Temporal role of crop residue burning (CRB) in Delhi’s air pollution

Meghna Agarwala and Abhinav Chandel
Department of Environmental Studies, Ashoka University, 2, Rajiv Gandhi Education City, National Capital Region P.O. Rai, Sonepat, Haryana 131029, India
E-mail: meghna.agarwala@ashoka.edu.in

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Abstract
The National Capital Region of Delhi in India is one of the most polluted urban areas in the world, and its intense pollution episodes are attributed to crop residue burning (CRB). However, existing studies are limited in time and pollutant type, and do not often control for non-biophysical factors. We used ground-measured pollutant levels and aerosol optical depth (AOD) data to understand the role of CRB in Delhi’s air pollution from 2015 to 2018. While the CRB peak in October–November is associated with pollution episodes, biophysical conditions in the April–May CRB period allow the pollutants to disperse. Elevation in SO2 and ozone is associated with CRB from more distant source areas than elevations in PM2.5 and PM10: gaseous molecules such as SO2 may travel further than particulate matter; and NO2 may convert to ozone during long-range transport. Pollution levels are very high in December–January despite low CRB in this period. Given the high contribution of biomass burning in this period in source apportionment studies, it is unclear whether the sharp elevation in pollutant levels with temperature drop in this period can be explained only with meteorological conditions, or whether there are unquantified sources contributing to pollutant load in December–January, such as small-scale CRB that is undetected by the MODIS active fire product or local burning for heat. There are limitations to the substitution of ground-measured pollutants with AOD in analyzing drivers of pollution since AOD, unlike ground-measured pollutants, is unable to identify fine-scale drivers such as construction. Further studies that use seasonal emissions inventories, particularly for waste and household burning for heat, are required to understand their contribution to pollution in December–January as they may have a disproportionate impact on pollution and human health.

1. Introduction

The Indo-Gangetic plain (IGP) and east-central China are regions with the most polluted urban areas in the world, within which the National Capital Region (NCR) of Delhi is one of the most polluted urban areas (Cheng et al 2016). High urban pollution has caused poor health (Amann et al 2017) and economic losses due to closure of schools (Shyamsundar et al 2019) and lower productivity in offices (Graff-Zivin and Neidell 2012).

Recent scholarship has attributed heavy pollution episodes in the NCR to crop residue burning (CRB) in the states of Punjab and Haryana (Vadrevu et al 2011, Cusworth et al 2018, Liu et al 2018, Jethva et al 2018, Shyamsundar et al 2019, Beig et al 2019, Anand et al 2019, Ravindra et al 2019). These studies are usually restricted to peak pollution periods in October–November and April–May (Vadrevu et al 2011, Liu et al 2018, Anand et al 2019), and do not often control for temporal variation of other non-biophysical factors in their analyses (Beig et al 2019 did control for these for a November 2017 analysis). See table S1 for a review (available online at stacks.iop.org/ERL/15/114020/mmedia). Simultaneously, studies that do use non-biophysical predictors such as industries, power plants, road density, and population density do not include CRB as a source of pollution (Guttikunda and Calori 2013, Saraswat et al 2013). Source apportionment studies
disaggregate their results seasonally to find biomass burning, coal-fired thermal plants, automobile combustion, residential burning, road dust, crustal elements, and industrial emissions to be responsible for pollution in Delhi, but do not differentiate between biomass burning from CRB and other sources (Pant et al 2015, Sharma and Dixit 2016, Guo et al 2017, Sharma and Mandal 2017). Because both the IGP and eastern China have notable seasonal variations in polluted days leading to frequent heavy pollution episodes (Cheng et al 2016), a systematic analysis is required to identify the relative importance of CRB across temporal periods. Further, we need to identify source areas of CRB coming into Delhi at different times so that policy-makers may target the source areas of CRB at different times.

Studies understanding drivers largely focus on particulate matter (≤10 micrometers in diameter) (PM10) and particulate matter (≤2.5 micrometers in diameter) (PM2.5) even though research has shown the association of CRB to nitrogen dioxide (NO2), sulfur dioxide (SO2) (Mittal et al 2009), carbon monoxide (CO), ozone, volatile organic compounds (VOC) (Ravindra et al 2019), and black carbon (Kharol et al 2012). A statistical summary shows the elevation of these pollutants during CRB episodes (Ravindra et al 2019), but the long-range impact of CRB on these pollutants has not been tested systematically.

Use of remote sensing products allows analytical understanding of spatial and temporal drivers of pollutant loads over longer time frames than available through on-ground measurements; however, pollutants identified using remote sensing are limited to particulate matter (PM10, PM2.5), CO, SO2, and NO2 (Edwards et al 2006, van Donkelaar et al 2010, Gu et al 2017). Of these, aerosol optical depth (AOD) is available at ~1 km and is associated with particulate matter, while NO2 data has only recently become available at a high resolution (European Space Agency 2020). In India, AOD has been used to understand seasonal variations of pollution in the IGP (Prasad and Singh 2007a) and has been used to understand the impact of CRB on urban pollution (Vadrevu et al 2011, Liu et al 2018, Jethva et al 2018). Given the limited availability and high costs of on-ground measurements of pollutants, the extent to which remote sensing indices may substitute on-ground measurements in understanding drivers of pollution is unclear and needs to be investigated.

This study combines information from remote sensing products and bottom-up activity data to predict surface PM2.5, PM10, ozone, SO2, NO2, and satellite AOD. Particularly, it analyses temporal differences in pollutant sources, particularly in periods of high pollution load. This will help policy makers target their interventions to help reduce pollution, including in other urban areas with CRB-driven pollution episodes. The study also compares the ability of a remote sensing-derived dataset, AOD, to understand drivers and conduct analyses using ground-measured pollutants. This will help us elucidate the extent to which remote sensing measurements can substitute on-ground measurements in understanding processes driving pollution.

2. Methods

2.1. Study area

The state of Delhi, with a total area of 1483 square kilometers, is located in the River Yamuna floodplain that forms a part of the IGP. The IGP forms a tunnel with the Himalayan mountain ranges in the north and the Vindhya mountain ranges in the south. As a result, wind direction is usually aligned with the tunnel (see S4 for monthly wind direction and speed). The Delhi state has a sub-tropical climate with hot summers (April to June, temperatures from 41 °C to 45 °C) and moderately cold winters (November to January, with minimum temperatures in the range of 3 °C to 6°C in the coldest periods). The average annual rainfall in Delhi is 714 mm, 75% of which occurs during the monsoon in July, August, and September (Pant et al 2015, Sharma and Dixit 2016). The state is very heterogeneous and includes residential, industrial, agricultural, and green areas (Pant et al 2015).

2.2. Pollution data

For Delhi’s air pollution, most studies have either used pollution data from the US Embassy available from 2013 (e.g. Jethva et al 2018) or compiled data from the Central Pollution Control Board (CPCB) (e.g. Cusworth et al 2018) or through its associated System of Air Quality and weather Forecasting and Research (SAFAR) system (e.g. Beig et al 2019). These monitoring stations provide data on PM10, PM2.5, NO2, SO2, and ozone, but many air pollution-monitoring stations were set up recently and provide data after 2015. This means there were unequal numbers of pollutant data days for each station and ground measurements were not continuous for the time period for multiple sites (table S2). The US Embassy only provides data on PM2.5 (downloadable from https://in.usembassy.gov/embassy-consulates/new-delhi/air-quality-data), and we used mean daily values for further analysis.

For AOD, we downloaded data at 470 nm and 550 nm wavelengths from MODIS/Terra + Aqua MAIAC Land Aerosol Optical Depth Daily L2G 1 km, version 006, and extracted daily values for each of our pollution centers from 2014 to 2018. Although validation of PM2.5 has high accuracy values globally (van Donkelaar et al 2006), the validation accuracy is much lower in the IGP (Singh et al 2004, Prasad and Singh 2007b) and even lower in urban areas (Chu et al 2003) such as Delhi (Kumar et al 2007). Correlation
values in our samples match those in previous studies (Kumar et al. 2007) (details in S3).

2.3. CRB data
To quantify CRB, we combined the MODIS active fire product (MOD14A2 and MYD14A2) for each date and used data qualities 9 (high) and 8 (nominal) to map the burnt area (similar to Vadrevu et al. 2011, Liu et al. 2018). The algorithm used to detect fires in these datasets is based on thermal anomalies (Giglio et al. 2003, 2016, 2018). We then used the online Real-time Environmental Applications and Display SYstem tool of the National Oceanic and Atmospheric Administration (NOAA)’s Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model to generate back-trajectories (Stein et al. 2015) of air flowing into Delhi for each day (similar to Liu et al. 2018, Beig et al. 2019, Vadrevu et al. 2011; see S4). The model can generate a back-trajectory up to 72 h prior to each day and provide it as a point shapefile. We then created line shapefiles for each trajectory from the point shapefiles, and segmented the line shapefile by district, state, and country. For a 5 km buffer for each back-trajectory line segment, we then calculated the number of burning pixels that the back-trajectory line segment overpassed for 1, 2, and 3 d prior to each day (figure 1). This provided us with data on daily overpass over burnt area of wind back-trajectory area entering Delhi (figure 2) for winds traveling for 1, 2, and 3 d and the source area of CRB (S4).

2.4. Data on covariates
To control for factors that may confound analysis of the temporal contribution of CRB to pollution, we collected data on covariates. We excluded covariates with no measurable differences in temporal variation such as industrial areas and landfills. Therefore, our study does not lead to a predictive index but only tests differences in temporal drivers of pollution. We used remote sensing-derived indices for temperature, precipitation, and wind speed (table 1). Because precipitation and wind speed data was available daily, we used daily values for each station as our predictor. For temperature, which was available every 8 d, where values were an average of the previous 8 d, we interpolated temperature values for the 7 d in between for each station using linear interpolation.

We also collected data on construction since it contributes to particulate matter (Guttikunda and Calori 2013). However, because accurate data on construction across the city is not available, and previous studies use inventories of brick-kilns (Guttikunda and Calori 2013) or surveys of construction and demolition validated with satellite imagery (Sharma and Dixit 2016), we used building variation in an area in a year as a proxy for construction dust dispersed in the year. The idea is that the difference in built-up area between two years indicates the amount of construction that took place in that area in that year, and is thus a proxy for construction dust. Using Landsat imagery from 2014 to 2018 and Google Earth Engine (figure 3), we calculated the normalized difference built-up index (NDBI) to determine yearly construction levels (Zha et al. 2003). We then calculated the annual change in NDBI, dNDBI, where \( t \) refers to the year of interest and \( t-1 \) to the previous year:

\[
dNDBI = (NDBI_t + 1) - (NDBI_{t-1} + 1)
\]

We collected data on coal-based power plants in Delhi (contributors to PM2.5, PM10, and SO\(_2\); Guttikunda and Jawahar 2014); for this we used the closure of coal-based power plants in Delhi (Badarpur Thermal Power Station and Rajghat Thermal Power Station) as a temporal predictor. For Badarpur, there
were many periodic closures prior to the final closure that were compiled from media reports. We also collected data on thermal power plants outside Delhi (Panipat Thermal Power Station and Harduaganj Thermal Power Plant; 86 km and 182 km away from Delhi) even though previous studies have only shown local impact of coal-powered plants (Guttikunda and Jawahar 2014, Gupta and Spears 2017). Carbonaceous aerosols have an approximate travel time of 1–6 d (Pan et al 2013), leading many previous studies to use 200 km as a cut-off distance for pollution watershed (Liu et al 2018). Pollutants emitted by power plants, such as \( \text{SO}_2 \), may have a longer travel time as gaseous molecules have a longer duration in air than aerosols (Mittal et al 2009). To understand the impact of these distant power plants, we identified dates that wind blew from these power plants into Delhi using wind back-trajectories. We then used these dates as a predictor for powerplants outside Delhi.

For vehicular traffic, we concentrated on temporal variation in automobile numbers and policy changes instead of spatial characteristics because road density was uniformly associated with high pollutant levels across sites, excluding intersections (Sharma and Dixit 2016). We used annual automobile registration numbers in Delhi from a state-wise registered motors dataset (Delhi Government 2020). We also created predictor variables for policy changes aimed to alter the vehicle patterns in Delhi to combat air pollution, such as the environmental tax aimed at
Table 1. Data and sources for analysis.

| Data                          | Source                                                                 | Spatial resolution                      | Temporal resolution | Units of measurement |
|-------------------------------|------------------------------------------------------------------------|-----------------------------------------|---------------------|----------------------|
| **Response**                  |                                                                        |                                         |                     |                      |
| Air pollution data PM10, PM2.5, NO₂ and SO₂ | CPCB online portal                                                   | 16 automatic weather stations of Delhi  | Daily               | μg m⁻³               |
| AOD at 470 and 550 nm         | MODIS/Terra + Aqua MAIAC AOD daily L2G 1 km, version 006             | ~ 1 km                                  | Daily               |                      |
| **Biophysical**               |                                                                        |                                         |                     |                      |
| Land surface temperature      | MOD11A2, version 6                                                    | ~ 1 km                                  | 8 d (average of previous 8 d/interpolated temperature values for the 7 d in between for each station using linear regression) | K                    |
| Precipitation                 | TRMM 3B42, version 0.25 degrees                                       | 0.25 degrees                            | Daily               | mm                   |
| Wind speed                    | GLDAS catchment land surface model L4 GRACE-DA1 V2.2                 | 0.25 degrees                            | Daily               | m s⁻¹                |
| **Other predictors**          |                                                                        |                                         |                     |                      |
| Incoming CRB                  | MOD14A2 and MYD14A2 for crop burning NOAA’s HYSPLIT model for back-trajectories | Does not vary (post-HYSPLIT model)      | Daily (post-HYSPLIT model) | Area burnt (km²)     |
| Construction                  | NDBI calculated from Landsat                                          | 30 m                                    | Annual              | Index                |
| Power plants                  | Dates of closure for Raighat and Badarpur power plants, Dates that wind back-trajectory overpasses Harduaganj and Panipat for those power stations | Does not vary                          | Daily               | 1 = open 0 = closed  |
| Diwali                        | Diwali dates                                                          | Does not vary                           | Daily               | 1 = Diwali 0 = No Diwali |
| Traffic                       | Automobile numbers Policy A: environmental tax for commercial vehicles entering Delhi from Nov 7, 2015 Policy B: Start of alternate route bypassing Delhi, operational since May 2018 | Does not vary                           | Annual              | Numbers 1 = Policy present 0 = Policy absent |

altering vehicle patterns in Delhi from Nov 7, 2015 (Hindustan Times 2015), which could disincentivize heavy commercial vehicles from entering Delhi (henceforth, called Policy A); we also considered the eastern peripheral highway that has been operational since May 2018, which provides an alternate route for commercial traffic that can then forego entering Delhi (Policy B). Moreover, we used annual dates for the seasonal festival of Diwali as a predictor because it is celebrated with fireworks and often coincides with the peak of incoming CRB. However, Diwali is celebrated on a small time dimension when compared with air systems that occur throughout the year.

2.5. Analysis

For the analysis, our generalized linear mixed model used the following equation:

\[
\text{Pollution}_{ij} \sim \text{Biophysical factors}_{ij} + \text{Incoming CRB}_{ij} + \text{Construction}_{ij} + \text{Powerplants}_{ij} + \text{Diwali}_{ij} + \text{Automobiles}_{ij} + \text{Traffic policy}_{ij} + (1|\text{Location}) + (1|\text{Date}).
\]

Wherein ground-measured pollutant data (PM2.5, PM10, NO₂, SO₂, and ozone) and AOD at 470 nm and 550 nm (at location \(i\) and date \(j\))
were used separately as response variables to understand predictors from 2015 to 2018. Use of a random effect for location allows us to test the impact of temporal factors despite variation across locations (Bolker 2007; R package ‘lme4’; Kuznetsova et al. 2017). Because the aim of this paper is to understand drivers of temporal variation, we only tested for significant temporal differences in factors.

All continuous predictors were standardized to the mean using the formula \( z = \frac{x - \text{mean}}{\text{std}} \). We employed the Akaike information criterion (AIC) to select the best model and identify the relative importance of predictors (Burnham 2004). We also used the AIC to understand the interaction between CRB and the seasons, which were defined as December–January, February–March, April–May, and June–September. Although most studies do not separate October–November from December–January (e.g. Anand et al. 2019), we separated the two periods in our analysis because both periods have elevated pollutant levels but very different regimes for incoming CRB (figure 2).

\[ \text{Pollution}_{ij} \sim \text{Biophysical factors}_{ij} + \text{Incoming CRB}_{ij} \times \text{Season} + \text{Construction}_{ij} + \text{Powerplants}_{ij} + \text{Automobile}_{ij} + \text{Traffic policy}_{ij} + (1|\text{Location}) + (1|\text{Date}). \]

To understand the relative contribution of CRB from different source areas, we used state-wise incoming CRB instead of total incoming CRB in equation 1 (equations 3, S5). To understand the effect of CRB on pollution outside of the peak CRB of October–November, we used equation 2 without October–November days (equation 4, S5). We further re-used equation 2 with only December–January days (equation 5, S5) to understand drivers during that period.

3. Results and discussion

3.1. Temporal role of CRB

Incoming CRB has a significant positive association with all pollutants except for ozone (table 2). Models that include interaction with season have a lower AIC than those without the interaction (S5). Incoming CRB is high during two periods of the year: October–November, when it is associated with high pollution loading in Delhi (Vadrevu et al. 2011, Liu et al. 2018, Cusworth et al. 2018, Beig et al. 2019); and April–May when it is not (Liu et al. 2018). We found that October–November values are significantly higher for all pollutants except SO2 and ozone. A lack of increase in pollutant levels due to CRB in April–May compared with a high increase in pollutant levels due to CRB in October–November (as also seen in Liu et al. 2018) may be explained by higher dispersal in warmer temperatures than in cooler temperatures due to differences in boundary layers (Jethva et al. 2005, Tiwari et al. 2014). Wind speeds are also higher in April–May (S4).

Four months in the year have high pollution levels (October–January: figure 2(b)): while CRB is associated with heavy pollution loading in October–November, it does not explain high pollution levels in December–January (table 2). In models without October–November, pollutant levels were significantly high for PM10 and ozone for December–January (table 2). A significant interaction effect of CRB in this period on PM10 levels implies that, given CRB levels in this period, PM10 values are higher than expected. This effect is also clearly visible in figures 2 and 4, where PM2.5 and AOD levels dip after the October–November peak and rise again in December–January when CRB levels are low. CRB is not significant for any pollutant in models run exclusively for December–January (table 2). Elevated pollutant levels in December–January does not appear to be a lag effect of Diwali and CRB pulses—a lag pattern would show a steady decrease in PM2.5 over a longer period due to slower pollutant dispersal. Pollutant removal may be accelerated by wet deposition (precipitation may temporarily decrease pollutant levels but the pollutants are then re-airborne once the precipitation event ceases—but there were no precipitation events coinciding with the period of decline in pollution level), or dispersion may be increased at higher wind speeds (wind speed is associated with decreasing levels in December–January). Details are presented in figure 4 (S6 for other pollutants). Instead, an increase in pollutant levels occurs after a periodic dip every year.

One explanation for the subsequent increase in pollutant levels later in the winter could be that the MODIS active fire product was not able to capture CRB later in the winter when fires were smaller (Cusworth et al. 2018). Farm sizes in India are small (mean 1.08 ha) (Government of India 2011) and the 1 km resolution of the MODIS active fire product may not be able to capture individual farms practicing CRB; however, it may be more successful when a majority of farmers are practicing CRB and the effective burn area increases. However, the fact that potassium levels (a specific indicator of biomass burning) are lower later in the winter (4 µg m\(^{-3}\)) compared with the peak CRB period in early November (~15 µg m\(^{-3}\)) (Sharma and Dixit 2016) suggests that biomass burning is lower in this period.

We do not think we underestimated the temporal variation of other factors. Industrial predictors were significant in all models (table 2, S5). Closure of the Badarpur power plant was associated with lower PM10, SO2, and ozone levels. Days when wind blew from the Panipat power plant to Delhi was associated with higher SO2 levels. Despite this significant contribution of power plants to pollution
Table 2. Model results. Beta-coefficient and significance of predictors (p-values) for PM2.5, PM10, AOD at 470 nm and 550 nm, NO\textsubscript{2}, SO\textsubscript{2}, and ozone.

|                      | PM2.5    | PM10     | AOD at 470 nm | AOD at 550 nm | NO\textsubscript{2} | SO\textsubscript{2} | Ozone  |
|----------------------|----------|----------|---------------|---------------|---------------------|---------------------|--------|
| **Equation 1**       |          |          |               |               |                     |                     |        |
| Temp                 | $-33.27^{***}$ | $-45.10^{***}$ | $-94.63^{**}$ | $-70.32^{***}$ | $-2.50^{***}$       | $-$                 | $4.67^{***}$ |
| Precipitation        | $-4.07^*$ | $-9.08^*$ | $-$           | $-$           | $-$                 | $-$                 | $-0.83.$ |
| Wind                 | $-13.14^{***}$ | $-17.08^{***}$ | $-124.36^{***}$ | $-120.05^{***}$ | $-3.46^{***}$       | $-$                 | $-$     |
| CRB total (all days) | $14.62^{***}$ | $21.33^{***}$ | $-$           | $-$           | $1.73^{***}$        | $0.83^{***}$        | $-$     |
| CRB day 2            | $-$      | $-$      | $94.11^{***}$ | $86.79^{***}$ | $-$                 | $-$                 | $-$     |
| Construction         | $4.70^{***}$ | $-10.24^{***}$ | $-$           | $-$           | $-$                 | $-1.22^{***}$       | $0.78.$ |
| Policy A             | $-$      | $21.04^*$ | $-$           | $-$           | $-$                 | $4.23^{***}$        | $-$     |
| Total Vehicles       | $-$      | $-$      | $-$           | $-$           | $2.65^{***}$        | $-$                 | $-$     |
| Cars                 | $-$      | $-$      | $-$           | $-$           | $-38.60^*$          | $-$                 | $-2.5^{***}$ |
| Buses                | $-$      | $-$      | $117.48^{***}$ | $106.21^{***}$ | $-2.76^{***}$       | $-$                 | $-2.5^{***}$ |
| Panipat              | $-$      | $-$      | $-$           | $-$           | $-$                 | $1.64^*$            | $-$     |
| Badarpur             | $-$      | $35.47^{***}$ | $160.31^{**}$ | $117.52^*$   | $-5.36^{**}$        | $1.43^*$            | $5.78^{***}$ |
| **Equation 2 (selected variables)** |          |          |               |               |                     |                     |        |
| Apr.–May             | $-$      | $104.38^{***}$ | $-$           | $-$           | $11.58^{***}$       | $-$                 | $10.05^{***}$ |
| Oct.–Nov.            | $39.21^{***}$ | $61.32^{**}$ | $586.70^{**}$ | $610.80^{***}$ | $9.3^{**}$          | $-2.59^*$          | $-$     |
| Dec.–Jan.            | $-$      | $-$      | $-$           | $-$           | $-$                 | $-4.84^*$           | $-$     |
| Jun.–Sep.            | $-$      | $-$      | $-$           | $-$           | $23.39^{***}$       | $-6.38^{**}$        | $-$     |
| CRB total "Dec.–Jan." | $-$ | $-$ | $-$ | $-$ | $-$ | $-13.05^*$ | $-$ |
| CRB total "Jun.–Sep." | $-$ | $-$ | $-$ | $-$ | $61.55^{**}$ | $-$ | $-$ |
Table 2. (Continued).

|          | PM2.5 | PM10  | AOD at 470 nm | AOD at 550 nm | NO₂  | SO₂  | Ozone |
|----------|-------|-------|---------------|---------------|------|------|-------|
| **Equation 3 (selected variables)** |       |       |               |               |      |      |       |
| Haryana  | 1.39  | −2.89 | −0.86         | −8.09         | 0.84 | 0.19 | 0.43  |
| India    | 1.84  | 3.27  | −26.10        | −27.04        | 1.95 | 0.53 | 1.83  |
| Nepal    | −0.83 | −1.71 | −6.27         | −6.61         | 0.047| −0.04| −0.08 |
| Pak      | −0.42 | −3.25 | −40.10 *      | −40.23 *      | 0.92 | 1.015| 1.101 |
| Punjab   | 16.21 | 32.86 | 94.02 **      | 92.18 **      | 2.25 | 0.693| 1.45  |
| **Equation 4 (selected variables)** |       |       |               |               |      |      |       |
| Dec.–Jan.| −     | 61.51 | −             | −             | −    | −2.78| 6.38  |
| CRB (total or day 1) Dec.–Jan. | −     | 2520.72 | −         | −             | −    | −9.18| −     |
| **Equation 5** |       |       |               |               |      |      |       |
| Temp     | −     | −     | −             | −             | 4.96 | 1.44 | 2.68  |
| Precipitation | − | −     | −             | −             | 4.67 | −    | −     |
| Wind     | −18.55* | −30.81* | −179.63** | −184.74**    | −    | −    | −     |
| CRB (total or day 2) | −5.51  | −9.4  | −57.88.      | 26.75         | −0.12| −0.68| 0.33  |
| Construction | − | −19.45** | −         | −             | −    | −2.52| −     |
| Panipat  | −     | −     | −             | −             | 4.75 | −    | −     |

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

*See S5 for full results.
in Delhi (Guttikunda and Jawahar 2014, Guo et al. 2017), powerplants were closed in the winter in many years, and hence were not significant contributors to pollution in December–January (table 2). Similarly, construction had a significant positive association with PM2.5 at all scales (table 2, S5). Construction does not increase in winter; in fact, concrete resuspension is lower in winter (Sharma and Dixit 2016). Automobile numbers and policy changes were not significant in our models, probably due to the short time period (4 years) of our study; in this four-year period, the year with peak automobile numbers coincided with the year with the highest CRB, thus confounding analysis. While a long-term study would have provided more meaningful results, this study was limited to 2015–2018 due to availability of ground-measured pollutant data. Nevertheless, traffic also does not increase in winter. Therefore, overall, quantified local factors do not appear to provide an explanation for elevated pollutant levels in December–January. Crustal components of PM2.5, PM10, and chloride also decrease in winter (Sharma and Dixit 2016) suggesting a reduced contribution of road dust, airborne fly ash, and soil to pollutant load at this time.

Source apportionment studies find a sizable contribution of biomass burning to particulate matter in December–January, indicating local sources present in Delhi (Pant et al. 2015, Sharma and Dixit 2016, Guo et al. 2017); one study attributed ~23% of pollution in December–January to local biomass burning but the contribution was negligible in the summer (Pant et al. 2015). Furthermore, while 10% of biomass burning in this region is for cooking (Sharma and Dixit 2016), this region also burns biomass in winter for heating (Guttikunda and Calori 2013), and the increase in pollutant levels appears to be associated with a sharp dip in temperature (figure 4). Given elevated chloride levels at this time—which is interpreted as the burning of municipal solid waste (MSW) due to its plastic content (Sharma and Dixit 2016)—MSW burning may also be elevated at this time to provide heat (Guttikunda and Calori 2013). Our study did not quantify seasonal biomass burning as a predictor. Studies typically use census data that quantifies biomass use as fuel (Guttikunda and Calori 2013, Sharma and Dixit 2016), which lacks the temporal variations required for our study, or use population density as a proxy for residential burning at a regional scale (Guo et al. 2017), which may not be appropriate in a smaller study area such as Delhi where densely populated areas often host small-scale and unregistered industrial units. One study also used secondary data from previous studies to model seasonal variation in use of biomass burning for heating (Guttikunda and Calori 2013), but this lacks the temporal and spatial resolution required for our study. Although our study did not quantify residential biomass burning, source apportionment studies suggest its important contribution to December–January pollution. Given the potential impact of biomass and MSW burning for heating, collection and use of non-static inventories that quantify biomass use for heating is required.

Another explanation for the increase in pollutant levels in December–January could be the drop in the boundary layer due to sudden drop in temperature, thereby further restricting pollutant dispersal and forcing greater interaction between existing pollutants (Jethva et al. 2005, Tiwari et al. 2014). The elevated presence of smog precursors, PM10 and ozone (the highest concentration of ozone is in December–February; Gao et al. 2020), may precipitate higher formation of smog. However, it is unclear whether biophysical conditions alone cause increases in pollutant levels or whether biophysical conditions interact further with an elevated source of biomass.

Figure 4. AOD at 470 nm in the period between the CRB peak and December’s elevated levels.
burning in December–January (Tiwari et al 2014). This phenomenon needs further investigation as each unit of pollutant added by local biomass burning or CRB in December–January may have disproportionate impacts on pollutant levels.

3.2. CRB and pollutant type
While SO\textsubscript{2} levels in Delhi are within permissible limits, sulfur oxides are strong contributors to unhealthy winter air in Delhi (Sharma and Dixit 2016) and are directly associated with hospital admissions (Sunyer et al 1997). While our study found CRB associated with SO\textsubscript{2} (table 2), previous studies have found elevated levels of SO\textsubscript{2} associated with CRB but not proportional to CRB. This is explained by the low amount of sulfur in crop residue (Mittal et al 2009); however, chemicals emitted during CRB may depend on the crop burnt (Sahai et al 2011), and variations in which crops are burnt may explain the lack of proportionality.

The association of CRB with NO\textsubscript{2} (table 2) can be explained by direct emission of NO\textsubscript{2} during CRB (Mittal et al 2009), which has consequences for the immune system and respiratory morbidity (Wong et al 1999, Mcconnell et al 2010). However, elevated NO\textsubscript{2} levels during non-CRB periods, particularly during periods of dust storms (April–July), suggest that agricultural fertilizers may also contribute to NO\textsubscript{2} levels (Mittal et al 2009) both during CRB and also during dust storms. This requires further investigation.

looseness-22 Nitrogen dioxide is a precursor to ozone and may explain the elevation in ozone levels (since CRB is not associated with significant increases in ozone: table 2); this has consequences for crop yield and health (Sunyer et al 1997, Gao et al 2020). Although previous studies have found that the contribution of CRB to ozone is negligible, their models did not capture the high concentration of ozone in India (Gao et al 2020). Patterns of ozone in India show minimal values in summer and the highest concentration in winter, with an increase beginning during the CRB peak season in October (Gao et al 2020). Moreover, 49% of the sources were located outside India, which suggests that vehicle and residential sectors, local sources to which ozone was most sensitive, did not explain the variation (Gao et al 2020); this thus suggests a more significant role of CRB in ozone concentrations. The role of ozone formation from NO\textsubscript{2} following CRB needs further study, particularly in winter because winter concentrations of NO\textsubscript{2} and ozone are associated with adverse health impacts across the world (Sunyer et al 1997, Wong et al 1999).

Given that continuous availability of data on pollutants such as SO\textsubscript{2}, NO\textsubscript{2}, and ozone at multiple sites allowed us to identify their patterns and potential drivers, continuous monitoring of other CRB-associated pollutants, such as VOCs, black carbon, and CO identified in studies with smaller time frames and or limited spatial coverage (e.g. Ravindra et al 2019), is required to understand their patterns and drivers.

3.3. Source areas
CRB in Punjab explains most of the variation in PM2.5, PM10, and AOD (table 2). In contrast, the nearby state of Haryana, where CRB is also very high, the variation is not significant because its temporal pattern and distance to Delhi are very similar to those of Punjab; thus, Haryana could not be statistically differentiated from Punjab. This does not suggest that the contribution of CRB in Haryana is not important but that it may require a mechanistic model for quantification instead of a statistical model as used in this study.

CRB in Pakistan and greater distances within India are responsible for the variation in SO\textsubscript{2} and ozone (and distant areas in India for NO\textsubscript{2} as well) (table 2). Gaseous pollutants such as NO\textsubscript{2} and SO\textsubscript{2} have a longer residence time in air than other aerosols, and particulate matter from CRB has been known to travel as far as from Russia to Finland and the UK (Witham and Manning 2007). Therefore, the impact of SO\textsubscript{2} may be seen at greater distances than other pollutants. Ozone is produced from photochemical reaction of nitrous oxides in the lower troposphere of the tropics (Edwards et al 2006) and may thus be increasingly produced over longer distances, hence providing a possible explanation for more distant source areas for ozone. Meanwhile, NO\textsubscript{2} may not be significant since it reduces in frequency due to conversion to ozone.

3.4. Differences in AOD and ground-measured pollution
Model results for PM2.5 and PM10 were different from model results for AOD. Although AOD is able to identify CRB as a predictor for pollution, it was not able to identify more fine-scale drivers such as construction (see S7 for a discussion on construction). The validation accuracy for AOD is low in the IGP compared with the rest of the world (Guo et al 2009). The accuracy in urban areas such as Delhi is also supposed to be lower than in non-urban areas due to other sources of air pollution, vegetation cover, and proximity to water sources (Kumar et al 2007). In addition, AOD is measured at the pixel level while ground-measured pollution is point data. The pollutant load is measured for an entire atmospheric column for AOD but only at 5 m above ground level for ground-measured pollutant data. Temporally, the overpass time may not match the time for ground-measured pollution data collection, and the temporal window for which the pollutant is measured is also different (Kumar et al 2007). These differences may explain the low correlation of pollutant data (PM2.5 and PM10) with AOD (S3) and the lack of a match
in more fine-scale predictors such as construction. Therefore, while the use of AOD is appropriate for understanding variation in major contributors to pollution such as CRB in October–November, it is not appropriate for understanding more fine-scale predictors.

The ease of using AOD means that studies using AOD will tend to focus on PM2.5 because it is closely associated with AOD (e.g. Vaden et al 2011, Liu et al 2018), and obscure the role of other pollutants. For example, while the closure of the Badarpur power plant was associated with reductions in PM10 levels, the closure of the plant was not associated with a reduction in AOD. It is not possible for AOD to identify other pollutants, such as SO2 and ozone, showing significant reductions with the closure of the Badarpur power plant (Guttikunda and Jawahar 2014). Large sources, such as large power plants and refineries, upwind of Delhi are thought to contribute to the long-range transport of sulfur pollutants (Sharma and Dixit 2016), and AOD is unable to identify the elevation in SO2 on days when winds blew in from the Panipat power plant since AOD is not correlated with these pollutants. Use of other remote sensing products in quantifying these pollutants will need to be investigated.

4. Conclusions

An action plan for combating air pollution by India’s apex planning body, the NITI Aayog, focuses on initiatives to reduce CRB (Shyamsundar et al 2019), regulations for traffic, energy, and industry, and promotion of liquified petroleum gas (LPG) cylinders instead of biomass for cooking (NITI Aayog 2018). However, reducing residential biomass burning for heat may also reduce pollution in two of four months of heavy pollutant loading. A seasonal emissions inventory for biomass burning for heating, quantifying CRB at a higher resolution, and mechanistic chemical transport models that explicitly test the interaction of temporal heating emissions and mechanistic transport models with atmospheric chemistry and biophysical conditions is required to understand the mechanism behind the high pollution load in December–January. Subsequently, limiting local burning (through the provision of smokeless heating devices) or limiting CRB later in the winter (through understanding its drivers and disincentivising it) may have disproportionately positive impacts for pollution and health outcomes.

Given the health impacts of NO2, SO2, and ozone—particularly in winter months for NO2 and ozone (Sunyer et al 1997, Wong et al 1999)—the mechanistic long-range transport of these chemicals needs to be investigated using both remote sensing and ground measurements. The interaction of these chemicals with others may be key in driving high pollutant levels in December–January. Our analysis was limited by available pollutant data, consistently available only from 2015; the data only allowed us to identify previously unreported patterns and hence potential sources. Continuous monitoring of other emissions from CRB, such as VOCs, black carbon, and CO, is required across space and time to understand their drivers and impacts.

The limited match of AOD analysis with analyses of other pollutants suggests that AOD may be used for understanding long-term patterns in PM2.5 but not for other pollutants (including PM10) or for fine-scale drivers such as construction. The efficacy of other remotely derived pollutants also needs to be investigated.

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Data availability statement

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

Ethical statement

This manuscript in full or part has not been submitted elsewhere. This research did not use any human or animal subjects and all data used in the research is publicly available. All authors approve this manuscript. MA conceived and executed this project. AC compiled the data and devised new methods for measuring construction.

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