W.m-2. As percentage threshold increases, the mean number of days identified as fire affected globally decreases (from 117 to 65 days), as does the national PW PM2.5. The decrease in PW PM2.5 varies with the extent of landscape fire activity. In India, decreases from 3.2 to 0.32 µg.m-3 are seen when switching between a 10% and 90% threshold, whilst in Angola where fire activity is confined within a very intense fire season a decrease from 13.3 to 8.5 µg.m-3 occurs. The 0.5 W.m-2 and 30% of days threshold applied to identify fire affected months used in this analysis omits regions that experience lower intensity and/or sporadic landscape fire activity. Examples include parts of the south-east USA and eastern China (Figure S3), where agricultural landscape fires occur with typically small/lower intensity characteristics. The potential health impacts of landscape fire smoke on populations residing in these regions is therefore largely unaccounted for. Window size influences the spatial extent of the area we find is impacted by smoke emissions, and as window size increases from 11 x 11 to 31 x 31 the global average PW PM2.5 increases from 1.8 to 2.3 µg.m-3. The largest increase (from 0.6 to 1.74 µg.m-3) is found in south Asia. In India, for example, the PW PM2.5 increases from 0.8 to 3.8 µg.m-3 with this change in window size. Smaller differences are found over Africa, where fire activity is more spatially extensive, with the continual average PW PM2.5 increasing from 3.3 to 4.7 µg.m-3 using the same 11 x 11 to 31 x 31 window size change. Over Canada and Russia, a larger increase in the PW PM2.5 (0.25 to 1.05 µg.m-3) is found with increasing window size because fire activity there is more spatially separated into discrete events.

Figure 6 shows for Delhi (Northern India) and Pontianak (Sumatra, Indonesia) in 2018 the CAMS-generated surface level PM2.5 concentration timeseries (BC+OM only), along with our estimate of the anthropogenic background (non-fire) PM2.5 signal (green line) subtracted to generate the fire-contribution for each month of the fire affected season. The ‘fire affected season’ itself is indicated by the grey bars, and for Delhi the temporal offset seen between this and the fire activity (upper plot) result from fires south of the city which do not transport smoke in the direction of Delhi. Our anthropogenic background estimate for Delhi captures the surface level PM2.5 trend very well, and the difference between this and the overall PM2.5 surface level concentration represents our estimate of the PM2.5 contribution coming from landscape fire sources (which are located west of Delhi in the Punjab and Haryana, Sembhi et al., 2020). The November ‘fire affected’ season we identify for Delhi is related to rice residue burning in these Indian States, and the baseline background is estimated to be 197 µg.m-3, which falls within the 130–290 µg.m-3 range found for Delhi by Cusworth et al. (2018) and is similar to the 15 year average 171 – 202 µg.m-3 calculated by Chowdhury et al. (2019). In Pontianak the non-fire source is far lower than in Delhi and appears reliably estimated based on the non-fire season values, and in Portugal (not shown) our annual average PM2.5 baseline background varies between 0.04 (2018) and 6.3 (2017) µg.m-3, consistent with the estimates of Kollanus et al. (2017) for a high fire year (3-5 µg.m-3; 2005) and a low fire year (0.01-0.03 µg.m-3; 2008).

Brauer et al. (2019) previously used the GFED v4.1 fire emissions inventory and the National Aeronautics and Space Administration (NASA) Goddard Institute for Space Studies (GISS) climate model to estimate the contribution of landscape fires to global surface level PM2.5 concentrations for the year 2016. Comparison of our results to those of this study at a 2.5 x 2.0° grid cell scale indicate a moderately low bias of 1.7 µg.m-3, though a relatively high RMSE and scatter at 5.9 and 5.7 µg.m-3 respectively. Frequency distribution analysis of the intercomparison data indicates that 77% of grid cells are within +/- 3 µg.m-3 of one another, but 20% of CAMS estimates are higher by more than 4 µg.m-3, whereas only 2% of the NASA GISS estimates are higher by the same amount. On a continental basis (Table S2), the greatest difference is found in Africa, where the bias and RMSE are 4.1 and 7.51 µg.m-3 respectively. It is also clear that the correspondence between the two datasets is quite variable, perhaps reflecting differences in the fire emissions inventories used by the two approaches and the differing methods used for estimating fire contributions to the surface level PM2.5 concentrations. A similar analysis is conducted over the Pacific Northwest (an area ~ 20° × 10°) using landscape fire emitted PM2.5 surface concentration estimates from the US Forest Service Airfire BlueSky dataset (O'Neill, et al., 2018), this being based on a modelling framework coupling fuel consumption (CONSUME), meteorological (WRF) and dispersion (CALPUFF or HYSPLIT) models to predict fire growth and forecast PM2.5 emissions from landscape fires (Larkin et al., 2009). Hourly PM2.5 surface level concentrations were available between July and September 2018 and were used to calculate mean PM2.5 over this time frame, these being regridded from 4 km to 0.25° to account for any offset between them and the CAMS datasets. Comparison to CAMS values reveals a large difference, with average PM2.5 concentrations of 14.8 µg.m-3 and 0.29 µg.m-3 for the CAMS and BlueSky respectively – leading to a bias and RMSE of 14.5 µg.m-3 and 29.8 µg.m-3respectively. Maximum daily PM2.5 surface level concentrations show similar temporal dynamics, though the CAMS estimates are on average 15× higher and frequently exceeding 1000 µg.m-3 in contrast to a peak of <320 µg.m-3 in the BlueSky dataset. These differences will in part be due to the differing fire emissions inventories employed (e.g. Strand et al., 2012; Lui et at 2020; Vongruang and Primonsree, 2020), but also by the fact that the smoke is released at the surface in CAMS (up until July 2019) whereas in the BlueSky they are released at a height of 100m. Surface PM2.5 concentration is very sensitive to the plume rise scheme applied, with higher injection heights lowering the surface concentration (Li et al., 2020; Majdi et al, 2019). The more intense fires in the Pacific Northwest typically result in greater smoke emissions rates than those found in (e.g.) Africa and Australia, which may explain the large discrepancies in landscape fire PM2.5 concentrations found. Li et al. (2020) illustrate the variability found in surface PM2.5 concentrations from landscape fires due to the use of different meteorological fields, fire emissions inventories and the plume rise schemes, which together resulted in a maximum range of 1000 µg.m-3. In addition to differences in the magnitude of the surface level PM2.5 concentrations, the area affected by the smoke is also quite different between the two methods - with the CAMS area being on average 69% smaller than that estimated by the BlueSky system. This highlights a limitation in the methodology applied herein when landscape fires that affect a grid cell occur at distances further away than the window size (~150km), which is more is likely to be the case in north America and the Boreal region where long-range transport of smoke from particularly intense fires can occur (e.g. Saarnio et al., 2010; Dirksen et al., 2009; Brey et al., 2018).



*Figure 6: CAMS-derived time-series of daily fire activity (top row) and PM2.5 surface level concentration (bottom row) in 2018 for two locations. Top row shows fire radiative power areal density (W.m-2), accumulated within a window of 21 × 21 0.125° gridcells surrounding (a) New Delhi (India) and (b) Pontianak (Sumatra). Bottom row shows ambient atmospheric surface level PM2.5 concentration for (b) New Delhi and (b) Pontianak (Sumatra), with the contribution from non-fire sources during the fire-affected period identified and shown by the green lines (see main text). ‘Fire affected’ period is based on the FRP data shown in (a) and (b) and is indicated by the grey bar. Temporal offsets between fire activity and the smoke affected period result in Delhi from fires south of the city, which unlike those in the West do not transport smoke in the direction of Delhi.*

Our mapping of the mean annual PM2.5 surface level concentration contributed to by landscape burning is shown in Figure 7a, and it is important to realise that this is not representing just the fire emissions in each grid cell, but those coming in from surrounding areas and even surrounding countries. Figure 7b shows the fraction of the overall mean annual PM2.5 surface level concentration contributed to by landscape fires. It is mostly in parts of the boreal and tropical forests and the tropical savannahs where landscape fires contribute most (Figure 7b). For 2016-19 we calculate an overall global mean excess PM2.5 surface level concentration of 3.2 µg.m-3 coming from landscape fires, and whilst 90% of gridcells have fire-contributions of less than 15 µg.m-3 parts of the Boreal forest (Canada and Russia) and the tropical or sub-tropical areas of southeast Asia, central and West Africa and the Amazon show contributions of up to 80 µg.m-3. For example, in northern Laos concentrations peak at around 100 µg.m-3 (Figure 1a) and represent almost the entire PM2.5 source for this area (Figure 7b), and is associated with shifting cultivation, rice residue burning and large-scale land clearance of forests (Muller et al., 2013). By comparison, savannah and grassland regions in South America, southern Africa and northern Australia show typical landscape fire-sourced PM2.5 concentrations of less than 30 µg.m-3, even though they are the location of significant fire activity (Figure 1b). Such differences are likely to be driven by the far higher forest and peatland fire PM2.5 emissions factors (Akagi et al., 2011; Wooster et al., 2018; Andreae et al., 2019) and fuel consumption rates and totals (Van Leeuwen et al., 2014; Huijnen et al., 2016; Roberts et al., 2018; Ivanova et al., 2019) compared to those of grassland and savanna fires.

a)

Map

Description automatically generated

b)

*Map

Description automatically generated*

*Figure 7: (a) Mean annual PM2.5 surface level concentrations resulting from landscape fire-emitted PM2.5, and (b) the fraction of the overall mean annual PM2.5 surface level concentration (OM+BC) resulting from landscape fires.*

**6. nations and populations most impacted by landscape fire emissions**

The population weighted (PM) PM2.5 concentrations due fire emissions are understandably lower than those from all emissions sources but remain comparatively high in many places. Countries in Asia, such as China, India, Nepal and Pakistan experience poor air quality due to both fire and anthropogenic sources. In contrast, Laos, Myanmar, Cambodia, and Thailand are affected mostly by landscape fire emissions, with population weighted PM2.5 ranging from 4 – 28 µg.m-3. The spatial distribution of PW PM2.5 in Africa is like that shown for all sources in Figure 4a as anthropogenic emissions are low in many countries. Six countries exceed the WHO annual 10 µg.m-3 guideline; with the worst fire-sourced air quality found in countries in Africa including Sierra Leone, Guinea and DRC, with annual PW PM2.5 concentrations exceeding 17 µg.m-3.

Our data confirm that landscape biomass burning is the largest contributor to the population weighted PM2.5 concentration in many countries. Figure 7b presents the ratio of fire emitted PM2.5 to total PM2.5 which highlights the significant contribution that landscape fires play in controlling surface level atmospheric PM2.5 concentrations in the boreal region, central Africa and central South America. In Africa, on average fire emitted PM2.5 makes up 14.2% of national annual average PM2.5 atmospheric concentrations, and the largest contributor by percentage is in DRC where they make up 45% of PM2.5 sources. Fire emitted PM2.5 has a lower contribution on average in Asia at 4.3%, with a maximum of 61% (Laos) and minimum of <<1% in Afghanistan. In Europe, North America and South America, the average contribution of fire emissions to the national total PM2.5 annual mean concentration is 2.5%, 7.1% and 9.1% respectively. Figure 8a shows the populations exposed to fire emitted PM2.5 where India again features prominently and hosts the greatest number of people worldwide exposed to landscape-fire generated ‘hazardous’ (PM2.5 > 250 µg.m-3) air quality. However, unlike for the all-source values, the Democratic Republic of the Congo (DRC) is identified as a particularly affected location – something that can be also identified on the map of Figure 7a.

Overall our analysis shows that the vast majority of the global population (6.5 billion) reside in areas where landscape fires make a minimal contribution to overall air quality (< 12 µg.m-3,AQI related to fire sources classed as ‘good’), but 43.9 million people live in areas classed as ‘unhealthy’ (PM2.5 >55 µg.m-3) due to landscape fires. Globally, 4 million people on average are exposed to ‘hazardous’ (PM2.5 >250 µg.m-3) air quality for at least one day per year as a direct result of landscape fires, with 84% of these being in countries listed in Figure 8a, dominated by Africa and south and south-east Asia. When assessed in terms of the percentage of the population exposed (Figure 8b), Laos (2.5%) and Sierra Leone (2.5%) have the greater percentage of their population at risk from ‘hazardous’ (PM2.5 >250 µg.m-3) air quality coming from landscape fire sources. The temporal variation of global average (2016 – 2019) population weighted PM2.5 (Figure S4) due to landscape fire emissions indicates March and April as being the worsted affected months. During this time, fires are prevalent across the tropics north of the equator (Figure S5) with south and SE Asia particularly affected. Fire occurrence in North Africa and northern South America elevate PW PM2.5 concentrations between November and February whilst biomass burning in southern hemisphere Africa and South America have greatest impact between May and September. Figure S6 shows the annual average daily PW PM2.5 in four countries (India, DRC, Laos and Brazil), which experience landscape fire activity during different times of the year. India broadly had two fire seasons with the greatest impacts in March/April and November, whilst Laos has a single fire season in April but which results in significantly degraded air quality. The extreme magnitude of the PW PM2.5 in Laos and Myanmar, which peaks at ~90 µg.m-3 over the same timeframe, significantly contribute to the increased global mean PW PM2.5 shown in Figure S4 at this time. In Brazil, the greatest exposure to PM2.5 occurs in August and September whilst, in the DRC, PM PM2.5 concentrations are influenced by the fire seasons in both northern (February/March) and southern hemisphere Africa (May-August). It is clear from Figure S6 that the landscape fire PM2.5 display significant daily variations, depending on the strength of the emissions source and the population density.

a)

A screenshot of a cell phone

Description automatically generated

b)

A screenshot of a cell phone

Description automatically generated

*Figure 8. Countries whose populations have the greatest exposure to harmful levels of landscape fire-emitted ambient atmospheric PM2.5 according to our analysis and the US EPA’s Air Quality Index (AQI) definitions of PM2.5 exposure (Table S1). (a) Top 15 countries having the greatest numbers of people exposed to hazardous air quality due to landscape fire emissions, and (b) top 15 countries with the greatest percentages of their populations exposed to ‘hazardous’ (PM2.5 >250 µg.m-3) air quality due to landscape fire emissions. Note that the x-axis is reverse logarithmic in (a).*

**7. Global Burden of Disease Estimation**

Sections 4 and 6 have highlighted the extent to which national populations are exposed to poor air quality as a result of both all source and fire emitted PM2.5 contributions. In the most extreme case, such exposures can result in mortality of individuals. The methodology developed by the Global Burden of Disease initiative (GBD 2010, 2013; Lim et al., 2012; Vos et al., 2015) to quantify the health impacts caused by air pollution uses annual average atmospheric PM2.5 concentrations and applies to these integrated exposure–response functions (IERs) for specific causes of death (e.g. ischaemic heart disease, lung cancer) (Cohen et al., 2015; Brauer et al., 2016). Key limitations are that the annual average PM2.5 concentration may not adequately represent regions exposed to smoke during only part (or even all) of the fire season, and cause-specific IERs may not be appropriate for landscape fire emitted PM2.5. Instead of this approach, we used the methodology of Johnston et al. (2012), accounting for both short-term ‘sporadic’ exposure and longer-term ‘chronic’ exposure. As with Johnston et al. (2012), we first classed cells to be affected by landscape fire smoke if their fire-emitted PM2.5 surface level concentration (Figure 7a) exceeds the 90th percentile of the log-normally distributed PM2.5, which we find to be 3.9 µg.m-3. This is close to the 3 µg.m-3 found by Johnston et al. (2012), even though that work was based on a different fire emissions inventory (GFED), a different atmospheric model (GEOS-Chem) and was calculated over an earlier set of years (1997-2006) to that used here (2016-2019). Using this metric, we find nearly half a million (475,992) 0.125° CAMS grid cells whose air quality is significantly fire affected, equating to 0.9 % of total global land area (not including Greenland or Antarctica). We split these cells into those that are chronically affected and those that are sporadically affected by smoke from landscape fires, using criteria defined by Johnston et al. (2012). Chronically affected cells are defined as those where our mean monthly fire-sourced PM2.5 surface level concentration (Section 5) exceeds the 3.9 µg.m-3 threshold for three months per year in three out of the four years examined, and this is relevant to 156,282 CAMS grid cells globally. The remaining 319,710 fire-affected cells are classed as sporadically affected by landscape fire smoke. We also performed a second calculation, restricting chronically affected cells to those affected for three months per year in all four years. This identifies fewer cells (93,204) as being chronically affected, with the remainder (382,788) again classed as sporadically affected.

For the grid cells classed as having their air quality sporadically affected by landscape fire smoke, we followed Johnston et al. (2012) and estimated smoke-related mortality (M) as a function of the number of days per year that the fire-emitted excess PM2.5 concentration exceeds a series of thresholds (300, 200, 100, 50, 40, 30, 20, 10, 5, 4, 3, 2, and 1 µg.m-3):

[6]

where is the annual mortality in each cell, is the PM2.5 smoke threshold of possible thresholds, is the number of days between and , and is the relative rate exposure estimate for short-term exposure. The annual mortality estimate () is based on the WHO national scale all-age (0 - 60 years) mortality rates for 2016 which is integrated with the WorldPop age-gender distributed dataset introduced in Section 2.2. Johnston et al. (2012) calculated as the mean of values from a series of past studies looking at PM2.5 exposure and health impacts, finding for PM2.5 concentrations between 5 and 200 µg.m-3 a linear response of a 0.11% increase in mortality per 1 µg.m-3 increment of PM2.5. Impacts coming from PM2.5 < 5 µg.m-3 are omitted, whilst those from PM2.5 > 200 µg.m-3 are fixed at that value.

Similarly, as per Johnston et al. (2012), the mortality rate of cells identified as chronically affected by landscape fire smoke is determined via:

[7]

where is the average annual background PM2.5, is the counterfactual concentration and is the relative rate for long-term exposure, taken as a linear response of 0.64% per 1 µg.m-3 increment applied to the mean annual PM2.5 concentration up to 50 µg.m-3, after which concentrations are set to 50 µg.m-3. The counterfactual concentration is an estimate of the fire emitted PM2.5 surface level atmospheric concentration that would exist naturally in the absence of anthropogenically set fire (Bowman et al., 2011). Unlike Johnston et al. (2012), who calculated the counterfactual concentration on a WHO sub-regional basis, here we calculate it here at both a 0.125 ° grid cell-based and national scale as the minimum monthly running mean PM2.5 concentration.

Identifying the chronically affected grid cells as those which have three months classed as smoke affected in three out of four years, and estimating the counterfactual concentration on a national basis, we calculate the annual mortality due to fire emitted PM2.5 to be close to three quarters of a million citizens (677,745). This is 0.52% of total global mortality according to the WHO 2016 national mortality rate, but between 8 and 21% of global annual mortality ascribed to ambient air pollution (Giannadaki et al., 2017; WHO, 2016, Lelieveld et al., 2015; Burnett et al. 2018). The highest mortality levels resulting from landscape fire emissions occurs in Africa (338,494) and Asia (278,879), with far fewer (59,033) in the Americas and Europe combined. Locations identified as being chronically affected by landscape fire smoke emissions account for the vast majority (97%) of these figures. The African country with the highest average annual mortality related to landscape fire emitted PM2.5 is the DRC (106,487) and in Asia it is China (89,369). However, when stratified according to the percentage of their overall mortality levels, populations in Sierra Leone and Laos respectively suffer the greatest health consequences in Africa and Asia respectively, with 10.6% and 11.8 % of their annual average overall mortality (due to all causes of mortality; WHO, 2016) respectively caused by fire-emitted PM2.5.

Looking at the sensitivity of these results to the use of the counterfactual concentration, when the counterfactual is calculated on a gridcell basis rather than a national basis, the annual average global mortality estimate due to landscape fire smoke drops by 3% to 655,792, whereas when no counterfactual is applied it rises to 1.22 million. The latter highlights the potential maximum impact that we estimate landscape fire emissions have on human mortality, even from fires that are a ‘natural’ part of ecosystems and not instigated by human actions. Mortality estimates derived when chronically affected gridcells are defined as being fire-affected for three months in all four years are 25% lower (513,685) but which still equates to between 6 and 16% of global annual mortality ascribed to ambient air pollution (Giannadaki et al., 2017; WHO, 2016, Lelieveld et al., 2015; Burnett et al. 2018)

**8. Summary and CONCLUSIONS**

We have assessed the global impact of surface level PM2.5 on air quality and human exposure to ambient air pollution, using outputs from the Copernicus Atmospheric Monitoring Service (CAMS). Analysis of the spatial distribution of annual surface level PM2.5 highlights the degraded air quality experienced by populations of arid regions in north Africa, the Middle East and south Asia, where dust aerosols dominate and elevate the mean annual population weighted PM2.5 above 50 µg.m-3, well above the WHO annual recommended limit of 10 µg.m-3. Countries in south Asia, particularly India and China, also show similarly high (>50 µg.m-3) annual average population weighted PM2.5 levels (Figure 4a) largely due anthropogenic emissions, principally from residential, energy and industrial sources (Zhang et al., 2007; Upadhyay et al., 2018). Consequently, the greatest number of people exposed to hazardous air quality throughout the year are found in India and China. Approximately, 59% of countries world-wide have an annual average population weighted PM2.5 exceeding the WHO annual 10 µg.m-3 guideline, and globally on average 1.5 billion people are subjected to ‘unhealthy’ (>55 µg.m-3) air quality and 67.2 million of these to ‘hazardous’ (>250.5 µg.m-3) air pollution.

Using an approach to isolate the contribution that landscape burning makes to overall PM2.5 surface level concentration, we calculated the impact of landscape fires on air quality and the degree of human exposure to PM2.5. In Laos, Myanmar, Cambodia and Thailand, fire emissions were found to account for 61%, 29%, 22% and 14% respectively of the mean annual surface level PM2.5 concentrations, which compares to 30%, 24%, 13% and 16% respectively found by Reddington et al. (2019) in 2014/15 using the WRF-Chem model and the EDGAR and Fire Inventory from NCAR (FINN) inventory. Conibear et al. (2018) estimate the population weighted PM2.5 concentration related to biomass burning in India (2014) as 1.6 µg.m-3, essentially the same as estimated herein (1.56 µg.m-3). Globally, we find for 2016-19 an overall global mean excess PM2.5 concentration of 3.2 µg.m-3 contributed to by landscape fires, with the largest contributions in parts of the Boreal forest (Canada and Russia) and tropical or sub-tropical areas of southeast Asia, central and West Africa and the Amazon. The highest values are found in northern Laos, where values peak at 100 µg.m-3 and are likely to be associated with shifting cultivation and rice residue burning and possibly the large-scale land clearance of forests. Population weighted PM2.5 exposure exceeds 25 µg.m-3 in Laos and is also close to that in Sierra Leone. Using the approaches previously adopted by Johnson et al. (2012) we estimated annual average mortality related to exposure to fire emitted PM2.5 to be 677,745, with highest mortality in Asia (278,879) and Africa (338,494). 267,382 of these deaths (39%) are related to children less than 5 years old according to the intersection of our data with those from the WorldPop population database. Countries in Africa and Asia with the highest average annual mortality from fire-emitted PM2.5 are the DRC (106,487) and China (89,389) respectively. However, when stratified according to the percentage of national all-cause mortality due to fire emitted PM2.5, the nations of Sierra Leone (10.6%) and Laos (11.8%) in Africa and Asia respectively suffer the greatest health consequences. To place this in context, as of 10th July (2020), 554,721 deaths had resulted from the corona virus pandemic (European Centre for Disease Prevention and Control, 2020). Our estimate of nearly three quarters of a million excess deaths annually from landscape fire emissions is 50% higher than the 339,000 estimated by Johnston et al. (2012). Lelieveld et al. (2015) estimate 234,000 premature deaths in Africa (2010) due to all-source PM2.5, 90,000 of which occur in those less than 5 years old. Our corresponding mortality estimate for Africa and the mortality rate for those under 5 are somewhat higher for the fire-only sources, at 338,494 and 201,212 respectively, with 34% of the latter occurring in the DRC (68,590). Kollanus et al. (2017) estimate 1,080 deaths in Europe in 2005 (an average fire year, see Figure S1) which is close to our estimate (1159). It is clear that significant differences exist between these mortality estimates, arising from methods applied to estimate PM2.5 concentrations from source emission estimates, differences in the assumed populations at risk and the relationship between mortality rate and PM2.5 exposure. The landscape fire PM2.5 concentrations estimated here are higher than those of other studies which will contribute to the differences in mortality totals. We find that landscape fires represent between 8 and 21% of global mortality related to ambient air pollution, so is certainly a significant contributor (Giannadaki et al., 2017; WHO, 2016, Lelieveld et al., 2015; Burnett et al. 2018). Whilst we have estimated excess deaths using published dose response functions used previously in similar works, there are limited studies of the long-term health effects of landscape fire smoke exposure and future health consequences of the younger generation are uncertain. Nonetheless, this study has highlighted the impact that landscape fire emissions have on air quality and annual mortality at the national scale and the role that systems such as CAMS can play in better understanding these interactions. The method developed herein is not directly able to be applied in close to real-time to estimate landscape fire emissions health impacts, even though the surface level PM2.5 concentration data is provided in near real time by CAMS. For example, currently we use data either side of the fire season to estimate the non-fire sourced contribution to the surface level PM2.5 concentrations. However, the approach could be adapted – for example to use only the pre-fire PM2.5 concentrations to estimate the non-fire contribution, or if the CAMS data were updated to record the PM2.5 concentration coming from different sources. Furthermore, the health impacts due to total ambient atmosphere PM2.5 concentrations could be estimated now in NRT, including in forecast mode up to five days ahead, based on their being appropriate exposure–response functions.

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