 doi:10.20944/preprints202103.0243.v1

The summer 2019-2020 wildfires in east coast Australia and their impacts on air quality and health in New South Wales, Australia

Hiep Duc Nguyen (1)(4)(5)(*), Merched Azzi (1), Stephen White (1), David Salter (1), Toan Trieu (1), Geoffrey Morgan (2), Mahmudur Rahman (1), Sean Watts (1), Matthew Riley (1), Lisa Tzu-Chi Chang (1), Xavier Barthelemy (1), David Fuchs (1), Kaitlyn Lieschke (1), Huynh Nguyen (3)

(1) Department of Planning, Industry and Environment, NSW, PO Box 29, Lidcombe 2141, NSW, Australia

(2) University Centre of Rural Health, North Coast, University of Sydney, Lismore, NSW 2480, Australia

(3) Faculty of Engineering & Information Technology, University of Technology Sydney, Ultimo, NSW 2007, Australia

(4) Environmental Quality, Atmospheric Science and Climate Change Research Group, Ton Duc Thang University, Ho Chi Minh City, Vietnam

(5) Faculty of Environment and Labor Safety, Ton Duc Thang University, Ho Chi Minh City, Vietnam

(*) Correspondence: hiep.duc@environment.nsw.gov.au, nguyenduchiep@tdtu.edu.vn

Abstract

The 2019-2020 summer wildfire event on the east coast of Australia was a series of major wildfires occurring from November 2019 to end of January 2020 across the states of Queensland, New South Wales (NSW), Victoria and South Australia. The wildfires were unprecedent in scope and the extensive extend of the wildfires has caused smoke pollutants transported not only to New Zealand but across the Pacific Ocean to South America. At the height of the wildfires, smoke plumes were injected into the stratosphere at height up to 25km and hence transported across the globe.

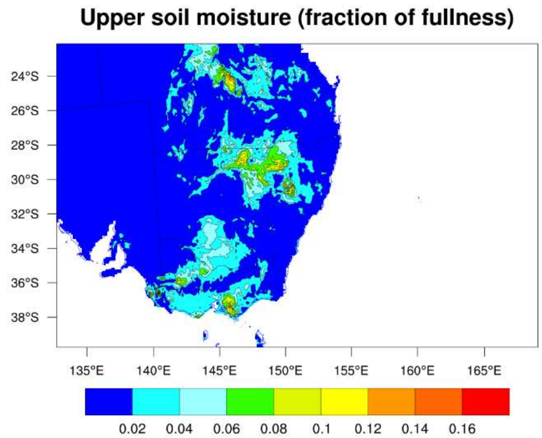
Based on meteorological and air quality simulation using WRF-Chem model, air quality monitoring data collected during the bushfire period and remote sensing data from MODIS and CALIPSO satellites, the extend of the wildfires and the pollutant transport, and their impacts on air quality and health on exposed population in NSW can be analysed. The results showed that WRF-Chem model using Fire Emission Inventory from NCAR (FINN) predicts the dispersion and transport of pollutants and the predicted concentration of $PM_{2.5}$ and other pollutants from wildfires reasonably well when compared with ground-based and satellite data. The impact on health endpoints such as mortality, respiratory and cardiovascular diseases hospitalisation across the modelling domain is then estimated. The estimated health impact is comparable with previous study based only on observation data, but the results in this study provide much more detailed spatially and temporally with regards to the health impact from the 2019-2020 wildfire.

Keywords: Wildfires, summer 2019-2010, WRF-Chem, pollutant transport, air quality effect, health impact.

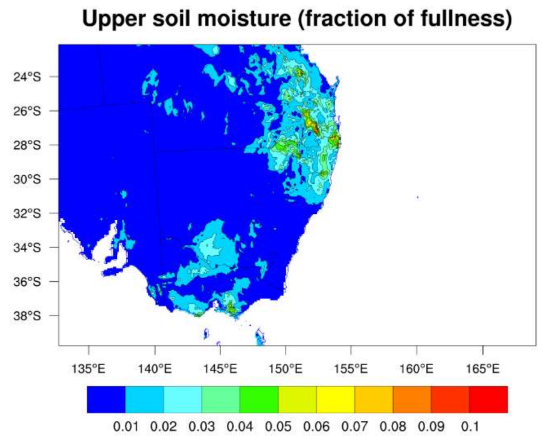
 doi:10.20944/preprints202103.0243.v1

1. Introduction

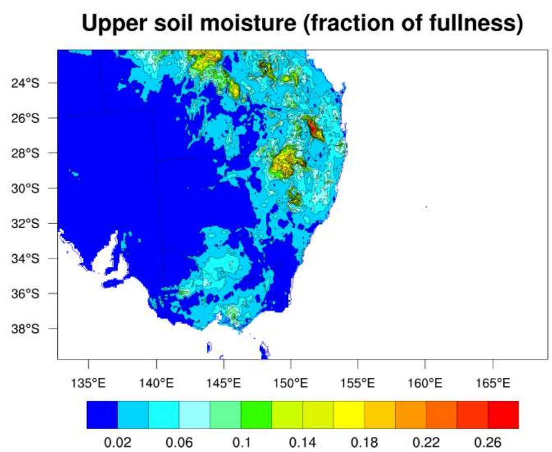
New South Wales (NSW) and most of eastern Australia was in drought from 2018 to the end of 2019. Wildfires in the northern NSW and central Queensland occurred earlier in austral spring from 7 September to the end of the month. In October 2019, spring rain then relieved part of western NSW. This resulted in increasing vegetation growth which increased the likelihood of fires subsequentially during summer due to more fuel load available when meteorological condition is more favourable to ignite fires. Favourable condition, such as high temperature, low humidity, low soil moisture making the Forest Fire Danger Index (FFDI) at danger level, occurred in the summer 2019 in eastern Australia. The soil moisture map for the month November, December 2019 and January 2020 as shown in Figure 1. The upper soil and root zone soil moisture as a fraction of fullness is low in most of NSW, north west Victoria and South Australia, especially in December 2019.



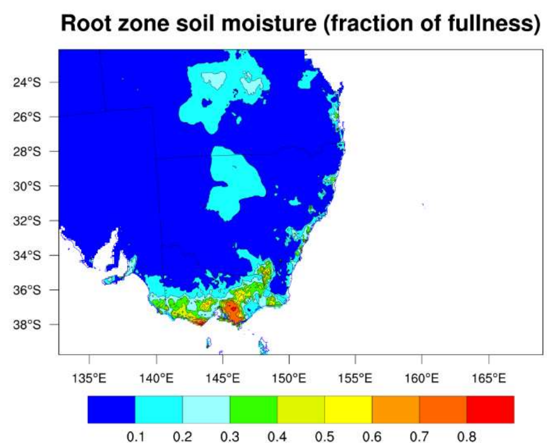
(a)



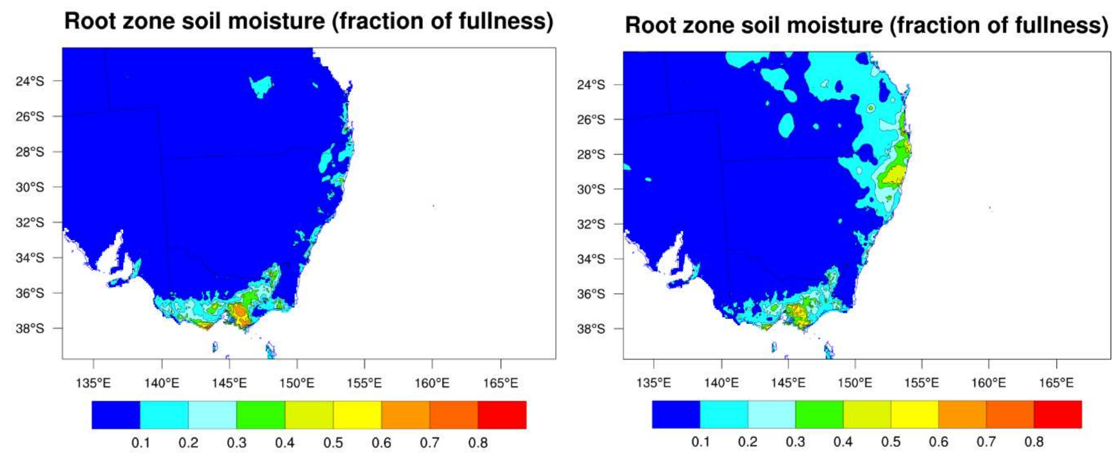
(b)



(c)



(d)



(e) (f)

Figure 1 – Upper soil moisture in November 2019 (a), December 2019 (b) and January 2020 (c). Root zone soil moisture in November 2019 (d), December 2019 (e) and January 2020 (f) (Source: Bureau of Meteorology, Australia Water Resource Assessment (AWRA) http://www.bom.gov.au/water/landscape/#/sm/Actual/day/-28.4/130.4/3/Point////2019/4/10/)

As for fuel load, the change in vegetation cover from October when dry bare land cover much of western NSW to November after spring rain is significant as shown in Figure 2. After the rain, the drought was then only confined to far western NSW and higher vegetation growth occurred much of the rest of NSW and Victoria.

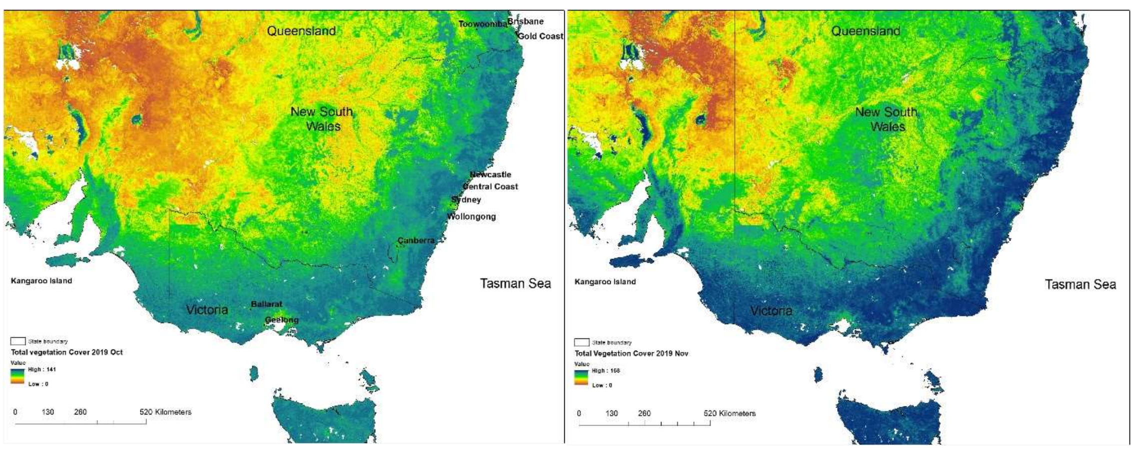


Figure 2 – Vegetation cover over south east Australia in October (left) and November 2019 (right) (source:http://www-data.wron.csiro.au/remotesensing/MODIS/products/public/v310/australia/monthly/cover/).

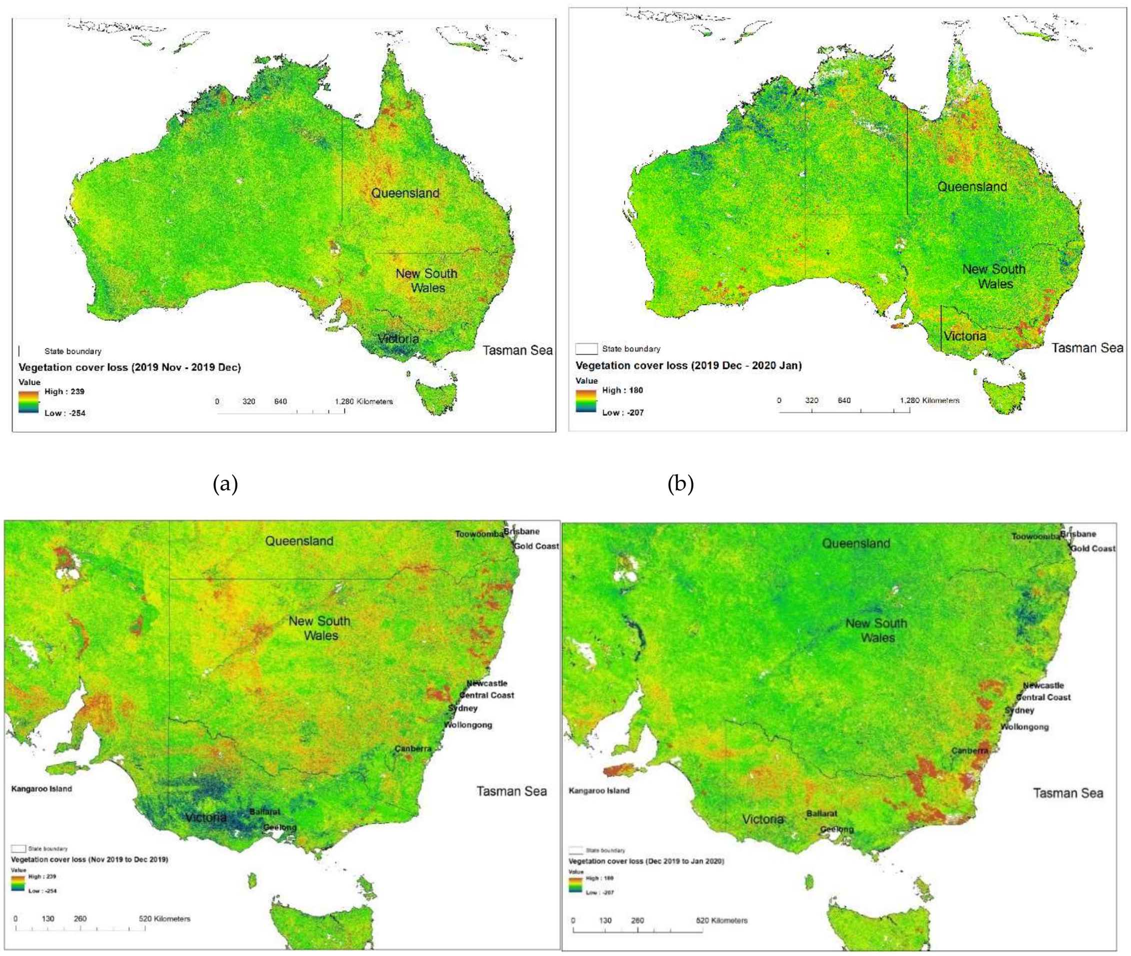
In November, the rain alleviated the drought condition in mid-west NSW and promoted the green shoot with increase vegetation cover along the coast of NSW and Victoria.

With low soil moisture and high fuel load along the coast, the occurrence of high temperature and low humidity in late spring and early summer of 2019 caused wildfires to be started and gradually the fires consumed much of the south east coastal areas of Australia where relatively high fuel load was concentrated. This convergence of extreme events or conditions (low soil moisture, high fuel load, high temperature and low humidity) over the large region of the south eastern coast of Australia results in a compound megafire event consisting of many wildfires lasting from early November 2019 to mid-January 2020. This compound extreme climate event can be expected to

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 March 2021 doi:10.20944/preprints202103.0243.v1

occur more frequently in the future under climate change scenarios of a global warming world from increasing anthropogenic greenhouse emission.

For NSW, the austral late spring and summer wildfires started in the northern part of the state and the Blue Mountains near Sydney in late October, November, December 2019 followed in early January 2020 and onwards, in the southern part of the state to the border with Victoria, with large areas near the coast on fires. Victoria and South Australia also had many fires during January starting from 3-5 January 2020. Figure 3 shows the monthly vegetation cover loss from November to December 2019 due to wildfires (vegetation cover in November subtracted from December 2019) and from December 2019 to January 2020 over Australia and over NSW. The summer 2019/2020 wildfire is unprecedented in scale as the fire occurred in several states and the burn area in NSW alone was 5.68 million ha while Victoria was 1.58 million ha [1]. Thirty-three people lost their lives due to this black summer 2019/2020 wildfires [2].



(a) (b)

(c) (d)

Figure 3 – Vegetation cover loss from November to December (a) and (c) and from December to January (b) and (d) show the two stages of the summer 2019-2020 wildfires: north coast of NSW, Blue Mountains in November and December 2019 and the south coast toward Victoria, Victorian East Gippsland, the Mallee region west of Bendigo, South Australia and Kangaroo Island, and south Western Australia in January 2020.

The 2019-2020 summer wildfires were of such intense and widespread that it was known later as the Black Summer wildfires. Figure 4 shows the total area burnt for NSW after the summer 2019-2020 bushfire event. The intensity of the wildfires has caused smoke plumes and emitted air pollutants dispersed over a wide region in the east coast of Australia, across the Tasman Sea to New Zealand in January 2020. Injected plumes of smoke and pollutants into the atmosphere high into the upper troposphere and at times into the stratosphere causing the smoke particles transported across the Pacific to South America (Argentina and Chile) and beyond [3]. The effect of the wildfires on environment and population exposure to emitted air pollutants were studied by many authors. Emitted pollutants from wildfire deteriorate ambient air quality affecting people health, deposition of fire pollutants such as Fe element on water body surface like ocean also stimulates the growth of phytoplankton. After dust deposition, pyrogenic (fires and anthropogenic combustion) Fe is the second largest source of Fe deposition on the ocean and is an important contributor to daily, seasonal, and interannual variability of Fe in the ocean basins [4].

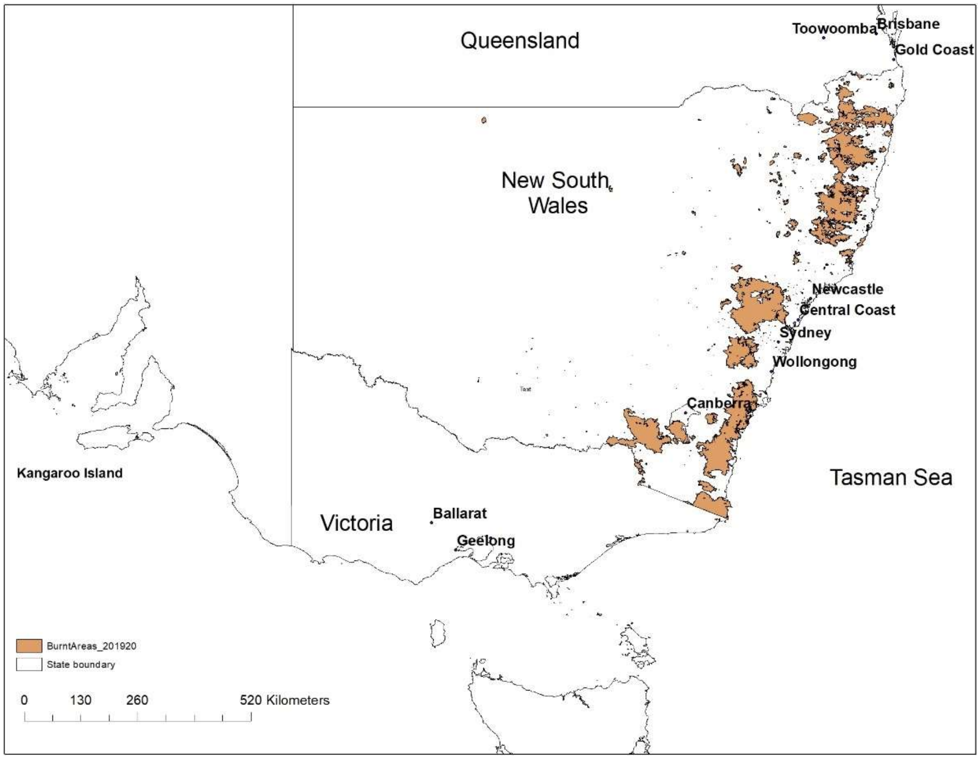


Figure 4 – Total burnt areas in NSW in summer 2019-2020 bushfire event (Source: DPIE)

It was estimated the wildfires released 400 megatonnes of carbon dioxide (CO_2) into the atmosphere, equal to three-quarters of Australian industry emissions in 2018–19 [5]. Besides greenhouse gas CO_2, wildfires emitted a wide range of pollutants such as nitrogen oxides (NO_x), particles (PM_{10}, $PM_{2.5}$), various species of hydrocarbons. These pollutants can cause serious health effect on exposed population, especially the susceptible people such as children and the aged people. Knibbs et al. 2018 [6] have shown exposure of NO_2 in children results in reduced lung function and asthmatic conditions in susceptible children. Increase in $PM_{2.5}$ concentration has been shown to have impact on a number of health endpoints on exposed population, such as increase in mortality rate, respiratory and cardiovascular diseases hospitalisation [7]. Health cost of population exposure to smoke particles from wildfire events in Tasmania between 2010 and 2019 was estimated to be AUS$ 16 million annually on average but for extreme wildfire increase up to AUS$ 34 million [8].

A number of studies has been recently conducted to estimate the impact of the 2019-2020 wildfires [9] [10] or review the effect of wildfires on a number of health endpoints including respiratory, chronic obstructive pulmonary disease (COPD), cardiovascular, asthma diseases hospital admissions [7]. As the summer wildfires 2019-2020 is unprecedented in temporal duration and spatial scale and affecting most of the populated east coast of Australia covering the 3 states of Queensland, New South Wales and Victoria, and air quality monitoring data is sparse across this large domain and not adequate to determine the exposure accurately for health impact, therefore this study uses a modelling approach to calculate the ground pollutant concentration at high spatial resolution for air quality and health impact study.

Previous studies have used air quality models such as CCAM-CTM [11], WRF-CMAQ [12] [13] to assess the impact of fires on air quality by determining the dispersion, transport of emitted pollutants across the study domain. In

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 March 2021 doi:10.20944/preprints202103.0243.v1

our study, to determine the impact of wildfires on air quality and health due to population exposure to particulate pollutants, WRF-Chem air quality model is used to predict the increase in $PM_{2.5}$ concentration over NSW due to wildfires during the summer 2019-2020 wildfires. The increase in $PM_{2.5}$, at each grid point in the modelling domain, due to wildfires is used to assess the impact on health endpoints. The results from the model are also evaluated using observed meteorological and air quality data from the NSW DPIE monitoring data network and remote sensing data from MODIS Aqua/Terra and CALIPSO lidar satellites.

2. Data and Methodology

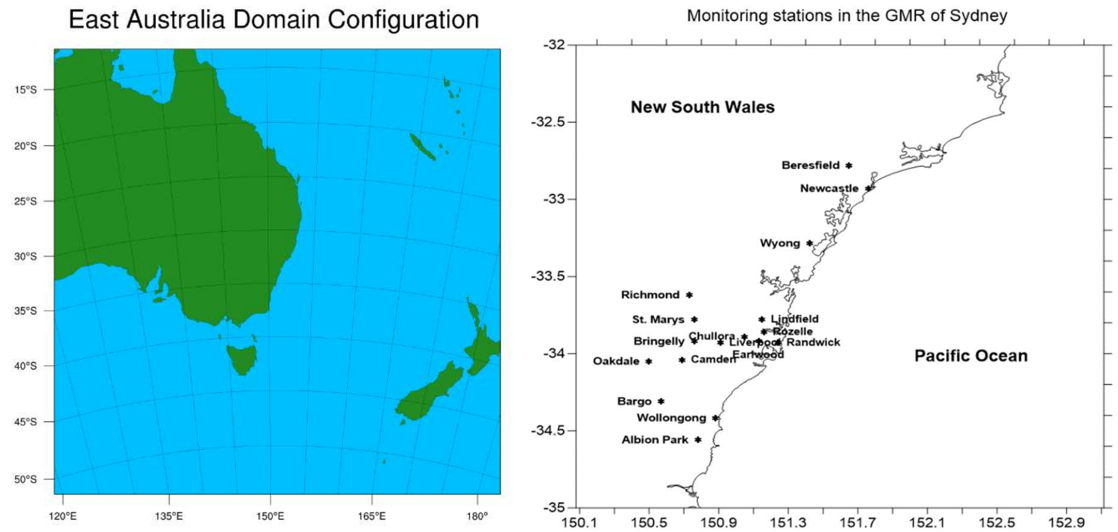
As the focus of the study is on fine particle concentrations of $PM_{2.5}$ due to wildfires and its impact on health, air quality monitoring data, especially $PM_{2.5}$, for the wildfires period are obtained from the Department of Industry, Planning and Environment (DPIE) of New South Wale air quality monitoring network. Figure 5 shows the monitoring stations in NSW. During the wildfires period, additional monitoring stations were deployed in the northern NSW.

In addition to ground-based monitoring data, the satellite data is used to compare with model prediction and to determine the extent of the pollutant transport. Satellite data of hot spots, smoke plumes and Aerosol Optical Depth (AOD) were obtained from MODIS Aqua/Terra satellites while aerosol vertical profiles came from CALIOP lidar onboard CALIPSO satellite. These data provide on the daily basis spatial distribution of aerosols and smoke plumes over the east coast of Australia from Victoria to New South Wales and Queensland while vertical aerosol profiles from CALIOP lidar provides one or two-day intervals over the bushfire regions. Output from the MERRA-2 (Modern-Era Retrospective Analysis for Research and Applications, Version 2) reanalysis system developed by NASA will be used to determine the concentration distribution of $PM_{2.5}$. MERRA-2 is the air quality model with assimilation from various observation sources including satellite.

For higher resolution output, we use WRF-Chem with emission from Fire Emission Inventory from NCAR (FINN) to model the air quality over eastern Australia. FINN is based on detected hot spots (Thermal Anomalies) product from MODIS Terra/Aqua satellites, and on vegetation type assigned at each fire pixel based on MODIS Collection 5 Land Cover Type (LCT) product with 16 land cover/land use (LULC) classes from IGBP (International Geosphere–Biosphere Programme) land cover classification. Fuel load density at each active fire location is determined from the MODIS Vegetation Continuous Fields (VCF) product. The emission factors of emitted species from fires for each of the vegetation types were obtained from previous studies in literature, such as [14] for savanna and grassland type and crop residue type. The maximum burned area at each fire pixel is assumed to be $1km^2$ but scaled to VCF fuel cover data if present at that pixel. And finally, the fraction of the biomass assumed to burn at each fire point is assigned as a function of tree cover [15]. From the information above, the emission from fire pixels is then calculated. FINN provides emission of species suitable for air quality models [15]. The data sets are provided on the daily basis with 1-hour time resolution and approximately $1km^2$ spatial resolution globally for 3 different air chemistry mechanism: GEOS-CHEM, MOZART-4 and SAPR99. The data sets can be downloaded from http://www.acom.ucar.edu/acresp/MODELING/finn_emis_txt/. In this study, the MOZART/GOCART (Model for OZone And Related chemical Tracers/ Goddard Chemistry Aerosol Radiation and Transport) option for chemistry is chosen for WRF-Chem simulation.

As for meteorological driver used in WRF-Chem, the National Centre for Environmental Prediction (NCEP) Final Analysis (FNL) Reanalysis data provides the boundary and initial meteorological conditions for WRF-Chem to downscale to the modelling domain. In this study, the modelling domain is based on Lambert projection with 386 x 386 grid points at resolution 12km x 12km. There are 32 model vertical sigma levels. The centre reference coordinate is at 150.994^{o} longitude and -33.921^{o} latitude.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 March 2021 doi:10.20944/preprints202103.0243.v1



(a) (b)

Figure 5 – (a) WRF-Chem domain configuration (b) DPIE air quality monitoring stations in the GMR of Sydney

Figure 5 shows the WRF-Chem simulation domain and the air quality monitoring stations in the GMR of Sydney. The data from these stations will be used to validate the prediction from the model a well as determining the effect of the wildfires on the air quality. Table 1 shows some of the WRF-Chem physics and chemistry configuration options used in this study

Table 1 – WRF-Chem configuration in the namelist.input

Physical parametrisation	Namelist variable	Option	Model/scheme
Microphysics	mp_physics	3	WRF Single Moment
Land surface	sf_surface_physics	2	Noah Land-Surface Model
Surface layer physics	sf_sfclay_physics	1	Monin-Obukhov similarity
Planetary Boundary Layer	bl_pbl_physics	1	YSU scheme
Shortwave radiation	ra_sw_physics	4	Rapid Radiative Transfer Model (RRTMG)
Long wave radiation	ra_lw_physics=	4	Rapid Radiative Transfer Model (RRTMG)
Cumulus cloud	cu_physics	1	Kain-Fritsch scheme
Gas/aerosol Chemistry	chem_opt	112	MOZART/GOCART
Biomass burning option	biomass_burn_opt	2	Emission and plume rise for MOZCART
Sea salt emission	seas_opt	1	GOCART sea salt emission scheme
Photolysis	phot_opt	3	Madronich F-TUV photolysis
Dust scheme	dust_opt	3	GOCART-AFWA scheme

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 March 2021 doi:10.20944/preprints202103.0243.v1

Aerosol extinction coefficient approximation	aer_opt_opt	2	Maxwell-Garnett approximation
Aerosol radiative feedback	aer_ra_feedback	1	Turn on aerosol radiative feedback with RRTMG model

Validation of the model simulation is performed by comparing the prediction of meteorological and air quality prediction with observation at many monitoring sites in the DPIE NSW air quality monitoring network as shown in Figure 5b and remote sensing data from satellites.

The simulation of air quality over eastern Australia allows us to determine the ground concentration of $PM_{2.5}$ due to wildfires across NSW. In the simulation, biogenic emission is included but anthropogenic sources are turned off, so that only the effect of wildfires can be determined. From this, the exposure and health impact on population can be estimated. Health impact for different health endpoints (mortality, hospitalisation for cardiovascular and respiratory diseases) is based on the impact function (IF) calculated as:

$IF = RR^{\Delta X/10}$.

From which, the attributable number of the impact on health event of endpoint due to an increase of ΔX concentration in a population with an incidence rate is

AN = (IF-1) × Pop × incidence rate.

We focus on the simulation period starting from 1 November 2019 to 8 January 2020, when the wildfires mostly concentrated in New South Wales, Australian Capital Territory and Victoria where the majority of population in south east Australia live. The 2016 population data and the mortality rate for each of the census district (SA4 level) are obtained from the Australian Bureau of Statistics (ABS). As ABS does not provide hospitalisation data, the incidence rates for cardiac diseases hospitalisation are obtained from the NSW Department of Health for each of the Local Government Areas (LGAs) and respiratory diseases hospitalisation for each of the Local Health Districts (LHDs). The average of the incidence rates in the 3 years (2016, 2015 and 2014) for cardiac diseases hospitalisation and respiratory diseases hospitalisation are used in this study. The predicted daily $PM_{2.5}$ concentration grids are superimposed on the SA4s shapefiles to obtain the average $PM_{2.5}$ concentration in each of the SA4s. Incidence rates for cardiac diseases hospitalisation and respiratory diseases hospitalisation are projected to each of the SA4s from the LGAs and LHDs shapefiles and calculated as the average of the rates of intersected LGAs or LHDs with the SA4. The attributable number (AN) is calculated for each of the health end points based on SA4s. These Ans are then summed over all of the SA4s in NSW to estimate the effect of increased $PM_{2.5}$ from wildfires on population health.

The RR values for premature mortality and cardiovascular diseases hospitalisation health endpoints used in this study are based on World Health Organization's (WHO) Health Risks of Air Pollution in Europe project (HRAPIE) recommendations (WHO 2013) [16] of short-term concentration response coefficients for mortality and CVD diseases.

RR (mortality) = 1.0123 (CI: 1.0045, 1.0201)

RR (cvd) = 1.0091 (CI: 1.0017, 1.0201)

where CI is the confidence interval.

The RR value (1.23%) for mortality above corresponds to those in Xu et al. (2020) study. In their study, they have reviewed the effect of wildfire events in literature and reported that the daily increase of 10 $\mu g/m^3$ of $PM_{2.5}$ level has been associated with an increase of 0.8 to 2.4% in the risk of death from any cause or nonaccidental death for up to 4 days after the exposure

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 March 2021 doi:10.20944/preprints202103.0243.v1

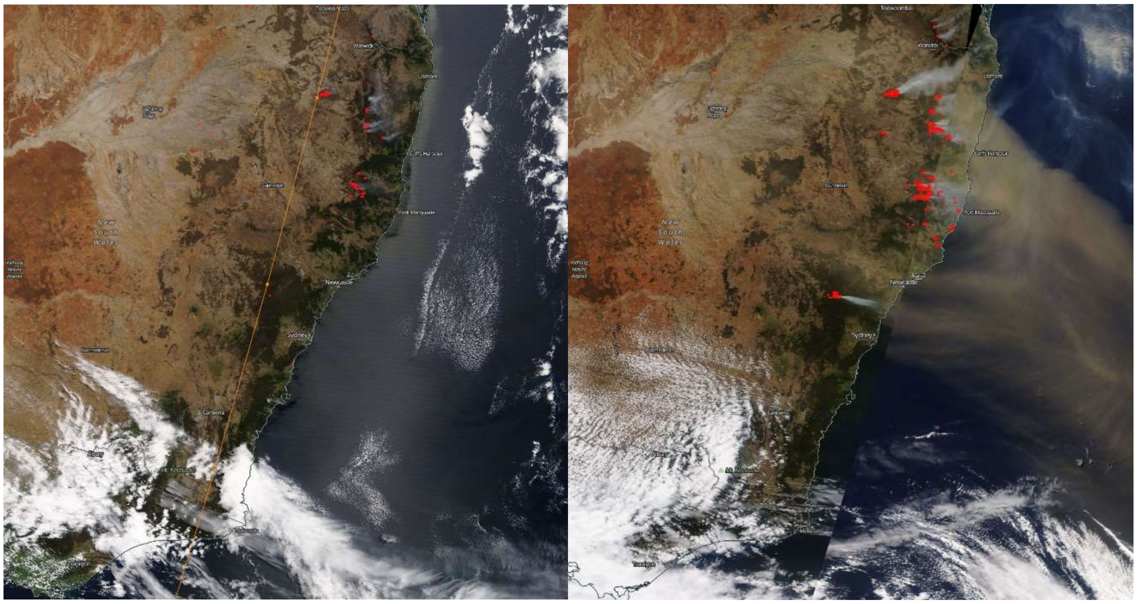
For respiratory hospitalisation, the RR 1.03 (CI: 1.01, 1.04) of $PM_{2.5}$ based on a study of the 2003 California wildfires [17], is used in this study. This value was also used by [18] [11] for wildfires or biomass hazardous reduction burnings (HRBs) in Australia.

Of the three RRs above (mortality, cardiovascular and respiratory diseases hospitalisation), the RR value for CVD is the smallest and reflects the effect of $PM_{2.5}$ on CVD hospitalisation is less than those of $PM_{2.5}$ on mortality and respiratory disease hospitalisation.

3. Results

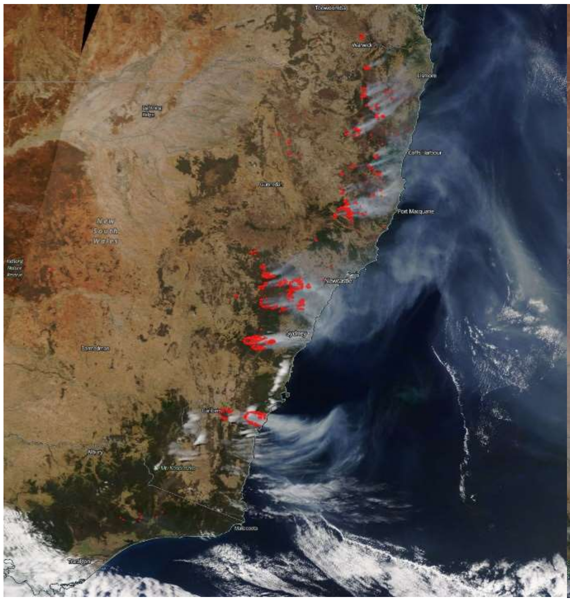
3.1 Meteorology and transport of wildfire pollutants

The wildfires started in late October, November mainly in northern NSW and the Blue Mountains. Filkov et al. 2020 [19] reported that Gospers Mountain fire in the Blue Mountains started on 26 October 2019 while the fires in northern NSW started in beginning of November and lasted for more than a month. Remote sensing data provided an overall view of the beginnings of the fires, their progress and endings. The MODIS Aqua/Terra satellite of hot spots and smoke plumes reveals the extend of the wildfires in early November to early December as shown in Figure 6.

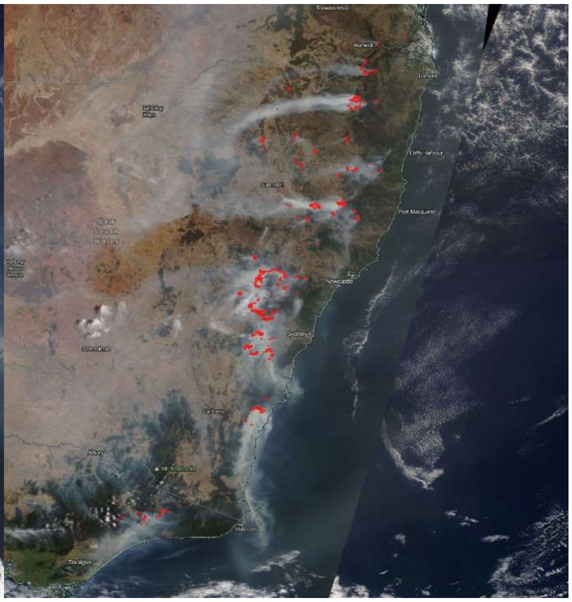


(a) (b)

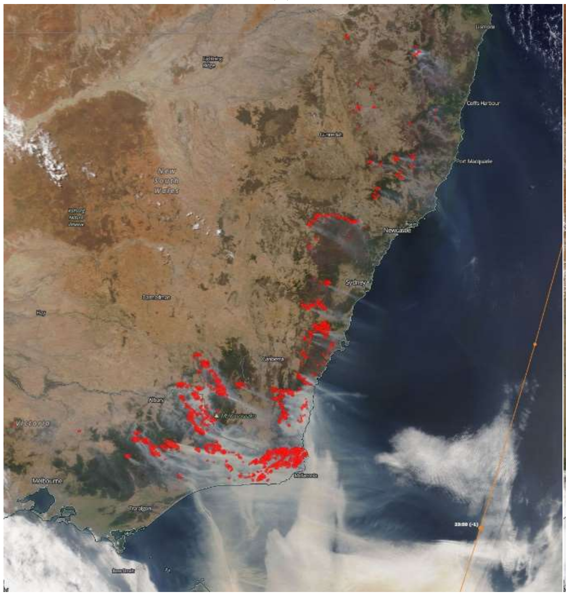
Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 March 2021 doi:10.20944/preprints202103.0243.v1



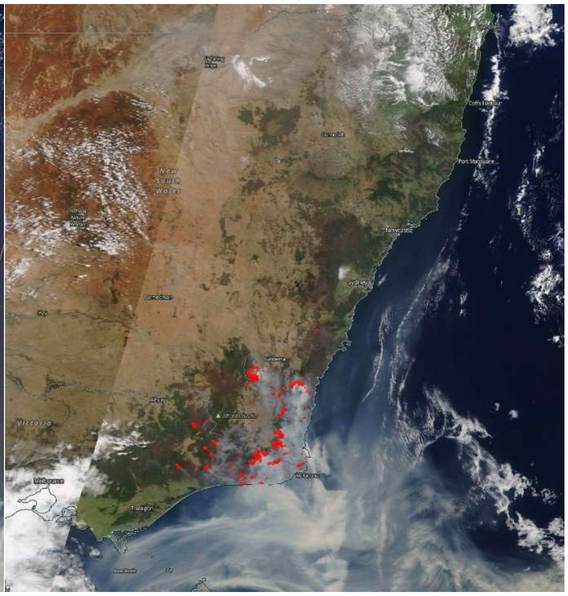
(c)



(d)

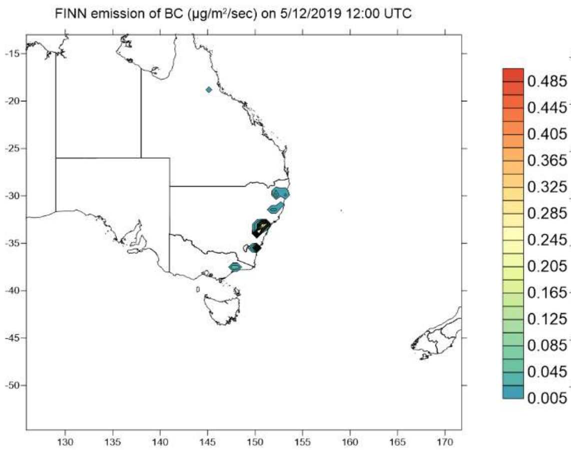


(e)

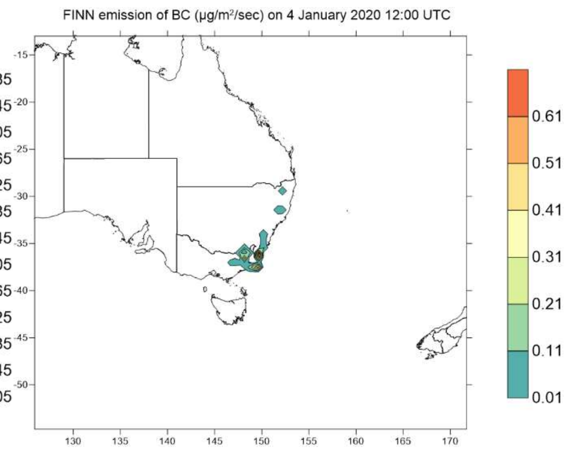


(f)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 March 2021 doi:10.20944/preprints202103.0243.v1



(g)

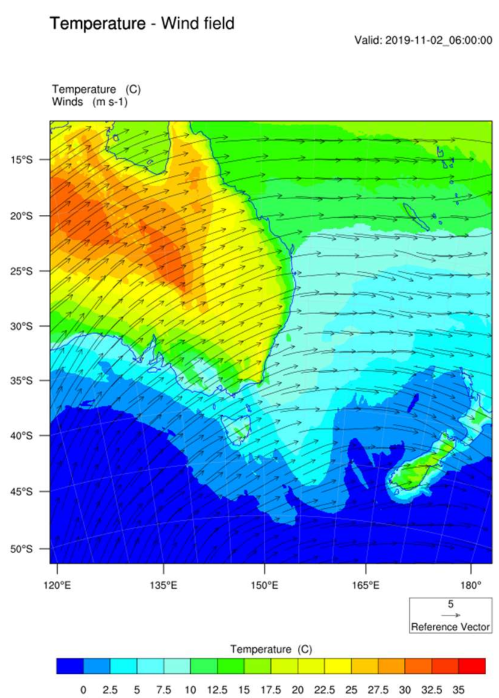


(h)

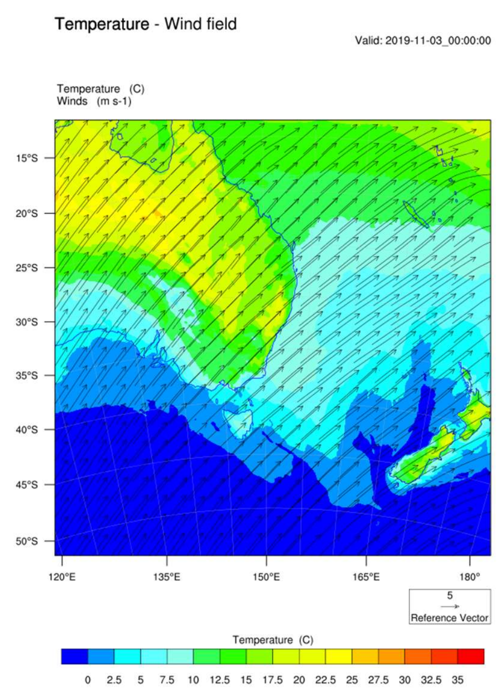
Figure 6 – Fires started in northern NSW and the Blue Mountains (north west of Sydney) as seen by MODIS Aqua/Terra satellite on 6 November 2019 (a) and 7 November 2019 (b). From early December to the end of the month, fires were more intense in the Blue Mountains and South Coast: 5 December 2019 (c) 18 December 2019 (d). By early January, fires were mainly in the south coast and border region with Victoria 4 January 2020 (e) and the East Gippsland (Victoria) toward the end of January 31 January 2020 (f). Emission of BC (Black Carbon), as a marker from wildfires, from FINN on 5 December 2019 12:00 UTC (g) and on 4 January 2020 12:00 UTC (h)

From the remote sensing data and simulation results based on meteorology and air quality dispersion model WRF-Chem, the progress of the Black Summer 2019/2020 wildfires across south eastern Australia in term of meteorological driver, emission and transport of air pollutants from wildfire sources is summarised below.

3.1.1 November and December 2019 period

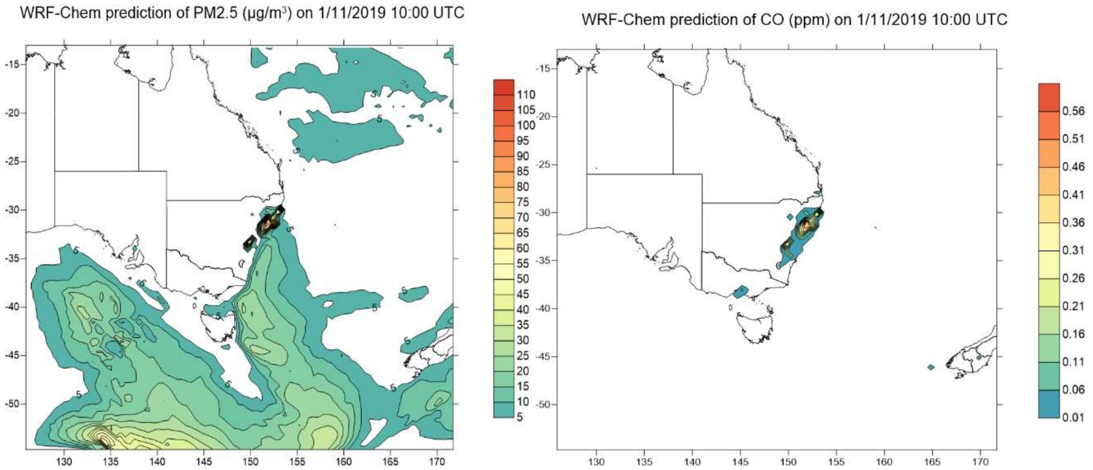


(a)



(b)

 doi:10.20944/preprints202103.0243.v1



(c)

Figure 7 – Predicted surface wind and temperature on (a) 2 November 2019 06:00 UTC and (b) 3 November 2019 00:00 UTC. (c) Predicted $PM_{2.5}$ on 1 November 2019 10:00 UTC with marine aerosols dominated over the coast and offshore. (d) CO concentration on ground with high concentration in the south west of the fires on 1 November 2019 at 10:00 UTC

Wildfires started in the first week of November in northern NSW. But not until 7 November 2029 that the effect on air quality was severe in the nearby coastal town of Port Macquarie for the next 16 days when peak $PM_{2.5}$ concentrations was above 100μg/m³ (with 2 days > 1000μg/m³). The predicted surface wind pattern for the first week of November (as shown in Figure 7) showed a south-easterly wind flow across the east coast of Australia and hence dispersed the pollutants offshore. However, upper wind patterns at 925mb, 850mb (as shown in Figure A.1 in the Appendix) were different from those on the surface. The plume after being injected into the upper atmosphere was drifted down south above ground and then intruded down causing high concentration of pollutants such as $PM_{2.5}$ on the ground as shown in Figure 7(c). In early December 2019, from 1 to 5, wind pattern at ground level and above ground was mostly south-westerly from the Southern Ocean, and after crossing the mountains of the Great Dividing Range, became more westerly. This can be seen by the direction of the smoke plumes as detected by MODIS Aqua/Terra satellites shown in Figure 6(c) and fire location corresponds with the FINN emission spatial pattern of BC in Figure 6(g). The animation clip of the wind flow and $PM_{2.5}$ concentration from 1 December 2019 0:0 UTC to 5 December 2019 0:00 UTC is provided in the Supplementary Materials.

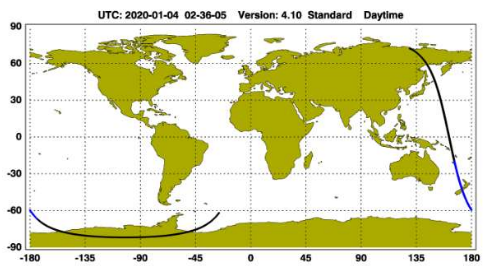
3.1.2 January 2020 period

Simulation using WRF-Chem for the period 01/01/2020 to 08/01/2020 based on FINN emission fluxes from fires detected by satellites as hotspots shows the pattern of air pollutants dispersion in eastern Australia. The emission pattern from wildfires corresponds with the hotspots as detected from MODIS Aqua/Terra satellites as shown in Figure 6e, 6f. The predicted surface wind fields over the simulation period of 1 to 8 January 2020 show that at the beginning from 1 January 2020 0:0 to 3 January 2020 7:0 UTC, moderate south westerly wind at ~5 m/s flowed over Victoria and NSW and gradually changed to westerly over Victoria and then NSW from 3 January 2020 16:00 UTC. The westerly and north westerly then dominated from 4 January 2020 16:00 UTC to 5 January 2020 14:00 UTC over the eastern Australia domain. From 5 January 2020 16:00 UTC to 7 January 08:00 UTC, more westerly wind bringing hot air from inland to the coast which was already subsumed under intense fires. The upper air movement was more complex with air circulation occasionally occurred to and from the coast and is not shown here. Figure S.1 in the Supplementary Materials shows some of the surface wind on selected days.

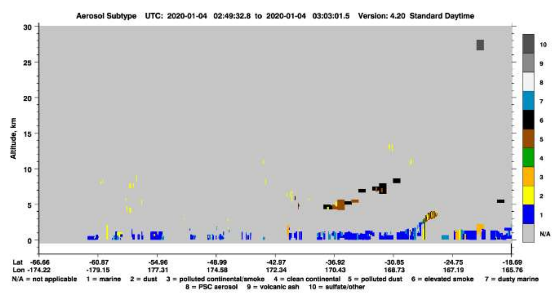
The AOD as predicted from WRF-Chem simulation on the 3 January 2019 in this study is compared with the AOD as predicted from a global model called WACCM (Whole Atmosphere Community Climate Model) from NCAR ACOM (Atmospheric Chemistry Observations & Modeling) group in the U.S. The AOD prediction from the WRF-Chem and WACCM models are remarkable similar. This is not surprising as both models used the same fire emission data from FINN. The AOD prediction also correspond well with the AOD observation as measured by MODIS Terra/Aqua satellites (see Figure S.2 of the Supplementary Materials).

The markers for wildfires are the emission of carbon monoxide (CO) and Black Carbon (BC). The prediction of ground concentration of these species from WRF-Chem simulation on 3 January 2019 showed the wildfires were concentrated in the east coast of Victoria near the NSW border. The simulation results on this day for $PM_{2.5}$ also showed the contribution of dust aerosols from dust storm in central Australia to the $PM_{2.5}$ ground concentration loading in addition to the smoke from the wildfires (see Figure S3 and S.3(c) in the Supplementary Materials).

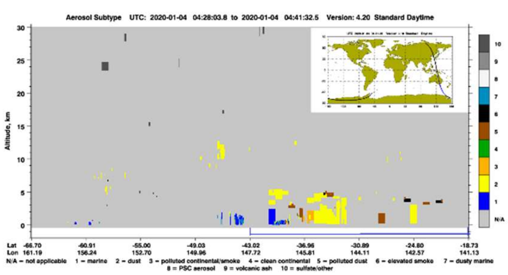
The dispersion of smoke and dust plumes into the atmosphere allowed the pollutants to be transported farther from the emission sources. Aerosol layers formed from the dispersion and transport of smoke in the atmosphere can be studied from WRF-Chem simulation. Observation data from CALIPSO lidar vertical profile is used to verify the prediction from WRF-Chem in the upper atmosphere. Figure 8 shows the CALIPSO aerosol profile on 4 January 2020 at 2:36 UTC and 4:14 UTC and WRF-Chem $PM_{2.5}$ predicted concentration along the satellite path. The CALIPSO satellite path on the 4 January 2020 at 4:14 UTC passed above central Australia and the satellite aerosol vertical profile showed thick dust layers above the dust sources in Lake Eyre Basin (LEB). This showed that dust event in Central Australia happened in early January 2020 when the wildfires on the East Coast of Australia were at peak before subsided toward late January 2020. WRF-Chem simulation used the AFWA GOCART dust emission scheme and the prediction of dust concentration corresponds reasonably well with CALIPSO observation.



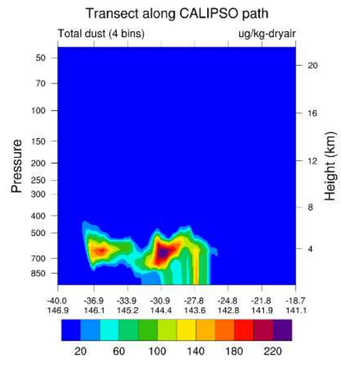
(a)



(b)

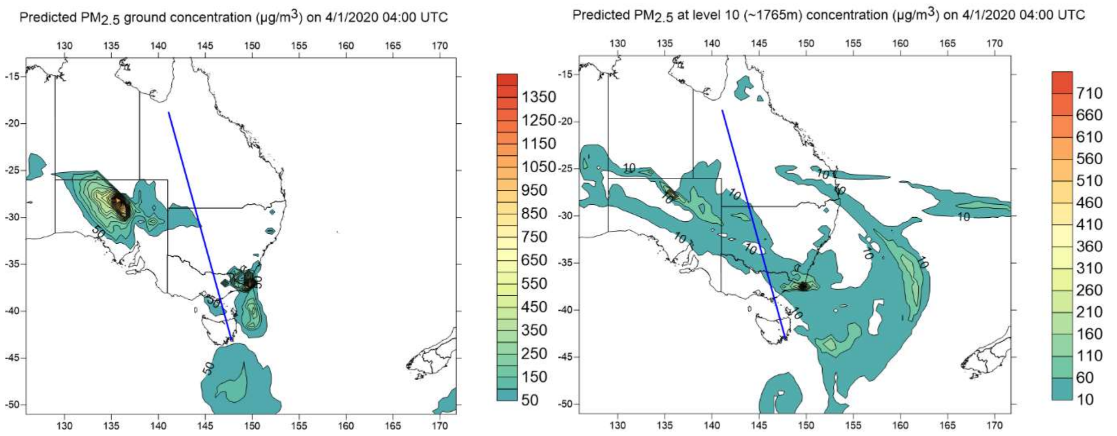


(c)



(d)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 March 2021 doi:10.20944/preprints202103.0243.v1



(e) (f)

Figure 8 – CALIPSO satellite path (a) and aerosol profile (b) over Coral Sea and New Zealand on 4 January 2020 at 2:36 UTC. The CALIPSO aerosol profile (c) and WRF-Chem prediction of transect of dust along the satellite path (d) and spatial distribution of $PM_{2.5}$ concentration at ground (e) and height ~1765m (f) on 4 January 2020 4:00 UTC.

Similarly, for the CALIPSO profile on the 7 January 2020, the WRF-Chem prediction can capture the vertical distribution of smoke aerosols. By this time, the wildfires subsided on the ground and the worse of the fires is over Figure A.2 of the Appendix shows the vertical profile on 7 January 2020. Dispersion of smoke aerosols at the height of the wildfires in earlier January to mid-January as shown by CALIPSO satellite lidar vertical profile in the Tasman Sea between Australia and New Zealand on the 15 January 2020 is such an extent that the smoke aerosols penetrated into the upper troposphere at 15km and into the stratosphere at ~25-30km south of New Zealand. Figure A.3 in the Appendix shows the lidar profile of different type of aerosols on the satellite path in the Tasman Sea on this date. The smoke layers at the upper troposphere height would travel farther beyond New Zealand.

The agreement between the prediction of $PM_{2.5}$ dispersion as well as spatial patterns due to wildfires with observation from satellites shows that the WRF-Chem model with FINN fire emission data can be used to predict the effect of wildfires on air quality such as the $PM_{2.5}$ concentration across NSW and hence the impact on health due to population exposure of air pollutants can be estimated.

3.2 Effect on air quality

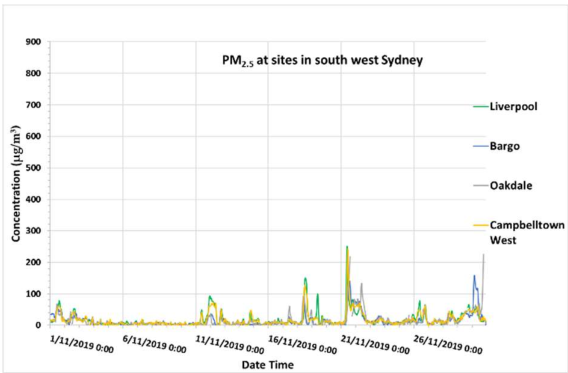
The soil moisture data provided from the Australian Landscape Water Balance AWRA-L Model (root zone and upper soil moisture) and the vegetation cover data from CSIRO from October to February are used to determine the fire risk. The spatial extent of the wildfires can be ascertained using MODIS Terra/Aqua hotspots and AOD and CALIPSO lidar satellite data.

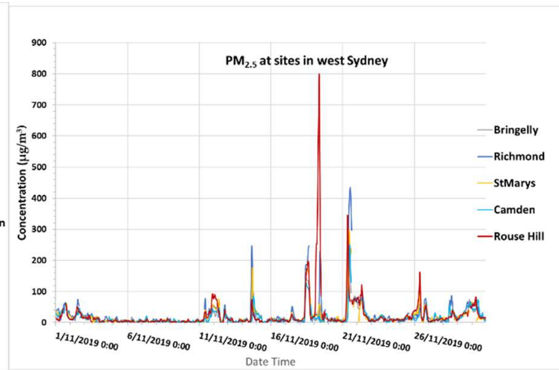
The air quality data from the DPIE air quality monitoring network is analysed to assess the impact of the wildfires on air quality and health. The time series of temperature and relative humidity in the GMR from 2019 December to January 2020 show that, when there is very high temperature occurring, the relative humidity is usually low. Figure S.4 in the Supplementary Materials shows the time series of temperature and relative humidity measured at Randwick and Liverpool. On 19 December 2019, the peak temperature reached 38.8°C, and 41.1°C at Randwick and Liverpool, the relative humidity was very low at 18.2% and 12.5% respectively. Similarly, on 31 December 2019, 4 January 2020 and 23 January 2020 peak temperatures measured at these sites correspond to low humidity.

With low soil moisture, high temperature and low humidity, the risk of fires increased. In northern NSW and in the Blue Mountains west of Sydney, the Central Coast, wildfires started from 6 November 2019 until the 4 to 7 December 2019 when fires were more intense and widespread. In November, fires were intense and widespread in northern NSW and caused very high concentration of $PM_{2.5}$ as measured at Armidale and Port Macquarie monitoring stations with peak concentration of 1269.3 $\mu g/m^3$ on 15 November 2019 at Port Macquarie and 917.6

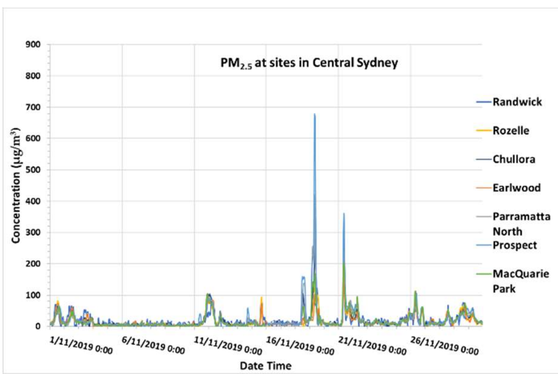
Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 March 2021 doi:10.20944/preprints202103.0243.v1

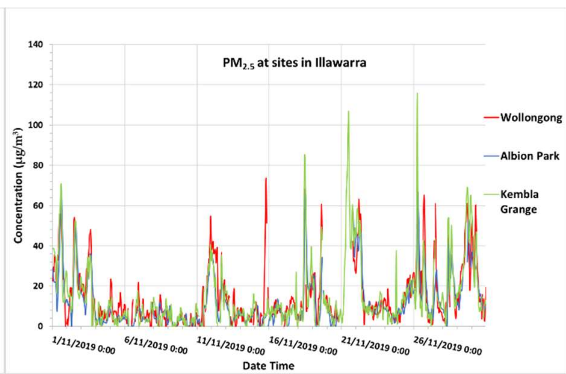
μg/m³ on 20 November 2019 at Armidale as shown in Figure 9. Elsewhere, fires in the Blue Mountains caused high concentration in the west Sydney and central Sydney with peak concentration 790 μg/m³ on 19 November 2019 at Rouse Hill and 677 μg/m³ on 19 November 2019 at Prospect respectively but elsewhere peak $PM_{2.5}$ concentration is only about 250 μg/m³ in south west Sydney (Liverpool and Campbelltown West), 245 μg/m³ in Central Coast and Lower Hunter (Wyong) and about 100 μg/m³ in the Illawarra (Kembla Grange). The Illawarra is least affected during November.



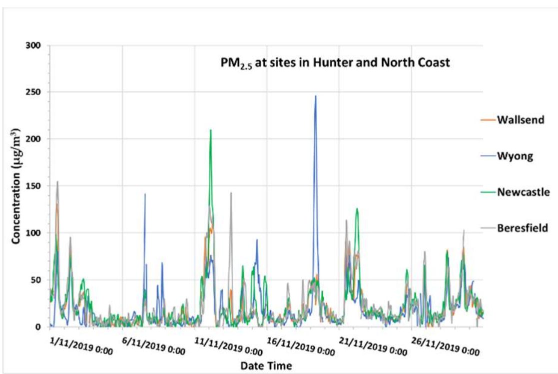


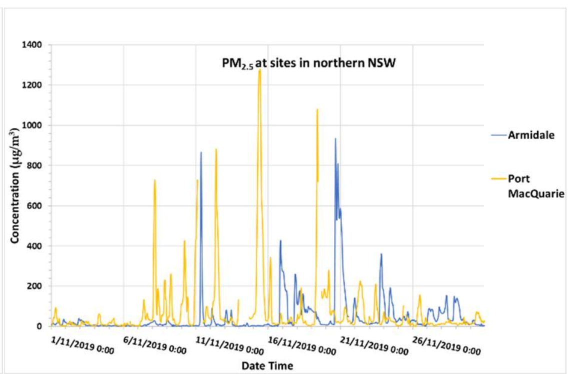
(a) (b)





(c) (d)





(e) (f)

Figure 9 – $PM_{2.5}$ concentration at monitoring sites in south west Sydney (a), west Sydney (b), central Sydney (c), Illawarra (d), Hunter (e) and northern NSW (f) from 1 November 2019 to 30 November 2019

From early December, the fires caused elevated concentration of $PM_{2.5}$ up to 273.7μg/m³ (6 December 2019 8:00) as measured at Port Macquarie. High $PM_{2.5}$ concentrations from 200 μg/m³ up to above 400 μg/m³ were measured at a number of stations in Sydney (Bringelly, Camden, Liverpool, Oakdale, Campbelltown West, Rozelle, Randwick,

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 March 2021 doi:10.20944/preprints202103.0243.v1

Parramatta North, Chullora, Earlwood, Macquarie Park, Prospect) and in the Lower Hunter-Central Coast (Wallsend, Newcastle, Beresfield and Wyong) from 3 December 2019 to 6 December 2019. Figure 10 shows the MODIS Aqua/Terra satellite image of the fires and AOD (Aerosol Optical Depth) caused by the fires on 3 December 2019.

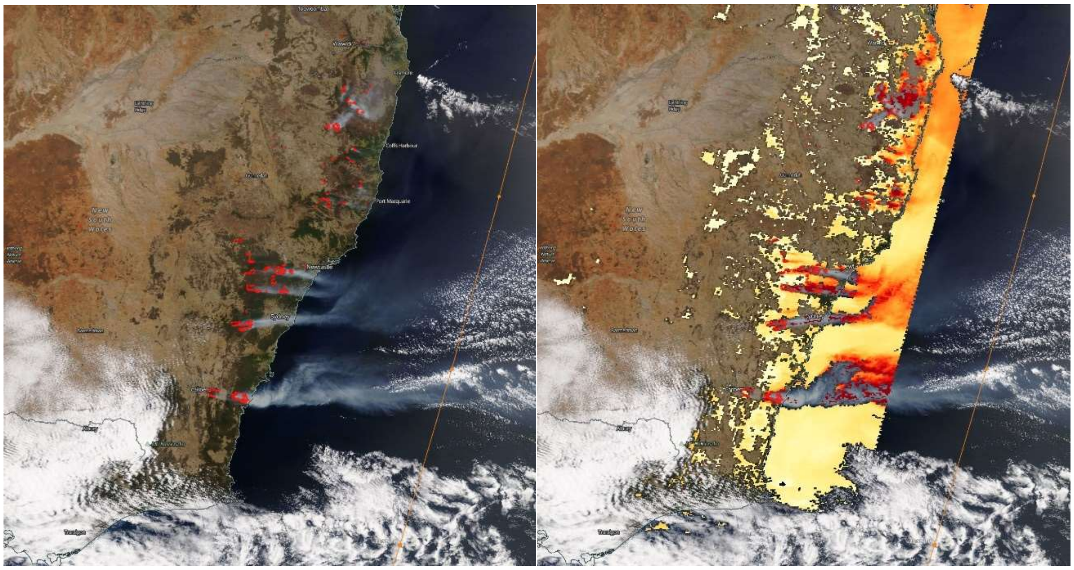
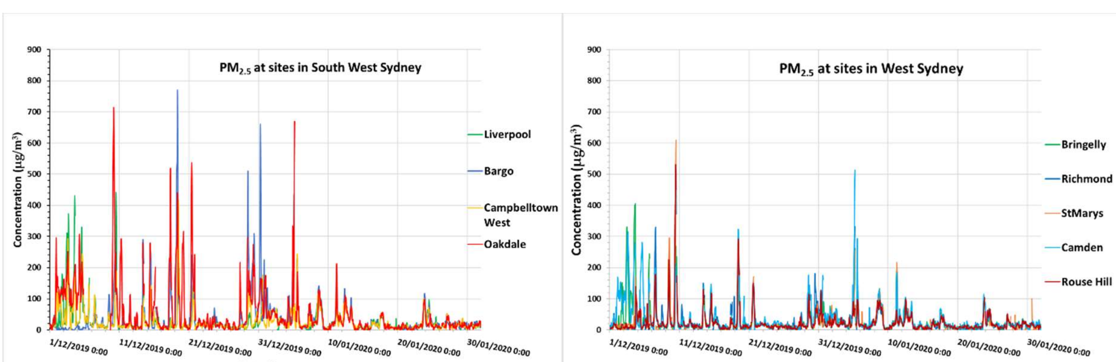


Figure 10 – MODIS Terra/Aqua thermal hotspots and image on 3 December 2019 00:00 UTC (a) and AOD from MODIS Terra land and ocean (b)

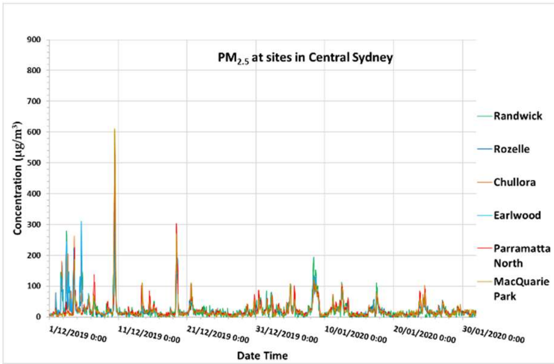
Figure 11 shows the time series of PM2.5 from 1 December 2019 to 30 January 2020 at monitoring sites in the GMR of Sydney and northern NSW. On 10 December 2019, at Rozelle, the $PM_{2.5}$ concentration was measured 533.5 μg/m³ at 13:00 hour, Macquarie Park 610.6 μg/m³ at 12:00, StMarys 608.7 μg/m³ 13:00, Rouse Hill 531.6 μg/m³ 12:00 and Wollongong 299.7 μg/m³ at 10:00. The concentrations were then falling until on 19 December 2019 when peak $PM_{2.5}$ concentrations were detected at level about and above 300 μg/m³ at Parramatta North, Macquarie Park, Camden, Rouse Hill, Wollongong, Kembla Grange. High concentration on 29, 30 and 31 December 2019 from 300 to above 600 μg/m³ also occurred at Bargo.

In January 2020, high $PM_{2.5}$ concentrations were detected at Camden, StMarys, Oakdale, Kembla Grange on 5 January 2020, Randwick, Wollongong, Kembla Grange, Albion Park on 8 January 2020 and at Wollongong, Kembla Grange, Albion Park on 10, 11 and 12 January 2020. From early January, the wildfires were more intense in the south coast of NSW and east and north west of Victoria.

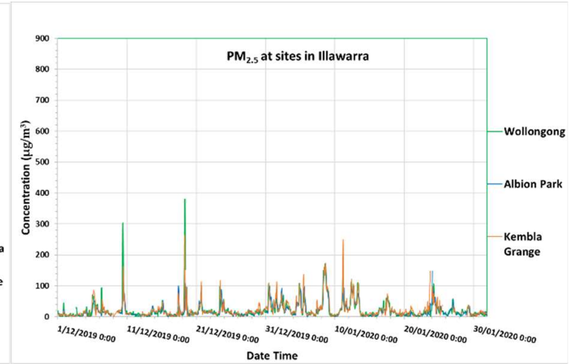


(a) (b)

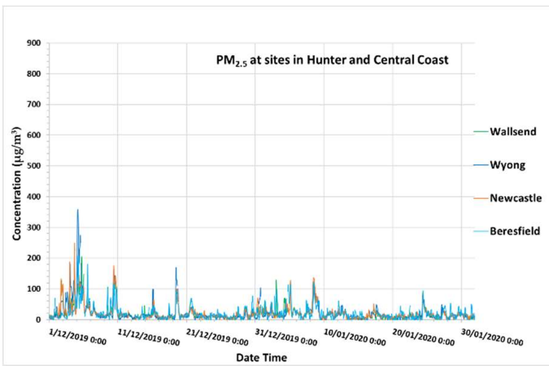
Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 March 2021 doi:10.20944/preprints202103.0243.v1



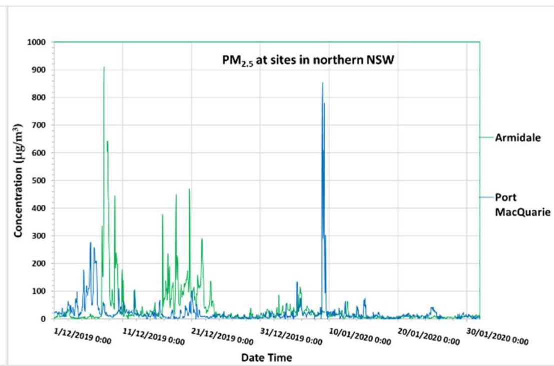
(c)



(d)



(e)



(f)

Figure 11 - $PM_{2.5}$ concentration at sites in South West Sydney (a), West Sydney (b), Central Sydney (c), Illawarra (d), Hunter (e) and northern NSW (f) from 1 December 2019 to 31 January 2020

Like $PM_{2.5}$, the ozone follows a similar pattern described herein. In early December and mid-December, high ozone concentrations were detected in the Lower Hunter and Sydney then from early January when the wildfires shifted to the south the Illawarra detected elevated concentration of ozone. Figure S.5 in the Supplementary Materials shows the ozone concentration time series during December 2019 and January 2020 at Sydney, Lower Hunter and Illawarra sites. Ozone levels exceed NSW air quality goal (10 pphm) at many sites during the wildfire period. At Randwick, ozone was measured at 11.2 pphm on 5 December 2019 14:00, a level that was never seen at this long-term site since the 1970s. On the 10th December 2019, the levels were 17.9 (12:00), 17.6 (12:00), 15.7 (12:00), 15.7 (13:00), 14.4 (13:00), 12.3 (13:00), 12 (13:00) and 11.6 pphm (13:00) at Earlwood, Chullora, Liverpool, Parramatta North, Bringelly, StMarys, Bargo and Richmond respectively.

On 19 December 2019, peak ozone concentrations were detected at levels of 17.9 (12:00), 15.7 (12:00), 13.2 (11:00), 11.4 (12:00), 15.4 (12:00), 11 pphm (13:00) at Rozelle, Earlwood, Parramatta North, Liverpool, Chullora and Bringelly respectively. And on 21 December 2019, high ozone levels 10.6pphm (14:00), 10.3 pphm (15:00), 10.6 pphm (15:00) were measured at Liverpool, Bringelly and Oakdale. High level 11.2 (30 December 2019 15:00), 10.6 (31 December 2019 10:00), 11.4 (31 January 2020 17:00), 11.6 (31 January 2020 16:00), 10.1 (31 January 2020 15:00) were detected at Richmond, Oakdale, Bargo, Oakdale and Bringelly respectively.

In the Lower Hunter and Central Coast, high levels of ozone above 10 pphm were measured at Newcastle 10.2 pphm (5 December 2019 13:00) and 10.4 pphm (19 December 2019 12:00), at Wallsend 10.5 pphm (19 December 2019 13:00) and Beresfield 12.6 pphm (21 December 2019 15:00). In the Illawarra, high level of ozone occurred at Wollongong 11.1 pphm (19 December 2019 13:00). Overall 10 December 2019 and 19 December 2019 were the two worst ozone days in the GMR region of Sydney.

Evaluation of WRF-Chem wildfires simulation using FINN emission data and NCEP reanalysis meteorological data sets is performed by comparing some of the predicted meteorological variables such as wind and temperature and the predicted concentration of $PM_{2.5}$ with observed data at the monitoring stations. Figure A.3 in the Appendix shows the results of the comparison at a number of sites in the GMR. Considering the 12km by 12km grid resolution used in model, the prediction at the hourly interval as compared with point observation is rather good for temperature and wind direction with temperature correlation and IOA (Index of Agreement) of ~0.83 and ~0.75 respectively (for the 3 sites Richmond, Liverpool, Beresfield). Predicted wind speed and $PM_{2.5}$ concentration are also reasonable (R^2 and IOA from 0.62 to 0.67 and 0.70 to 0.73 respectively for wind speed, from 0.2 to 0.25 and 0.33 to 0.45 respectively for $PM_{2.5}$). As we use only predicted daily average of $PM_{2.5}$ to study the impact of 2019/2020 summer wildfires on population health, the predicted $PM_{2.5}$ at the daily scale as compared to observed daily average is much better than at the hourly scale (R^2 and IOA from 0.6 to 0.75 and 0.61 to 0.86 respectively for daily $PM_{2.5}$). Figure 12 shows the daily average predicted $PM_{2.5}$ as compared to the observation at many sites in NSW.

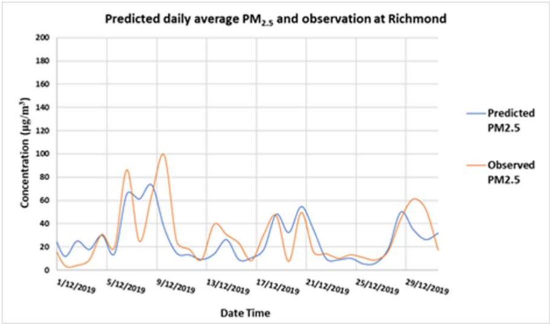
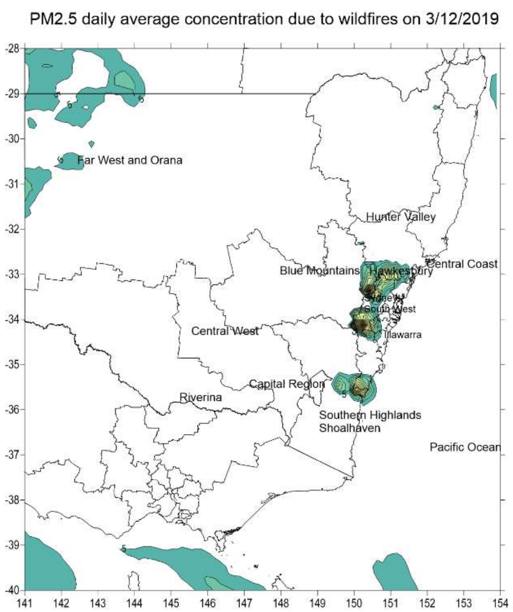
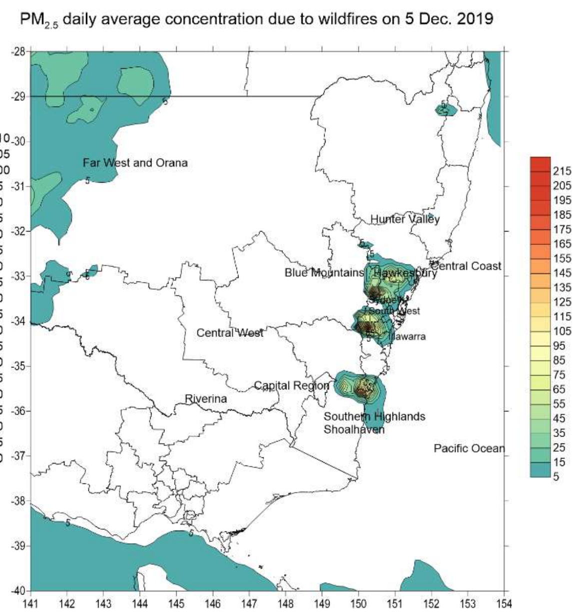


Figure 12 – Predicted and observed daily average $PM_{2.5}$ concentration at Wyong, Bringelly, Port MacQuarie, Beresfield, Earlwood, Liverpool, Chullora and Camden.

3.2 Population exposure to wildfire particulates and health effects

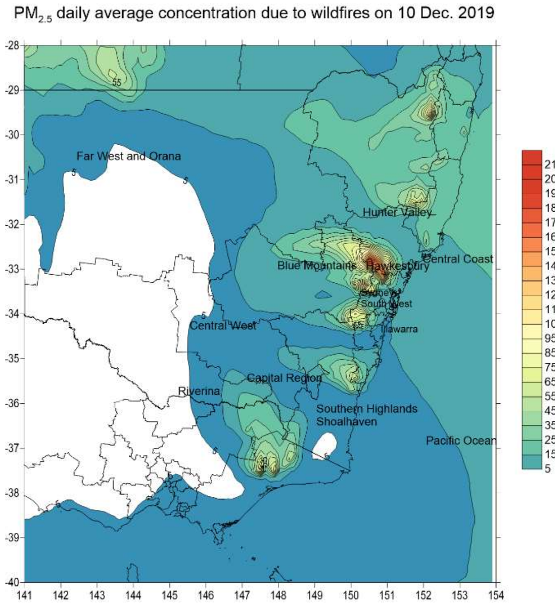
The increase in ground concentration of $PM_{2.5}$ in ambient air as a result of the wildfires will increase the mortality and morbidity of the exposed population. The spatial pattern of daily average $PM_{2.5}$ concentration changes in time and space. The peak increases in $PM_{2.5}$ concentration over NSW due to wildfires occurred in early December (7 to 10), mid-December (18 to 21) and toward the end of December 2019 (from 28 to 31 December) with high predicted $PM_{2.5}$ ground concentration as shown in Figure 13.



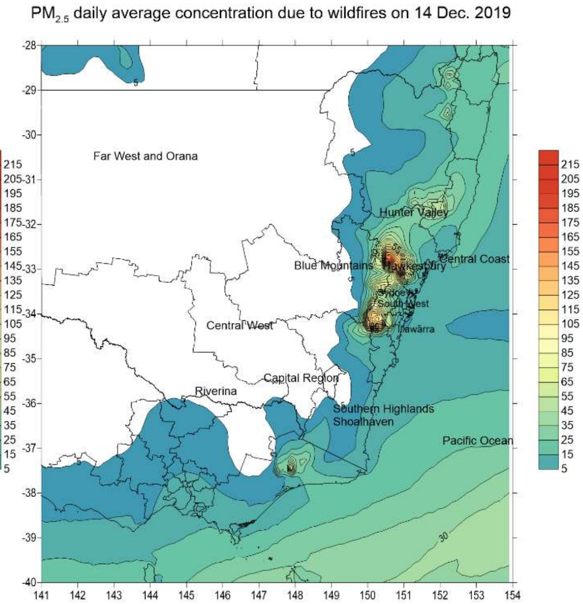


(a) (b)

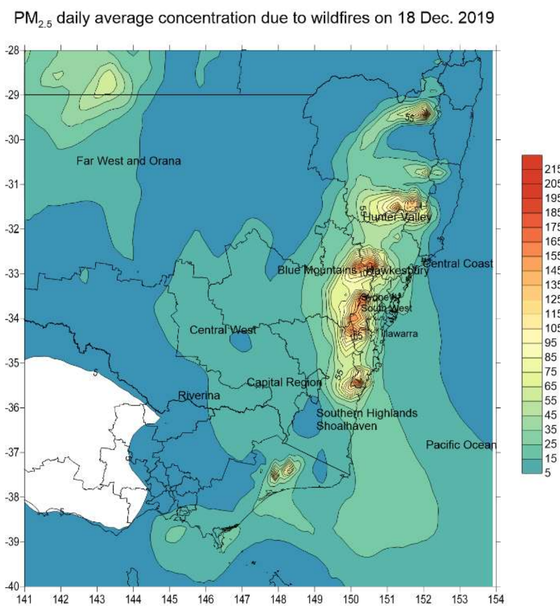
 doi:10.20944/preprints202103.0243.v1



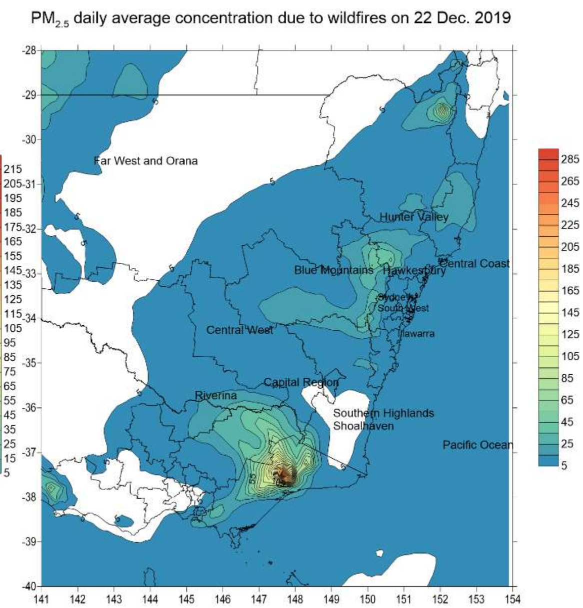
(c)



(d)

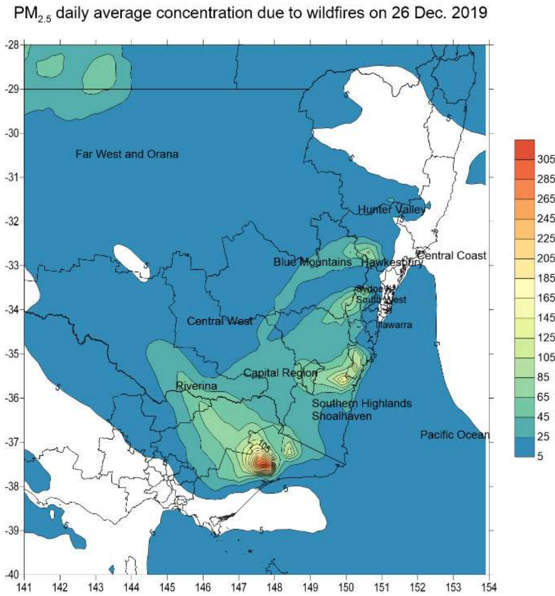


(e)

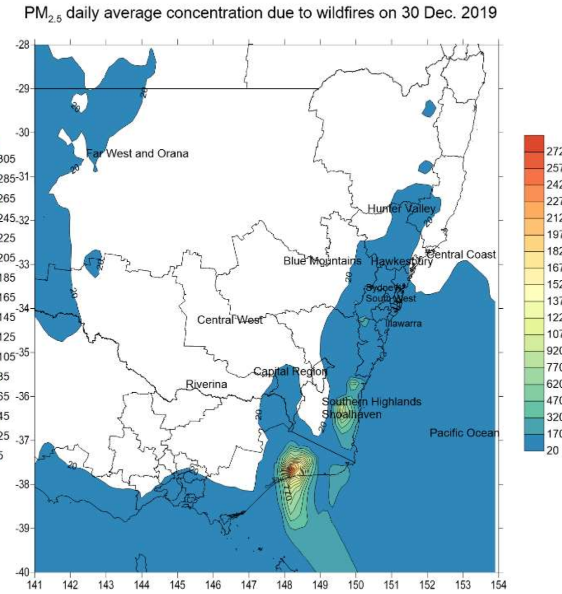


(f)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 March 2021 doi:10.20944/preprints202103.0243.v1



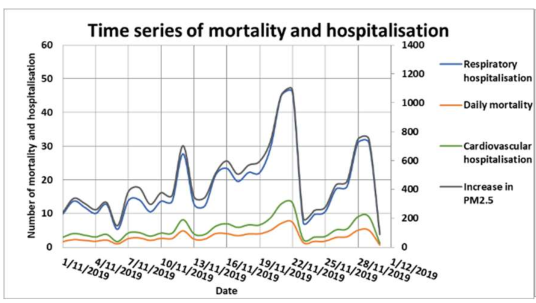
(g)



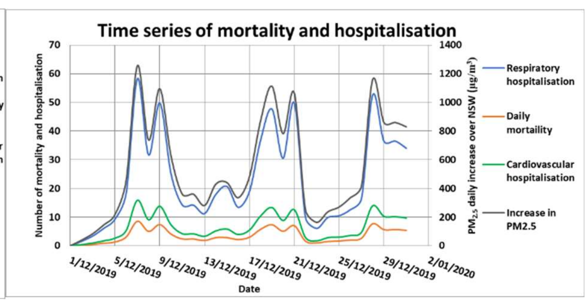
(h)

Figure 13 – Predicted increase in daily average PM2.5 due to wildfires over the Australian Bureau of Statistics (ABS) level-4 census districts (SA4) across south eastern Australia for some selected days in December 2019: 3 (a), 5 (b), 10 (c), 14 (d), 18 (e), 22 (f) 26 (g) and 30 (h) of December 2019. Note the PM2.5 scale is increasing toward the end of December.

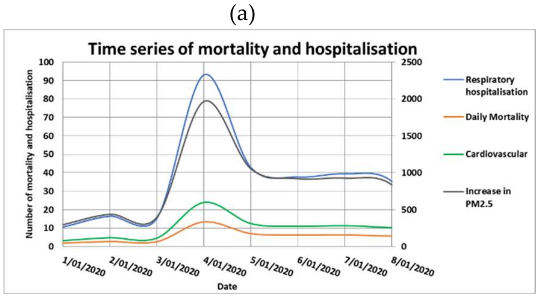
Figure 13 shows the spatial plots of predicted daily average of PM2.5 across the states of NSW and Victoria in south eastern Australia due to wildfires for a few selected days in December 2019. The boundaries of the census districts (SA4s) are shown in the map. The corresponding spatial plots for January 2010 are shown in Figure S.6 in the Supplementary Materials.



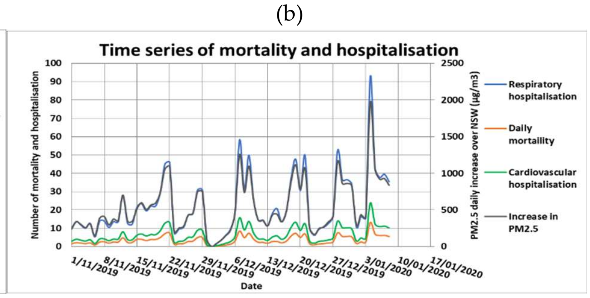
(a)



(b)



(b)



(d)

Figure 14 – Daily time series of increase in PM2.5 over all of census districts (SA4s) in NSW and the number of mortality and hospitalisation (cardiovascular and respiratory diseases) due to wildfires in November (a), December 2019 (b), 1 to 9 January 2020 (c) and combined period 1 November 2019 to 9 January 2020 (d).

The total mortality estimate for the period 1 November to 8 January 2020 is about 247 [CI: 89, 409] premature deaths, 437 [CI: 81, 984] cardiovascular diseases hospitalisation and 1535 [CI: 493, 2087] respiratory diseases hospitalisation. Borchers Arrigada et al. 2020b [9] in their study of the health impact due to this 2019-2020 wildfire event in eastern Australia has estimated that for NSW the mortality, cardiovascular and respiratory hospital admission are approximately 219, 577 and 1050 respectively. Their period of study from 1 October 2019 to 10 February 2020 is longer than that in our study. The extra time range as compared with the period in our study is whole of October 2019 and from 11 January to 10 February 2020. The impact of wildfires in the extra time ranges is not significant as the $PM_{2.5}$ concentration due to wildfires are low before 1 November 2019 and after 11 January 2020 when the wildfires subsided significantly. The population-weighted $PM_{2.5}$ levels were below 15μg/m^3 in these time ranges as presented in Figure 1 of their study. The results from our study correspond with those of [9] for mortality while our cardiovascular diseases hospitalisation estimation is less than that estimated in their study but our respiratory diseases hospitalisation is higher.

4- Discussion and Conclusion

This study uses air quality modelling tool, WRF-Chem, and global fire emission data FINN derived from remote sensing by satellites to assess the extent of the effect of "black summer" 2019-2020 wildfires in the south eastern coast of Australia on air quality and health. Monitoring data from ground-based stations and satellites are used to corroborate with modelling prediction of meteorological and air quality variables. The prediction from the model allows the evolution of the effect of the wildfires in terms of pollutant transport and dispersion to be understood and the air quality impact to be assessed in the east coast of Australia, in particular $PM_{2.5}$ concentration over the modelling domain. This high spatial resolution prediction of air quality concentration also makes it possible to estimate the health impact on population exposure in urban, rural and remote location to $PM_{2.5}$ from wildfires more accurate than assigning exposures from central monitoring stations [20] (Yao et al. 2016). This is especially important when no monitoring data available over potentially large geographic areas and hence assuming no spatial variability or interpolated of nearby monitoring data points to the areas can introduce exposure error or misclassification and bias epidemiologic effect estimates [21]. Lehtomäki et al. 2020 [22] have reviewed various studies of mortality from air pollutant ($PM_{2.5}$ and O_3) and found that there are wide range of mortality results using different health assessment tools and concentration-response functions in Nordic countries. They reported sensitivity analysis showed that high spatial resolution is necessary to avoid underestimation of exposures and health effects.

We decided to use WRF-Chem rather than WRF-CMAQ as the high resolution (1km by 1km) daily global FINN emission data set is available for WRF-Chem with MOZART chemistry mechanism. The fire radiative power as detected from satellites indicate the intensity of the fire and hence can be scaled to modulate the emission. The emission of pollutants from flaming and smothering stages of the fires is therefore be incorporated in the radiative power which the FINN data set considers. Wilkins et al. 2018 [12] in their study of wildfires effect using ground-based statistical data sets on air quality (ozone and particulates) from 2008 to 2012 in the U.S using CMAQ model have shown that the performance of the CMAQ model largely depended on the type of wildfires and emission estimates. In their study, the use of statistical data sets compiled by various organisations have large uncertainties in emission estimates. We use a single consistent FINN data set which relies on satellite sensor detection for fires and their radiative power.

Even though the summer 2019-2020 wildfires did not cause as many deaths as the Black Saturday wildfires in Victoria 2009 or the Ash Wednesday 1983 in Victoria and South Australia but the economic loss of properties and businesses in many regional towns, villages and the health impact due to persistent high particle concentration and exposure to people in major population centres are much more significant than those wildfires before. However, technology has also helped people to reduce their exposure to smoke. Campbell et al. 2020 [23] has reported the survey results based on 13% responses from more than 13,000 people who used AirRater, a free smartphone app that reports air quality and track user symptom in near real-time and help them to reduce exposure of smoke during the 2019-2020 wildfires. Respondents provided feedback that the app was very useful in helping them to make decision to avoid or minimise exposure such as staying indoor (76%), rescheduling or planning outdoor activities (64%), changing the location to a less affected areas (29%). During the peaks of wildfires, the number of people visiting a general practitioner (GP) actually dropped and the largest decreases in

GP attendances claims were seen in affected regions during weeks when air quality was recorded as particularly poor and this drop in GP attendance may also have been influenced by health advice to stay indoors [2].

Health alerts to the public from NSW Department of Health which worked in conjunction with other agencies such as the Department of Planning, Industry and Environment (DPIE) or the Rural Fire Services (RFS) of NSW also helped people to take actions to reduce their exposure to smoke. These interventional actions would reduce population exposure and hence theoretically affect the calculation of the estimated exposure and health effects from the method used in this study which assumes ambient concentration of $PM_{2.5}$ directly affect people fully. Mueller et al. 2020 [24] in their study of ambient air pollutant and health effect in northern Thailand including the period when there was intense agricultural biomass burning in March have found that the risk ratio (RR) between daily PM_{10} and outpatient visits were elevated most on the same day as exposure for chronic lower respiratory disease (CLRD) with RR = 1.020 (95% CI: 1.012 to 1.028) and cerebrovascular disease (CBVD) with RR = 1.020 (95% CI: 1.004 to 1.035), but there was no association with ischaemic heart disease (IHD) with RR = 0.994 (95% CI: 0.974 to 1.014). They also found that there was no evidence that high PM_{10} on biomass burning days showed a clear exposure response effect for CLRD and CBVD visits. They suggested that two possible reasons for this result is that particulates from biomass burning may be less harmful than that from other sources and that at higher PM concentrations identified as from biomass burning the risk decreases at high concentration levels. But the other factor that can influence the results is that people during episodic events of pollution will seek shelter or take measure to lessen their exposure to harmful pollutants in ambient air.

In addition to uncertainty in RR for each health endpoints, another source of uncertainty in the estimated results is the uncertainty in WRF-Chem model. The accuracy of WRF-Chem air quality model is depending on uncertainties of the emission input and the uncertainty of the WRF-Chem model itself (its meteorological and chemical components). Even though FINN provides the most detailed emission in both temporal and spatial scale, and its estimates are comparable to other emission data sets such as GFEDv3, the uncertainty assigned to the FINNv1 estimates is about a factor of 2 due to various assumptions such as land cover classifications, estimated burned area, fuel loading and consumption and emission factors [15]. Low cost sensors could be used to increase the availability of air quality measurement data in areas where standard monitoring network stations are lacking, and modelling output data can then be used to blend with these data using techniques such as Bayesian method to increase the accuracy of the estimated pollutant concentration for health impact calculation. Robinson 2020 [25] has used low cost sensor data in additional to DPIE monitoring station in Armidale (northern NSW) to show the spatial variability of $PM_{2.5}$ and hence help to improve the accuracy of exposure and health impact estimate due to wood heater during winter in this region.

Another approach to estimate the $PM_{2.5}$ concentration from wildfires at grid points is the use of machine learning or AI method instead of physical modelling method as in this study using WRF-Chem. Yao et al. 2018 [20] has used machine learning to estimate hourly exposure to $PM_{2.5}$ for urban, rural, and remote populations during wildfire seasons.

In this study we only focus on daily scale effect based on daily average predicted concentration. But the health effect of $PM_{2.5}$ exposure during wildfire seasons can be seen in sub-daily scale as Yao et al. (2020) [26] reported in their study that increased $PM_{2.5}$ concentration was associated with some respiratory and cardiovascular outcomes within 1 hour following exposure. Sub-daily scale population health impact can be done if the accuracy of the current modelling technology to predict the pollutant concentration is much improved. The current WRF-Chem air quality model does not take into account the fire spread and fire behaviour on this time scale. The studies and methodology of [27] [28] on short and long-distance fire spotting can be implemented in the air quality modelling system such as WRF-Chem to take into account fire behaviour and propagation.

There are other effects of wildfires on people welfare that should be addressed is the effect on mental health. People is anxious or worried about the wildfires and calls to the Lifeline crisis support hotline increased, resulting in the introduction of a telephone line for people affected by the bushfires [2]. The costs of the Black Summer 2019-2020 wildfires in term of physical property damage, biodiversity, people health and the economy were significant. Prescribed burning is essential for managing these wildfires. And with wildfires are increasing in south-eastern Australia and globally [29] due to climate change, Morgan et al. 2020 [30] in their study on the history of prescribed burnings in south eastern Australia found that even though significant progress of fire and ecosystem science has been achieved in the past 50 years but the current fire management will not sustain the full range of ecosystem processes and biodiversity, nor reduce to an acceptable level the impact of wildfires on human lives and property. They suggested more investment in training, human capacity and resources to safely and effectively deploy prescribed burning more widely to reduce future wildfire risks and the potential negative impacts of prescribed burning can be managed effectively with clear communication of the benefits of prescribed burning to the public. Handmer et al. 2021 [31] however stressed that for big event wildfires, a system approach to mitigate and manage the fire risks have to be considered. The approach pays special attention to the increase risk of large and extreme fires from tail dependence and spatial dependence. Tail dependence, in which extreme conditions (at the tail of each of the distribution) such as high temperature and low rainfall can occur concurrently or one extreme condition can enhance the chance of the other condition occurrence, makes the fire events more likely and more extreme from compound events. While spatial dependence reflects the fact that fire risk in one area can be connected with other areas due to extreme dryness occur everywhere over a large region with available fuel load. Fires over a local area in this situation can ignite or spread to far away areas through fire spotting or occur simultaneously and then connected to form megafires. Both tail dependence and spatial dependence conditions were present in the Black Summer 2019-2020 wildfires in eastern Australia. There ae methods available for assessing the tail dependence and spatial dependence [31]. Importantly, the Black Summer wildfires highlighted the role of climate change on the increasing number and scale of wildfires in eastern Australia and therefore effort to mitigate the effect of climate change or reduce the greenhouse emission should be considered seriously.

Supplementary Materials: Figures S1-S6.

Author Contributions: Conceptualisation, H.D., M.A., M.R. (Matthew Riley); methodology, H.D., D.S., S.W. (Sean Watt), S.W. (Stephen White), G.M; data procurement: D.S., T.T., K.L., M.R. (Mahmudur Rahman), X.B, D.F, H.N; formal analysis, H.D., D.S., S.W. (Sean Watt), and L.T.-C.C.; investigation, H.D., S.W. (Sean Watt) and S.W. (Stephen White); writing—original draft preparation, H.D.; visualisation, H.D. ; supervision, H.D., M.A. and M.R. (Matthew Riley); and project administration, H..D., M.A and M.R. (Matthew Riley). All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data available upon request to the corresponding author.

Acknowledgement: The following data sources are gratefully acknowledged: the CALIPSO satellite products from NASA Langley Research Center (http://www-calipso.larc.nasa.gov/products/lidar/browse_images/production/), U.S, the Australia Water Resource Assessment (AWRA) of the Bureau of Meteorology, Australia, FINN fire emission data sets from NCAR, U.S, MODIS Aqua/Terra satellite hot spots product from NASA, U.S, Final Analysis (FNL) Reanalysis data from the National Centre for Environmental Prediction (NCEP), U.S., and population health data from the NSW Department of Health, Australia.

Conflicts of Interest: The authors declare no conflict of interest

References

1. Davey, S., A. Sarre, A., 2020, Editorial: the 2019/20 Black Summer bushfires, *Australian Forestry*, 83:2, 47-51, DOI: 10.1080/00049158.2020.1769899

2. Australian Institute of Health and Welfare (AIHW), 2020, Australian bushfires 2019–20, Exploring the short-term health impacts, https://www.aihw.gov.au/getmedia/a14c3205-784c-4d81-ab49-a33ed4d3d813/aihw-phe-276.pdf.aspx?inline=true (accessed on 31/1/2021)

3. World Meteorological Organization (WMO), 2020, Australia suffers devastating fires after hottest, driest year on record, https://public.wmo.int/en/media/news/australia-suffers-devastating-fires-after-hottest-driest-year-record (accessed on 31/1/2021)

4. Hamilton, D., Scanza, R., Rathod, S., et al. 2020, Recent (1980 to 2015) Trends and Variability in Daily-to-Interannual Soluble Iron Deposition from Dust, Fire, and Anthropogenic Sources, *Geophysical Research Letters*, 47(17), DOI: 10.1029/2020GL089688

5. ECMWF (European Centre for Medium-Range Weather Forecasts) 2020. Copernicus Atmosphere Monitoring Service: Wildfires continue to rage in Australia. Reading, United Kingdom: ECMWF. Accessed on 12 February 2021, https://atmosphere.copernicus.eu/wildfires-continue-rage-australia

6. Knibbs, L., Cortés de Waterman, A., Toelle, et al., 2018, The Australian Child Health and Air Pollution Study (ACHAPS): A national population-based cross-sectional study of long-term exposure to outdoor air pollution, asthma, and lung function, *Environment International*, 120, 394–403. https://doi.org/10.1016/j.envint.2018.08.025

7. Walter, C., Schneider-Futschik, E., Knibbs, L., Irving, L., 2020, Health impacts of bushfire smoke exposure in Australia, *Respirology*, doi: 10.1111/resp.13798

8. Borchers-Arriagada, N., Palmer, A., Bowman, D., Williamson, G., et al., 2020a, Health Impacts of Ambient Biomass Smoke in Tasmania, Australia, *Int. J. Environ. Res. Public Health*, 2020, 17, 3264; doi:10.3390/ijerph17093264

9. Borchers Arriagada, N., Palmer, A., Bowman, D., Morgan, G., Jaluladin, B., Johnston F., 2020b, Unprecedented smoke-related health burden associated with the 2019–20 bushfires in eastern Australia, *Med J Aust*, doi: 10.5694/mja2.50545

10. Howard Z., Carlson S., Baldwin Z, Johnston F, Durrheim D., Dalton C., 2020, High community burden of smoke-related symptoms in the Hunter and New England regions during the 2019–2020 Australian bushfires. *Public Health Res. Pract.*, 2020; https://doi.org/10.17061/phrp30122007

11. Nguyen, H., Trieu, T., Cope, M., Azzi, M., Morgan, G., 2020, Modelling Hazardous Reduction Burnings and Bushfire Emission in Air Quality Model and Their Impacts on Health in the Greater Metropolitan Region of Sydney, *Environmental Modeling and Assessment*, 25(4), DOI: 10.1007/s10666-020-09705-x

12. Wilkins, J., Pouliot, G., Foley, K., Appel, W., Pierce, T., 2018, The impact of US wildland fires on ozone and particulate matter: a comparison of measurements and CMAQ model predictions from 2008 to 2012, *International Journal of Wildland Fire*, 27:684–698, https://doi.org/10.1071/WF18053

13. Ooi, M., Chuang, M., Fu, J., Kong, S., Huang, W., et al., 2021, Improving prediction of trans-boundary biomass burning plume dispersion: from northern peninsular Southeast Asia to downwind western north Pacific Ocean, *Atmospheric Chemistry and Physics*, https://doi.org/10.5194/acp-2020-1283.

14. Andreae, M., Merlet, P., 2001, Emission of trace gases and aerosolsfrom biomass burning, *Global Biogeochem. Cy.*, 15(4), 955–966.

15. Wiedinmyer, C., Akagi, S., Yokelson, R., et al., 2011, The Fire INventory from NCAR (FINN): a high resolution global model to estimate the emissions from open burning, *Geosci. Model Dev.*, 4, 625–641

16. WHO (World Health Organization). Health Risks of Air Pollution in Europe—HRAPIE Project Recommendations for Concentration–Response Functions for Cost–Benefit Analysis of Particulate Matter, Ozone and Nitrogen Dioxide. 2013. Available online: https://www.euro.who.int/__data/assets/pdf_file/0006/238956/Health_risks_air_pollution_HRAPIE_project.pdf (accessed on 22 January 2021).

17. Delfino, R. J., Brummel, S., Wu, J., et al., (2009), The relationship of respiratory and cardiovascular hospital admissions to the southern California wildfires of 2003. *Occup. Environ. Med*, 66. doi:10.1136/oem.2008.041376.

18. Horsley, J., Broome, R., Johnston, F., Cope, M., Morgan, G., (2018), Health burden associated with fire smoke in Sydney, 2001-2013, *Med. J. Aust.*, 208(7):309-310, DOI: 10.5694/mja18.00032

19. Filkov, A., Ngo, T., Matthews, S., et al. 2020, Impact of Australia's catastrophic 2019/20 bushfire season on communities and environment. Retrospective analysis and current trends, *Journal of Safety Science and Resilience*, 1:44-56, DOI: 10.1016/j.jnlssr.2020.06.009

20. Yao, J., Brauer, M., Raffuse, S., Henderson, S., 2018, Machine Learning Approach To Estimate Hourly Exposure to Fine Particulate Matter for Urban, Rural, and Remote Populations during Wildfire Seasons, *Environ. Sci. Technol.*, 52, 13239−13249, DOI: 10.1021/acs.est.8b01921

21. Yao, J., Eyamie, J., Henderson, S., 2016, Evaluation of a spatially resolved forest fire smoke model for population-based epidemiologic exposure assessment., *J. Exposure Sci. Environ. Epidemiol.*, 26 (3), 233.

22. Lehtomäki, H., Geels, C., Brandt, J., et al., 2020, Deaths Attributable to Air Pollution in Nordic Countries: Disparities in the Estimates, *Atmosphere* 11(5):467, DOI: 10.3390/atmos11050467

23. Campbell, S., Jones, P., Williamson, G., et al., 2020, Using Digital Technology to Protect Health in Prolonged Poor Air Quality Episodes: A Case Study of the AirRater App during the Australian 2019–20 Fires, *Fire* 3(3):40, DOI: 10.3390/fire3030040

24. Mueller, W., Loh, M., Vardoulakis, S., Johnston, H., et al., 2020, Ambient particulate matter and biomass burning: an ecological time series study of respiratory and cardiovascular hospital visits in northern Thailand, *Environmental Health*, 19:77, https://doi.org/10.1186/s12940-020-00629-3

25. Robinson, D., 2020, Accurate, Low Cost $PM_{2.5}$ Measurements Demonstrate the Large Spatial Variation in Wood Smoke Pollution in Regional Australia and Improve Modeling and Estimates of Health Costs, *Atmosphere*, 11(8):856, DOI: 10.3390/atmos11080856

26. Yao, J., Brauer, M., Wei, J., McGrail, K., et al., 2020, Sub-Daily Exposure to Fine Particulate Matter and Ambulance Dispatches during Wildfire Seasons: A Case-Crossover Study in British Columbia, Canada, *Environmental Health Perspectives*, 128(6):1-10, DOI: 10.1289/EHP5792

27. Storey, M., Price, O., Bradstock, R., Sharples, J., 2020a, Analysis of variation in distance, number, and distribution of spotting in Southeast Australian wildfires, *Fire*, doi:10.3390/fire3020010

28. Storey, M., Price, O., Sharples, J., Bradstock, R., 2020b, Drivers of long-distance spotting during wildfires in south-eastern Australia, *International Journal of Wildland Fire*, https://doi.org/10.1071/WF19124

29. Xu, R., Yu, P., Abramson, M., Johnston, F. et al., 2020, Wildfires, Global Climate Change, and Human Health, *New England Journal of Medicine*, DOI: 10.1056/NEJMsr2028985

30. Morgan G., Tolhurst K., Poynter M., et al. 2020. Prescribed burning in south-eastern Australia: history and future directions, *Australian Forestry*. 83:4–28. doi:10.1080/00049158.2020.1739883

31. Handmer, J., Hochrainer-Stigler, S., Schinko, T., et al., 2021, The Australian wildfires from a systems dependency perspective, *Environmental Research Letters* 15(12), DOI: 10.1088/1748-9326/abc0bc

Appendix

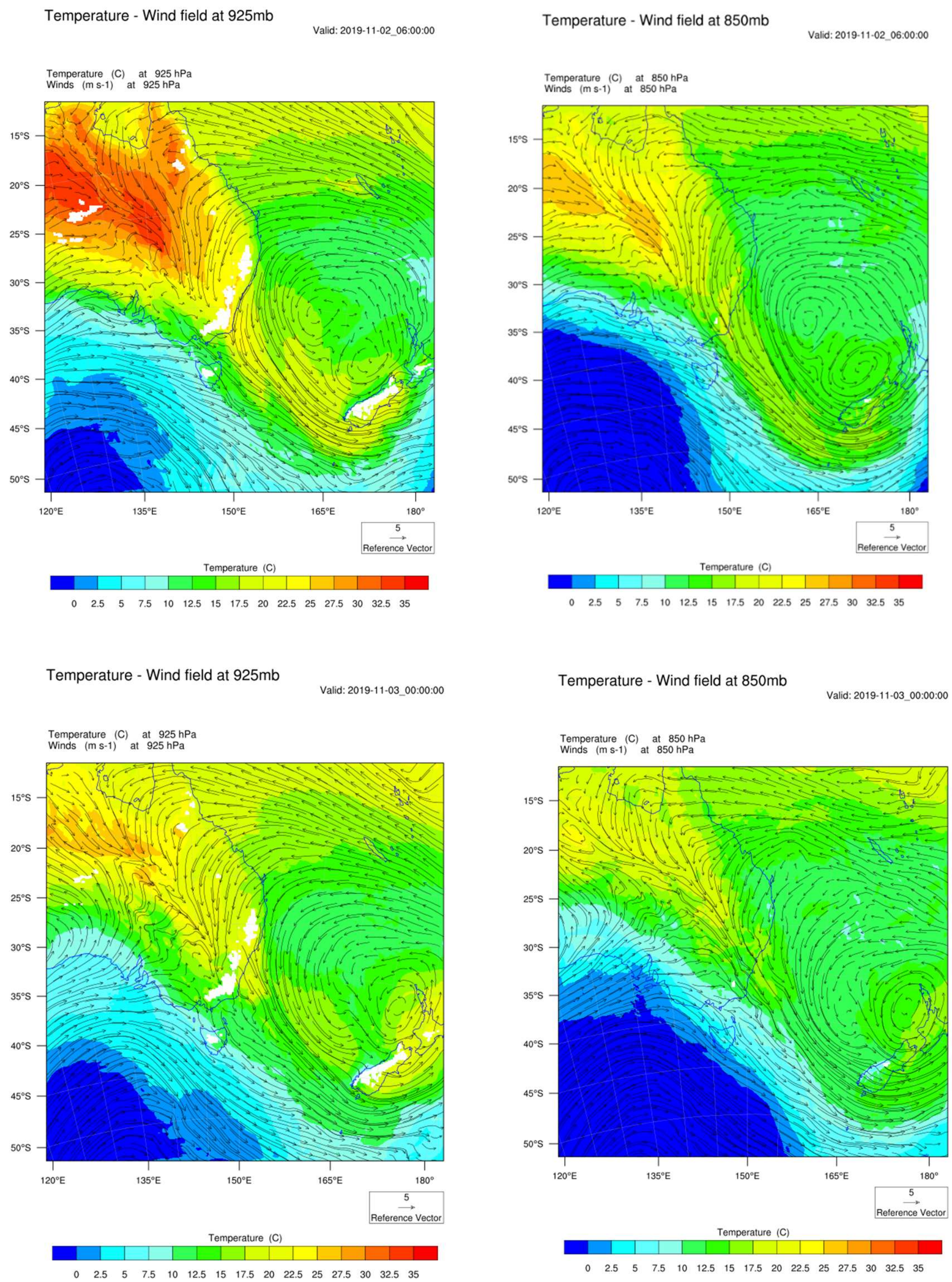
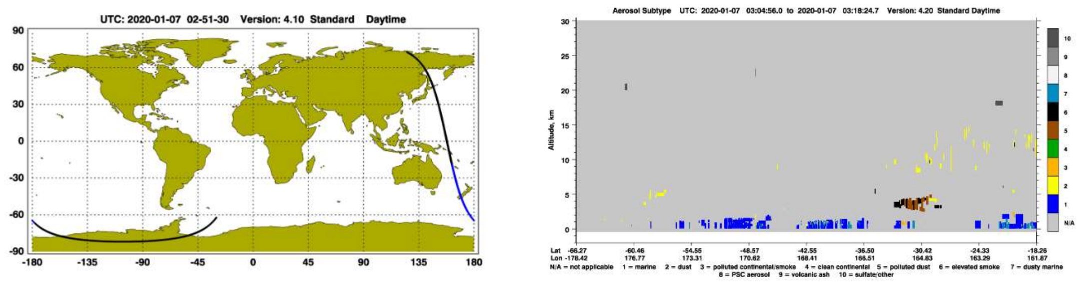
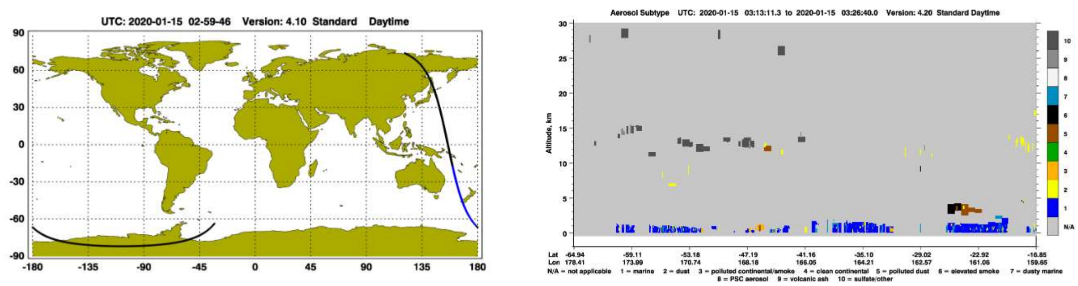


Figure A.1 – Predicted wind and temperature at 925 mb and 850 mb on 2 November 2019 06:00 UTC and 3 November 2019 00:00 UTC



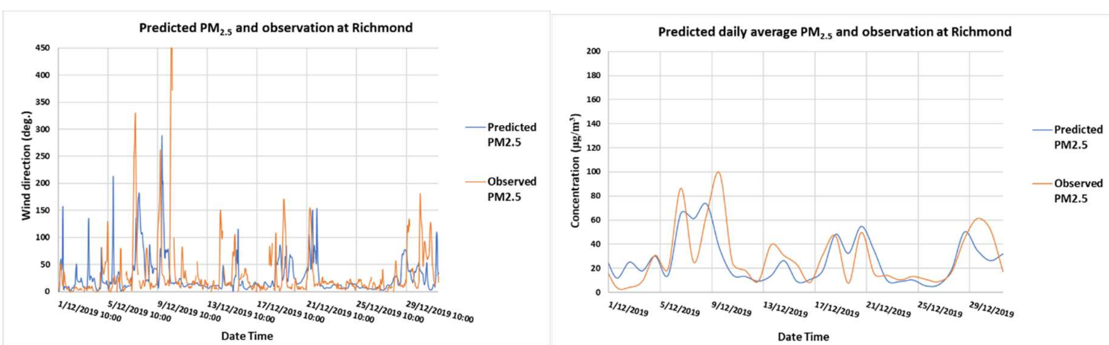
(a) (b)

Figure A.2 - CALIPSO satellite path (a) and aerosol profile (b) over Coral Sea and New Zealand on 7 January 2020 at 2:51 UTC. Smoke aerosols (black) over the Tasman Sea in the troposphere at ~3km to ~5km high.

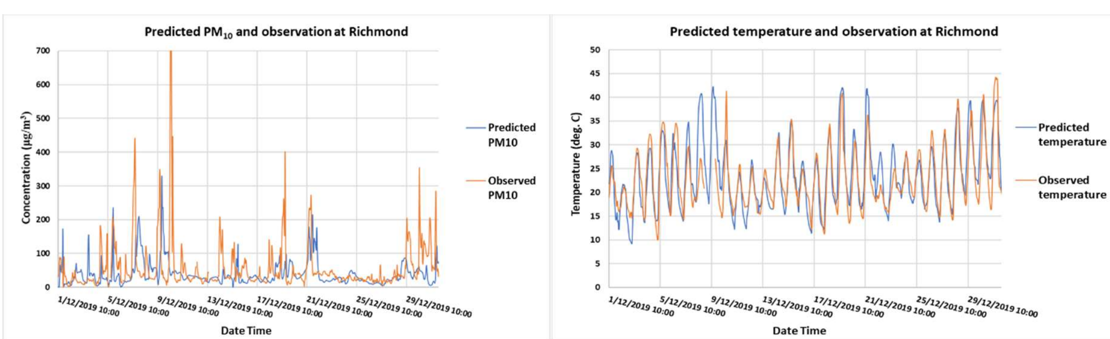


(a) (b)

Figure A.3 – CALIOPS lidar profile of aerosols on 15 January 2020 along the CALIPSO satellite path from south New Zealand to Tasman Sea and Coral Sea off Queensland (a) and aerosols type distribution above ground (b). Smoke aerosols (black) in the upper troposphere (10-15km) and stratosphere (25-30km) above the Tasman Sea and south New Zealand.

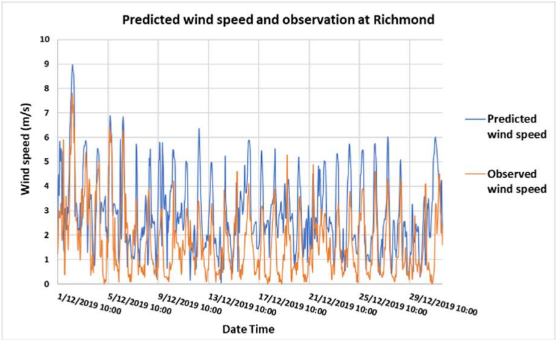


(a) (b)

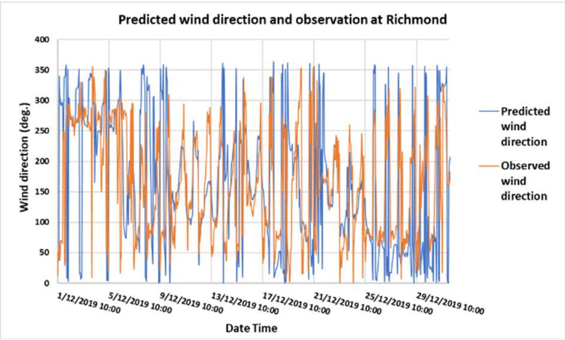


(c) (d)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 March 2021 doi:10.20944/preprints202103.0243.v1



(e)



(f)

Figure A.4 – Predicted and observed hourly $PM_{2.5}$ (a), daily average $PM_{2.5}$ (b), hourly PM_{10} (c), temperature (d), wind speed (e) and wind direction (f) at Richmond in the north west of Sydney in December 2019