Spaceborne detection of XCO₂ enhancement induced by Australian mega-bushfires

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Abstract

The 2019–20 Australian mega-bushfires, which raged particularly over New South Wales and Victoria, released large amounts of toxic haze and CO₂. Here, we investigate whether the resulting CO₂ enhancement can be directly detected by satellite observations, based on National Aeronautics and Space Administration’s Orbiting Carbon Observatory-2 (OCO-2) column-averaged CO₂ (XCO₂) product. We find that smoke from wildfires can greatly obscure satellite observations, making the available XCO₂ mainly locate over outer fringes of plumes downwind of the major mega-bushfires in eastern Australia in three orbit observations during November–December 2019, with their enhancements of approximately 1.5 ppm. This fire-induced CO₂ enhancement is further confirmed using an atmospheric transport model, Goddard Earth Observing System-Chem, forced by satellite observation-derived fire product Global Fire Emissions Database, version 4.1 and wind observations, with comparable simulated XCO₂ enhancements. Model simulation also suggests that the sensitivity of the downwind maximum XCO₂ enhancement is 0.41 ± 0.04 ppm for 1 TgC d⁻¹ fire emissions. In sum, though detectable to some extent, it remains a challenge to get the accurate maximum XCO₂ enhancements due to the gaps in XCO₂ detections obscured by smoke. Understanding the capability of OCO-2 XCO₂ detection is prerequisite for monitoring and constraining wildfire CO₂ emissions by inversions.

1. Introduction

The unprecedented 2019–20 Australian bushfires, which raged particularly over eastern Australia (the worst hit states were New South Wales and Victoria), drew worldwide attention. The worst fire incidents started at the beginning of November 2019. During November and December 2019, eastern Australia experienced record-breaking temperatures and widespread severe and extreme drought with decreased precipitation (supplementary figure 1 (available online at https://stacks.iop.org/ERL/15/124069/mmedia)), as indicated by previous studies (Boer et al 2020). This anomalous hot and dry climate may have been driven by natural atmospheric dynamics and anthropogenic global warming (Phillips and Nogrady 2020). The unusual positive Indian Ocean Dipole (IOD) in 2019 was one of the strongest such events in history. During the positive phase of IOD, decreased precipitation and warmer temperatures often occur over parts of Australia (Saji et al 1999, Saji and Yamagata 2003, Cai et al 2009). A sudden stratospheric warming above Antarctica can also cause the hot and dry conditions over Australia (Phillips and Nogrady 2020). These hot and dry conditions greatly contribute to catastrophic bushfires.
The mega-bushfires of 2019–20 burned vast areas of temperate broadleaf and mixed forests (Boer et al 2020, Nolan et al 2020). Approximately 5.8 million hectares were burned between September 2019 and early January 2020, accounting for around 21% of Australia’s temperate broadleaf and mixed forests (Boer et al 2020). The fires greatly threatened the Gondwana Rainforests, a World Heritage site (Kooyman et al 2020). The fires caused losses of USD billions from the economy, as well as deaths of more than 30 humans and countless animals. Concurrently, the mega-bushfires released large amounts of toxic haze and CO2, further threatening human health and contributing to the increase of global CO2 concentrations.

Orbiting Carbon Observatory-2 (OCO-2) is the Earth remote sensing satellite used by National Aeronautics and Space Administration (NASA) to measure the atmospheric CO2 concentration (Crisp et al 2008, Crisp and OCO-2 Team 2015). The OCO-2 column-averaged CO2 (XCO2) products have been used to detect the XCO2 enhancement over both megacity and volcanoes (Schwandner et al 2017), analyze the variations of XCO2 over the Niño 3.4 regions during the 2015–16 El Niño event (Chatterjee et al 2017), estimate the land–atmosphere carbon flux and fire emissions during the El Niño event (Heymann et al 2017, Liu et al 2017), and estimate the CO2 emissions by megacities (Zheng et al 2020) and single power plants (Nassar et al 2017). In the previous study (Heymann et al 2017), the XCO2 enhancement induced by fires was calculated as the difference between OCO-2 XCO2 and background XCO2 values on 0.5° × 0.5° grids, where background XCO2 was derived from a CO2 model ‘CarbonTracker’ and observations unaffected by fires determined by the Stochastic Time-Inverted Lagrangian Transport model. In contrast, we in this study will investigate whether OCO-2 can directly and clearly detect the XCO2 enhancement induced by Australian mega-bushfires, analogous to the study of Schwandner et al (2017), based on the combination of OCO-2 L2 XCO2 product and Goddard Earth Observing System (GEOS)-Chem model simulations. Understanding the capability of OCO-2 to detect XCO2 enhancement induced by eastern Australia’s fires is important for monitoring and constraining wildfire CO2 emissions over the whole of Australia.

2. Materials and methods

2.1. OCO-2 data

The space-based XCO2 measurements used to detect XCO2 enhancement in this study are retrieved from the OCO-2 mission (Crisp et al 2008, Crisp and OCO-2 Team 2015), which was launched into a near-polar orbit on 2 July 2014. The OCO-2 instrument has a narrow swath with the footprint <1.3 km × 2.25 km. Its retrieval algorithm was described by Crisp et al (2012) and O’Dell et al (2012). In this study, the XCO2 retrievals are the version 9r level 2 product, which can be retrieved from the Goddard Earth Sciences Data and Information Services Center. Version 9r is the latest version of the XCO2 dataset, containing bias-corrected XCO2 and other selected fields. In this analysis, we used the good quality XCO2 data, which were determined by the variable ‘xco2_quality_flag’ in the file.

2.2. Atmospheric transport model

The GEOS-Chem model version 12.5.0 (The International GEOS-Chem User Community 2019) was adopted in this study to simulate the XCO2 enhancement induced by Australian bushfires. It is a global 3D atmospheric chemistry model driven by meteorological fields which are freely available at the GEOS of the NASA Global Modeling Assimilation Office.

Specifically, the driving meteorological fields and boundary carbon fluxes are as follows:

(a) The meteorological fields are the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) (Gelaro et al 2017). MERRA-2 can utilize the newer microwave and hyperspectral infrared radiance observations, and is the first long-term global reanalysis to assimilate space-based aerosol measurements. In this study, we ran the GEOS-Chem model at the horizontal resolution of 4° × 5° and 47 hybrid sigma-pressure levels up to 0.01 hPa. In addition, in the analysis, we further used its variables of surface air temperature, U and V winds at 940 hPa, and aerosol optical depth (AOD).

(b) The fossil fuel emissions are from the Open-Data Inventory for Anthropogenic Carbon Dioxide (ODIAC) which is a global CO2 emission product from fossil fuel combustion (Oda and Maksyutov 2011, Oda et al 2018). In this study, we used the latest version of the ODIAC fossil fuel emission product ‘ODIAC2019’ with the original resolution of 1° × 1° from 2000 to 2018. The emissions in 2019 are obtained by the linear extrapolation.

(c) The wildfire carbon emissions are based on the Global Fire Emissions Database, Version 4.1 (GFED4.1) (van der Werf et al 2017). This product was constructed by combining Moderate Resolution Imaging Spectroradiometer (MODIS) burned area maps with active fire data from the Tropical Rainfall Measuring Mission (TRMM) Visible and Infrared Scanner and the Along-Track Scanning Radiometer family of sensors. Satellite-based fire activity and vegetation productivity were combined to estimate gridded monthly fire emissions and scalars which can be used to derive higher temporal resolution emissions. It has the original horizontal...
resolution of $0.25^\circ \times 0.25^\circ$. We distributed the monthly emissions into the daily values by use of the daily fraction variable (Mu et al. 2011). However, as for the diurnal cycle, in this study we uniformly distributed the daily emissions into each hour.

(d) The land–atmosphere carbon fluxes ($F_{TA}$) are simulated by VEGAS Near-Real Time (VEGAS NRT) (Wang et al. 2018). The VEGAS NRT was operationally run to present at $0.5^\circ \times 0.5^\circ$ with the automatically updated meteorological fields such as precipitation, surface air temperature, and radiations. The details for the meteorological fields were described in Wang et al. (2018). In this study, we regarded the difference between $F_{TA}$ and simulated fire emissions ($F_{fire}$) as ‘land–atmosphere carbon flux without fires’.

(e) The ocean–atmosphere carbon fluxes are from Takahashi et al. (2009) which have been scaled with atmospheric data at $4^\circ \times 5^\circ$ for 2000–2013. We rescaled the oceanic carbon fluxes for the following years using the Global Carbon Project datasets (Friedlingstein et al. 2019) relative to the year 2013.

2.3. Sensitivity experiments

Two sets of experiments were conducted for the main text, with their experimental designs as follows:

(a) Control experiment (denoted as ‘CTL’): full surface carbon emissions considered, including extrapolated ODIAC fossil fuel emissions, extrapolated oceanic carbon exchange, land–atmosphere carbon flux without fires simulated by VEGAS NRT, and GFED4.1 wildfire emissions.

(b) Sensitivity experiment (denoted as ‘S1’): same as CTL, but wildfire carbon emissions are set to zero over Australia from November to December 2019.

Thus, we can derive the XCO$_2$ and 3D CO$_2$ enhancement caused by the Australian bushfires from the difference between CTL and S1. We ran these two experiments from 1 January 2018 to 31 December 2019 with the CO$_2$ restart fields from previous long-term simulations.

3. Results

3.1. Australian bushfire carbon emissions and OCO-2 detections

Out-of-control wildfires hit the temperate forests, dominated by fire-prone Eucalyptus, in New South Wales and Victoria from the beginning of November 2019, causing an enhanced amount of carbon (or CO$_2$) release (figure 1(a)). On average, the carbon release in $0.25^\circ \times 0.25^\circ$ grid from the mega-fires between November and December 2019 is in general higher than 15 gC m$^{-2}$ d$^{-1}$, in which emissions can reach an extreme of up to 126.9 gC m$^{-2}$ d$^{-1}$ (figure 1(a)). Australia’s fossil fuel carbon emissions are also centered over its eastern coastal areas, around the major cities as well as the surrounding power plants (figure 1(b)). It is therefore a concern that fossil fuel emissions may interfere with the space-borne detection of XCO$_2$ enhancement induced by wildfires. Fortunately, the strength of fossil fuel carbon emissions is found to be much lower than that of the wildfire emissions in these two months. The total fossil fuel carbon emissions in the region of 144–154° E, 40–26° S is approximately 0.2 TgC d$^{-1}$, leading to a total of 12.2 TgC (or 44.7 TgCO$_2$) for the two months. In contrast, the strength of total wildfire carbon emissions in this region is close to zero before November, and then it becomes much stronger and more variable leading to emissions of approximately 119.0 TgC (or 436.3 TgCO$_2$) during November and December 2019 (figure 1(d)). The wildfire carbon emissions are therefore approximately ten times stronger than fossil fuel emissions in these two months. In addition, the simulated terrestrial ecosystems in this region show a weak absorption (excluding the simulated fire emissions) with the amplitude of 0.08 TgC d$^{-1}$ (figure 1(d)) because November and December are the austral late spring and early summer. Hence, the surface carbon emissions in this region are dominated by the mega-bushfire carbon emissions.

In this region, prevailing winds in the planetary boundary layer are west, west–southwest, and southwest, which blow the emitted CO$_2$ to the ocean (figure 1(c)). The average wind speed in November and December at 940 hPa is 6.3 m s$^{-1}$, resulting in about 5.6° longitude advection for 1 d.

We checked the OCO-2 XCO$_2$ orbit observations around eastern Australia’s mega-bushfires between November and December 2019, and selected three orbits that could be used to detect XCO$_2$ enhancement induced by wildfires. These three orbits were observed at around 03:30 Coordinated Universal Time (UTC) on 14 November 2019, 21 November 2019, and 28 December 2019. Figure 2 shows their respective distributions, associated with corresponding wildfire carbon emissions and atmospheric circulation. The XCO$_2$ values are gradually enhanced from the regions far away from the wildfires to the wildfire downwind areas (figures 2(a)–(c)). These variations are significantly different from the pulse of XCO$_2$ enhancements induced by the single power plant fossil fuel CO$_2$ emissions (supplementary figure 2), which is similar to the previous results (Nassar et al. 2017, Zheng et al. 2020). Taking the XCO$_2$ values furthest from the wildfires as the background levels, we used the available XCO$_2$ values over the fringe areas of plumes to calculate maximum XCO$_2$ enhancement in these three orbits with their respective
Figure 1. Carbon release by wildfires and fossil fuels. (a) Carbon emissions induced by mega-bushfires, averaged from November to December 2019. (b) ODIAC fossil fuel carbon releases, averaged from November to December 2018. Due to the unavailability of 2019 datasets, we here show data from 2018; the changes in fossil fuel carbon releases over Australia between 2018 and 2019 are likely to be negligible. The unit in (a) and (b) is gC m\(^{-2}\) d\(^{-1}\). The rectangular box in (b) shows the area where we calculate the prevailing wind and total carbon emissions. (c) Wind rose diagram at 940 hPa. (d) Total daily carbon fluxes by fossil fuel, mega-bushfires, and terrestrial ecosystems. The dots in (d) show the dates of clear OCO-2 orbit XCO\(_2\) observations.

Figure 2. Clear OCO-2 XCO\(_2\) observations at three orbits downwind of the Australian mega-bushfires associated with the corresponding spatial patterns of wildfire carbon emissions, AOD, and stream fields at 940 hPa. The OCO-2 XCO\(_2\) observations at 03:30 UTC with the 24 h averaged wildfire carbon emissions and stream fields before 03:30 UTC on (a) 14 November 2019, (b) 21 November 2019, and (c) 28 December 2019. The scatter plots at the right in (a)–(c) show XCO\(_2\) variation along the latitudes. According to the AOD and simulated XCO\(_2\) (see next figure) patterns, we choose the XCO\(_2\) data far away from the fires to calculate background XCO\(_2\) levels (blue dots here) and data over the fringes of plumes (coral dots) to calculate XCO\(_2\) enhancement against background XCO\(_2\). (d) Box plots for background XCO\(_2\) levels and enhanced XCO\(_2\) for the three orbits. (e)–(g) as (a)–(c), but with the spatial patterns of AOD.

Enhancements of approximately 1.5, 1.3, and 1.9 ppm (figure 2(d)). It is worth mentioning that the gaps of XCO\(_2\) in these three orbits over the wildfire downwind areas are mainly obscured by the amount of smoke emitted by the wildfires. This smoke can enhance the AOD at the local and downwind regions (figures 2(e)–(g)). The local AOD can be higher than 2.7, greatly
contaminating the OCO-2 XCO₂ observations. The missed observations were often located in the core wildfire-induced XCO₂ enhancement regions, probably leading to an underestimate of the maximum XCO₂ enhancement.

3.2. GEOS-Chem model simulations
The observed XCO₂ variations can be influenced by surface carbon emissions and atmospheric circulation. To further verify that the XCO₂ enhancement observed from the three orbits was caused by wildfire CO₂ emissions, we use the GEOS-Chem model to disentangle the wildfire-induced XCO₂ enhancement with sensitivity experiments (figure 3).

The simulated XCO₂ during November and December in the control experiment has similar spatial patterns and amplitudes compared with OCO-2 observations, although the simulated XCO₂ is approximately 1 ppm higher than results from OCO-2 (supplementary figure 3). In combination with the sensitivity experiment that sets the wildfire carbon flux over Australia as zero emissions during November and December 2019, we can derive the wildfire-induced atmospheric CO₂ variations. Figure 3 shows the spatial patterns for simulated XCO₂ enhancement at around 03:30 UTC on 14 November 2019, 21 November 2019, and 28 December 2019. The higher XCO₂ values from these three orbits observed by OCO-2 coincide with distributions of the simulated XCO₂ enhancement. Importantly, the simulated XCO₂ enhancements are basically comparable to the XCO₂ enhancements detected by OCO-2 (figure 2(d)), confirming that these directly detected XCO₂ enhancements are caused by wildfires.

The wildfire CO₂ emissions can also greatly enhance surface CO₂ concentration (supplementary figure 4). From the height–longitude cross-section, we can see that significantly enhanced CO₂ concentrated under 1 km height, and that the enhanced CO₂ in the free atmosphere will be quickly advected (supplementary figure 5).

4. Discussion
Although we have used GEOS-Chem model to verify that the OCO-2 XCO₂ enhancements observed at these three orbits are very likely induced by wildfire CO₂ emissions, one concern is the effect of the uncertainties of the OCO-2 data. Worden et al (2017) suggested that effects of aerosols or surface albedo can influence the accuracy of XCO₂ data. Therefore, we present the respective XCO₂ uncertainties at these three orbits in supplementary figure 6. The XCO₂ at 03:30 UTC on 21 November 2019 shows higher uncertainties with values approximately 0.6–0.8 ppm (supplementary figures 6(b) and (c)). Indeed, aerosols emitted by wildfires can increase the uncertainties at some pixels, but majorities of the uncertainties are smaller than 0.8 ppm. Therefore, it is convincing that the approximately 1.5 ppm XCO₂ enhancements downwind of the
major mega-bushfires in eastern Australia at the three orbits cannot be caused by the variations of retrieval uncertainties.

Additionally, we ran two extra sensitivity experiments (supplementary text 2) to explore the influence of carbon flux anomalies induced by the ecosystem and wildfires on the XCO₂ variations. We found that the XCO₂ can be significantly enhanced over the southeast regions of Australia and surrounding oceans by wildfire anomalies in November and December 2019, whereas the enhanced XCO₂ induced by ecosystem carbon anomalies without fires occurs over the northwest regions of Australia (supplementary figure 7). The amplitudes of XCO₂ anomalies induced by wildfire anomalies peak at approximately 0.45 ppm. We also calculated the OCO-2 XCO₂ anomalies based on the method of Chatterjee et al. (2017). Compared with the simulated amplitudes of XCO₂ anomalies over the southeast regions of Australia and surrounding oceans (supplementary figure 7(d)), the OCO-2 XCO₂ anomalies significantly underestimate the amplitudes over the corresponding regions (supplementary figure 8(a)). This phenomenon is largely caused by smoke contamination from wildfires, which can lead to higher AOD (supplementary figure 8(b)). In addition, the pattern of OCO-2 XCO₂ anomalies contains other information that makes it hard to clarify the influence of eastern Australia’s mega-bushfires. Therefore, it is hard to explore the anomalous XCO₂ variations as in the previous study that investigated the anomalous XCO₂ variations caused by the extreme El Niño (Chatterjee et al 2017).

5. Conclusions

Base on the NASA OCO-2 XCO₂ product, we in this study investigated whether the recent satellite observations can detect the XCO₂ enhancement induced by the Australian mega-bushfires in November–December 2019. We picked out three orbits downwind of the mega-bushfires in eastern Australia. Though the XCO₂ values at these three orbits exhibit the gradual increase from the regions furthest from the wildfires to the wildfire downwind areas, the XCO₂ values in the core wildfire-induced XCO₂ enhancement regions are obscured by the amount of smoke, making the spaceborne detection challenging. We suggest the approximately 1.5 ppm XCO₂ enhancements at these three orbits, calculating from the difference of available XCO₂ values over outer fringes of plumes and XCO₂ values furthest from the wildfires. This fire-induced XCO₂ enhancement was further confirmed by GEOS-Chem simulations. Based on the simulated results, we point out that the sensitivity of the downwind maximum XCO₂ enhancement is 0.41 ± 0.04 ppm with 1 TgC d⁻¹ fire emissions in the region of 144–154° E, 40–26° S.

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Data availability

All datasets used in this study are publicly available. The OCO-2 L2 products can be accessed at https://oco2.gesdisc.eosdis.nasa.gov/data/OCO2_DA TA/OCO2_L2_Lite_FP9r/; ODIAC fossil fuel emissions are from http://db.nerc.ac.uk/dataset/ODI AC/; GFED4.1 wildfire emissions are from https://www.georvic.eu/∼gwerf/GFED/GFED4/; MERRA-2 reanalysis datasets are available at https://igemao.gsfc.nasa.gov/reanalysis/MERRA-2/; TRMM 3B43 precipitation is available at https://disc.gsfc.nasa.gov/data sets/TRMM_3B43_7/summary; SPEI dataset is available at https://speic.ssic.es/index.html.

All data that support the findings of this study are included within the article (and any supplementary information files).

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