

Tracking NO₂ emission from thermal power plants in North India using TROPOMI data

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HIGHLIGHTS

- NO₂ emissions from thermal power plants in North India estimated from TROPOMI data.
- Top-down estimates show a significant correlation (R of 0.88) with bottom-up estimates.
- NO₂ emissions from the nine plants in the vicinity of Delhi varied in the range 8–30.6 kt/yr.
- 41–290% reduction during the COVID-19 lockdown relative to the previous year.

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ABSTRACT

Exposure to air pollution is the largest environmental health risk in India, where the coal-fed thermal power plants (TPPs) are identified as the single largest air pollution source. The key to an efficient air quality management plan is strict compliance of the TPPs with emission norms. Yet, in-situ measurements are lacking, and the bottom-up emission inventory is not periodically updated in India. Here we adopt a top-down approach to estimate NO₂ emission from nine TPPs within 300 km of the megacity Delhi using TROPOMI data. We first estimate the NO₂ lifetime for each TPP using an e-folding decay length along the wind direction and combine it with the NO₂ columnar molecular density to estimate the NO₂ emission. Our estimates show a correlation coefficient of 0.88, and a root mean square error of 4.15 kt/year with the ECLIPSE V5 bottom-up inventory. NO₂ emission in these TPPs varied in the range of 8.0–30.6 kt/year with considerable seasonal variability. Using this data, we report a decrease in NO₂ emission in the range 41–290% during the COVID-19 lockdown period relative to the same period in the previous year. As India launched the National Clean Air Program to control air pollution, our method would be highly useful in tracking the emission compliance of the TPPs across the country.

1. Introduction

Air pollution exposure is one of the leading health risk factors in India (Cohen et al., 2017). To minimize the staggering health burden of air pollution in India (Balakrishnan et al., 2019), the Government of India has launched the National Clean Air Programme (NCAP) in 2019 that has set a target of reducing particulate matter concentration in 2024 by 30% relative to the level in 2017.

Coal-combustion in thermal power plants (TPPs) and for domestic use is a major air pollution source in India (Gao et al., 2018; GBD MAPS Working Group, 2018). In India, coal is the primary choice as a fuel

for power generation because of its easy availability (Guttikunda and Jawahar, 2014). According to the Central Electricity Authority of India (CEA) 2019 report (http://www.cea.nic.in/reports/others/planning/pdm/list_power_stations_2019.pdf), India's total capacity of electricity generated by thermal, hydro, and nuclear power plants are 226.2 GW (81.2%), 45.4 GW (16.3%), and 6.8 GW (2.5%), respectively. Within TPPs, 88.9% of power is generated using coal as fuel, and the rest is from gas and diesel. Most of India's coal-fired TPPs use bituminous coal, which is the second standard coal after anthracite. The rest uses lignite coal, soft brown coal containing a high amount of water (after peat), and is the second most polluting coal type (Man et al., 2015).

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Burning these types of coals releases a high percentage of particulate matter, SO_2 , NO_2 , CO_2 , CO , volatile organic compounds, which degrades the air quality and contributes to global warming (Webb and Hunter, 1998; Zhu et al., 2018).

In response to a report by the Steering Committee on Air Pollution and Health set up by the Government of India, new emission norms were set up for the coal-fed TPPs in 2015 (MoEFCC, 2015). Recent studies based on satellite data (Li et al., 2017; Qu et al., 2019) concluded that the emission of SO_2 in India has increased by 50% since 2007, a large fraction of which was contributed by the TPPs. Several action points recommended by the NCAP to control emissions from the TPPs are as follows: (i) conversion of all older coal-based TPPs into natural gas fed power plants; (ii) requirement for optimizing the use of existing power plants by emphasizing capacity utilization of natural gas/clean fuel-based TPPs; (iii) stringent compliance with the emission norms prescribed in the direction dated December 2017 issued under EPA 1986 by all TPPs, and (iv) accentuation on improved power dependability to remove diesel generator activities especially in urban areas (NCAP, 2019).

Developing traditional bottom-up emission inventories and periodically updating them is the usual way to track the emissions from TPPs. However, in India, the emission inventories are not regularly updated, and the stack measurements are also not available, making it difficult to continuously track TPP emissions and assess if they violate the emission norms. High-resolution satellite data provide an opportunity to detect sector-specific sources of air pollution (Streets et al., 2013). Ever since the method to derive emission fluxes from remote sensing data was introduced by Beirle et al. (2011), the bottom-up inventories use the top-down methods as the foundation while building emission inventories for large industrial point sources and the power sector. In this study, we adopt this top-down approach to estimate NO_2 emissions from nine TPPs in the vicinity of the megacity Delhi using TROPospheric Monitoring Instrument (TROPOMI) NO_2 data product. NO_2 is an important criteria pollutant affecting human health and atmospheric chemistry (Zhao et al., 2021). We evaluate our top-down estimates with a widely-used bottom-up inventory and emissions estimated using data from the Central Electricity Authority (CEA), India. Our study focuses on exploring the satellite data to independently track TPP emissions in

India, where in-situ emission data are not readily available. Further, we examine the changes in NO_2 emissions during the COVID-19 lockdown period to understand how much the emissions were reduced due to the plants operating at a lower capacity.

2. Data and methods

2.1. TROPOMI data

TROPOMI, on-board the sun-synchronous and low-earth (825 km) orbit Sentinel-5 Precursor (S5P) satellite, contains four spectrometers: three that cover the ultraviolet-near infrared range with two spectral bands at 270–500 nm and 675–775 nm, and one for the shortwave infrared. It makes daily global observations (101.5 min temporal resolution) of crucial atmospheric constituents, including O_3 , NO_2 , SO_2 , CO , CH_4 , HCHO , and cloud and aerosol properties within its 2600 km swath with an equator overpass time of approximately 13:30 local solar time. Because of its high spatial resolution (pixel sizes $3.5 \times 7.2 \text{ km}^2$) and high signal-to-noise ratio, it is easy to distinguish the individual NO_2 plumes emitted from specific sources such as TPPs. Fig. 1 shows the spatial distribution of columnar NO_2 over northern India in 2019, along with the locations of nine coal-fired TPPs (Table 1). High NO_2 is visible

Table 1

List of the nine coal-fired TPPs with their capacity and estimated annual NO_2 emission in 2019 using satellite data.

Coal-fired TPPs	Capacity (MW)	Mean ($\pm 1\sigma$) NO_2 emissions (Kt/Yr) with top-down approach
Indira Gandhi TPP (IGTPP)	1500	13.68 ± 8.89
Panipat TPP (PTPP)	920	23.14 ± 15.92
Rajiv Gandhi TPP (RGTPP)	1200	8.30 ± 5.63
Yamuna Nagar TPP (YNTPP)	600	8.0 ± 3.63
Rajpura TPP (RTPP)	1400	18.86 ± 15.17
Guru Hargovind Singh TPP (GHSTPP)	920	12.32 ± 12.18
Talwandi Sabo TPP (TSTPP)	1980	13.56 ± 6.76
Dadri TPP (DTPP)	1820	30.56 ± 14.37
Harduaganj TPP (HTPP)	605	13.62 ± 6.94

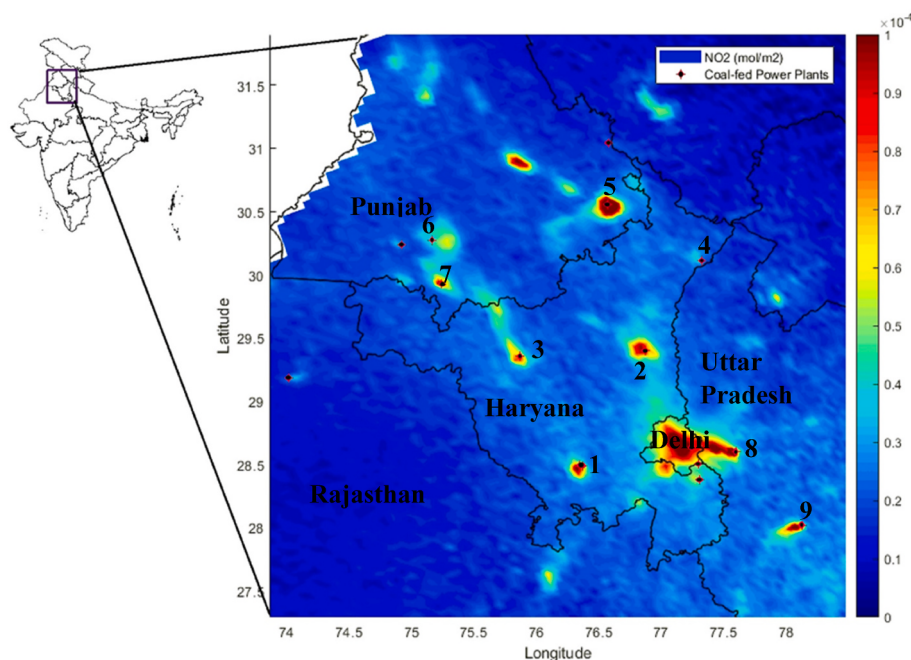


Fig. 1. Distribution of tropospheric NO_2 columnar density over north India on October 16, 2019 along with the locations of the TPPs (1: IGTPP; 2: PTPP; 3: RGTPP; 4: YNTPP; 5: RTPP; 6: GHSTPP; 7: TSTPP; 8: DTPP; 9: HTPP, see Table 1).

around the TPPs and over the Delhi city and adjoining satellite towns, where transport is the other critical emitting sector.

2.2. Wind data

Wind data are taken from the Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2), the latest atmospheric reanalysis of the modern satellite era produced by NASA's Global Modelling and Assimilation Office (Gelaro et al., 2017). The data are available at a spatial resolution of $0.5^\circ \times 0.625^\circ$ and a temporal resolution of 1 h (unit in m/sec, which is further converted into km/hr). In our analysis, we process the wind data of the lowest level (up to 500 m) between 12:30 to 2:30 p.m. to match with the local overpass time of TROPOMI. For this analysis, we have selected only those days in which MEERA2 wind speed is greater than 3 m/s because NO_2 decay under this condition is dominated by chemical removal, not variability in the winds (de Foy et al., 2014).

2.3. Retrieval of NO_2 emission from tropospheric column density

We first filter the TROPOMI NO_2 data by removing those pixels whose solar zenith angle is $\geq 80^\circ$ and cloud radiance fractions ≥ 0.5 . Then we re-gridded the data into $0.02^\circ \times 0.02^\circ$ spatial resolution and converted it from curvilinear to bilinear using the bilinear interpolation technique in the NCAR command language (NCL) tool. The bilinear interpolation technique uses a weighted average of four closest pixel values situated in diagonals from a given pixel to estimate that pixel's proper colour intensity value (Titus and Geroge, 2013). It is used to enhance the quality of the image after executing spatial transformation operations (Gribbon and Bailey, 2004).

The tropospheric vertical column density representing the vertically integrated number of NO_2 molecules per unit area between the surface and the tropopause is calculated using air mass factor (AMF) (Griffin et al., 2019). AMF is described as enhancing absorption when light traverses a slant path through a layer and represents a cornerstone of trace gas retrievals in the spectrum's UV-visible portion. It is the ratio of the slant column density (SCD) to the vertical column density (VCD). AMF is a unitless quantity and is a function of the solar angles, satellite viewing angles, the vertical profile shape of NO_2 , the effective cloud radiance fraction and pressure, and the surface reflectivity (McLinden, 2014).

In this study, operational TROPOMI NO_2 total SCD (SCD_{tot}), stratospheric SCD ($\text{SCD}_{\text{strat}}$), and tropospheric AMF (AMF_{trop}) are used to calculate the tropospheric VCD (VCD_{trop}). We first calculate the tropospheric slant column density (SCD_{trop}) by subtracting the $\text{SCD}_{\text{strat}}$ from the SCD_{tot} (Goldberg et al., 2019). SCD_{trop} is then converted to VCD_{trop} using the AMF_{trop} following:

$$\text{VCD}_{\text{trop}} = \frac{\text{SCD}_{\text{tot}} - \text{SCD}_{\text{strat}}}{\text{AMF}_{\text{trop}}} \quad (1)$$

Fig. 2 shows an example of the top-down NO_2 emission estimation for a TPP. The NO_2 plume emitted from the Talwandi Sabo power plant, Mansa in Punjab, on October 16, 2019, is clearly seen. The black dashed arrow line (direction of the arrow shows the direction of the wind) shows the distribution of NO_2 plume emitted from the coal-fired TPP, with the highest density over the TPP stack and its asymmetric changes along and across this line away from the stack due to wind. The plume is more dispersed along the wind direction, and the curve is less steep downwind than upwind.

For the estimation of NO_2 emission, a priori information on the NO_2 lifetime is required (Beirle et al., 2011; Verstraeten et al., 2018). NO_2 lifetime is mainly determined by the reaction of NO_x , which is oxidized to nitric acid (HNO_3) and organic nitrates (RONO_2), including peroxyacyl nitrates (RC(O)OONO_2). In the daytime, oxidation is mainly directed by photo-chemically produced hydrogen oxide ($\text{HO}_x = \text{OH} + \text{HO}_2 + \text{RO}_2$) radicals (Jena et al., 2014). NO_x lifetime can also be

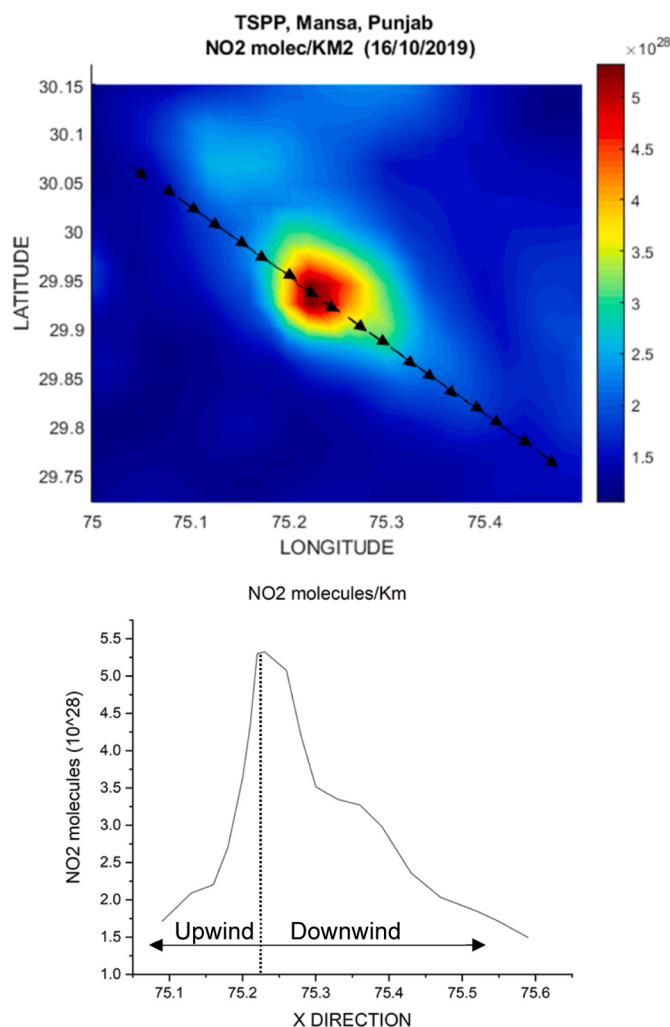


Fig. 2. NO_2 molecule density in and around the Talwandi Sabo power plant, Mansa, Punjab on October 16, 2019. The red and blue pixels indicate that the NO_2 levels are relatively higher and lower, respectively, due to the wind patterns. The bottom panel shows the variation of the NO_2 columnar density as a function of the distance (shown as longitude, E) in the upwind and downwind from the TPP (indicated by the dashed line) along the wind direction (indicated by the black dashed line). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

estimated using chemical transport model simulations with a deduced emission. However, the accuracy of the estimated lifetime of NO_x using the chemical transport model is mostly limited to determine the tropospheric NO_x and OH concentrations accurately, especially for the highly polluted regions like coal-fired TPPs because of the rapid reaction of this species in the atmosphere (Beirle et al., 2011; Jena et al., 2014).

We estimate the lifetime of NO_2 by calculating the observed e-folding ($1/e$) decay curve distance to fit an oversampling of re-processed NO_2 column measurements, detected by TROPOMI around each TPPs as described in (Leue et al., 2001). The mean NO_2 lifetime is calculated after the determination of $1/e$ length (in km) of the decay curve, which is static in behaviour and can be expressed by the equation

$$C(x) = C_0 \cdot e^{-x/L} \quad (2)$$

where $C(x)$ denotes the concentration of NO_2 molecules as a function of distance x (decay length). Jena et al. (2014) observed in their study that the observed decay rate of tropospheric NO_2 downwind of any source region can be used to estimate the NO_x lifetime by assuming a pseudo first-order loss of NO_2 which is a function of distance and wind speed.

Within a plume, the time spent along the transported downwind path is considerably short. For example, on the given day (Fig. 2), the decay length of the plume was 18.8 km and the lifetime was 1.28 h. Hence we assume that the change in NO_2/NO_x ratio along the transported path over every TPPs is negligible, which is in accordance to the previous studies (e.g., Beirle et al., 2011; Ghude et al., 2008). The lifetime of NO_2 over each TPP and for each day is calculated using the equation

$$\tau_{\text{eff}} = \frac{\chi_s}{W} \quad (3)$$

where, τ_{eff} is the time effective of NO_2 lifetime (in hr), χ_s is the e-folding decay length and W is the wind speed (in m/s) over the TPP. Our study region lies in the tropics, where OH concentrations are usually high because of high level of insolation and moisture availability (Kunhikrishnan et al., 2004; Leue et al., 2001). Hence, we feel that active chemistry and high OH concentrations are the most plausible explanation (in accordance to Dentener and Crutzen, 1993; Isaksen et al., 2009) of the estimated lifetime of NO_2 varying from 1 h to 3 h in this region. Finally, the total mass of NO_2 equals the emission rate times the lifetime; hence NO_2 emission is estimated as

$$E_{\text{NO}_2} = \frac{\alpha}{\tau_{\text{eff}}} \quad (4)$$

where, E_{NO_2} is the NO_2 emission (in molecules per hr, which is further converted into kiloton per year) and α is the total number of NO_2 molecules. Based on the daily analysis, we estimate the emission at an annual scale.

3. Results

3.1. Top-down vs. bottom-up approach

We validate our estimated top-down NO_2 emissions using the Evaluating the Climate and Air Quality Impacts of Short-Lived Pollutants (ECLIPSE) V5 global NO_2 emission data (Stohl et al., 2015). ECLIPSE V5 provides emission data of different gases emitted from various sources (like energy, transportation, biomass burning, industries, etc.) at a spatial resolution of $55.6 \text{ km} \times 42.2 \text{ km}$, for every five years (Stohl et al., 2015). ECLIPSE has used the bottom-up approach to estimate NO_2 emission for 2015 and projected the same for 2020. We have interpolated the emission data for 2019 based on the 2015 and 2020 emission estimates and re-gridded the ECLIPSE emission into 0.02° spatial resolution using the bilinear interpolation technique in NCL to evaluate our top-down approach. We note that the bottom-up emission was estimated based on the available data from the power sector and may have some uncertainty, which is difficult to quantify. Our top-down emissions show a high correlation ($R = 0.88$) and a low RMSE (of 4.15 Kt/Yr) with the bottom-up inventory (Fig. 3).

Since we do not know the representativeness of the ECLIPSE projection, we estimate NO_2 emission from these individual nine TPP independently. For this, we use the CEA 2019–20 report (https://cea.nic.in/old/reports/others/planning/pdm/list_power_stations_2020.pdf) that provided the working capacity of the plants, types of fuel used, and their year of installation. We referred to National Power Portal (NPP) monthly electricity generation data (<https://npp.gov.in/dgrReports>), which gives plant-wise monthly electricity generation in Million Unit (MU). The energy of a plan is estimated from its capacity, operating hours, and efficiency, as mentioned in the GAINS tutorial (accessible from <https://iiasa.ac.at/web/home/research/researchPrograms/air/GAINS-tutorial.pdf>). We find a similar correlation coefficient ($R = 0.88$) and slightly lower RMSE (3.73 Kt/Yr) when compared our satellite-based estimates for 2019 with these estimates.

The emissions from the individual TPP (Table 2) do not conform to their operating capacity. For example, the Talwandi Sabo TPP emitted 13.56 Kt NO_2 in 2019 at an operational capacity of 1980 MW, while the

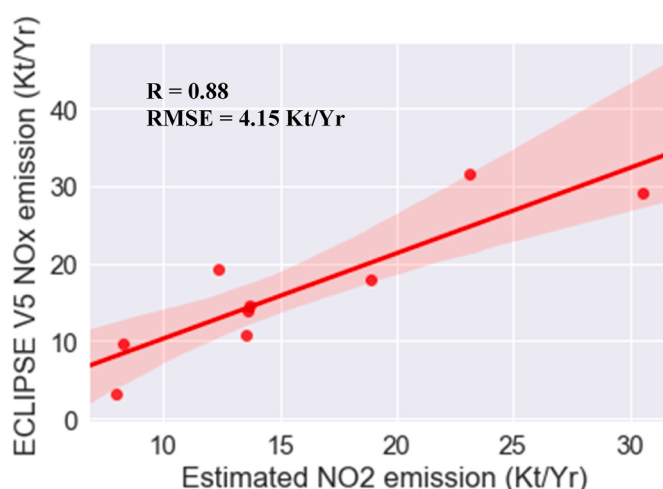


Fig. 3. Comparison between top-down hindcast and the ECLIPSE v5 emission forecast for the year 2019. The shaded region is 95% CI.

Table 2

Seasonal variability in NO_2 emission (unit: Kt/day) by the nine TPPs in 2019. The GHS TPP was closed in Oct–Nov 2019.

2019 NO_2 (Kt/Yr)	Winter	Pre-monsoon	Monsoon	Post-monsoon
IGTPP	0.028 ± 0.017	0.045 ± 0.026	0.025 ± 0.012	0.052 ± 0.032
PTPP	0.049 ± 0.034	0.077 ± 0.056	0.038 ± 0.024	0.116 ± 0.010
RGTPP	0.009 ± 0.007	0.019 ± 0.006	0.024 ± 0.010	0.028 ± 0.025
YNTTP	0.015 ± 0.005	0.021 ± 0.002	0.028 ± 0.013	0.011 ± 0.005
RTTP	0.043 ± 0.029	0.038 ± 0.027	0.048 ± 0.038	0.069 ± 0.057
GHSTPP	0.007 ± 0.001	0.020 ± 0.005	0.058 ± 0.044	No data
TSTPP	0.016 ± 0.004	0.046 ± 0.019	0.034 ± 0.013	0.041 ± 0.024
DTTP	0.088 ± 0.074	0.091 ± 0.039	0.079 ± 0.024	0.080 ± 0.048
HTTP	0.029 ± 0.008	0.032 ± 0.015	0.039 ± 0.025	0.048 ± 0.023

Dadri TPP emitted 30.56 Kt at a capacity of 1820 MW. The Indira Gandhi (1500 MW) and Rajpura (1400 MW) TPPs operated at almost the same capacity, but the former emitted 13.68 Kt NO_2 , 27.4% lower than the emission (18.86 Kt) from the latter. A similar contrast is observed between the Yamuna Nagar and Harduaganj TPP that operated at a capacity of 600 MW, but the latter emitted almost 70.11% higher NO_2 than the former. The Panipat TPP, despite having the lowest capacity (920 MW), is found to be one of the top (23.14 Kt) emitters of NO_2 .

The possible reasons behind the variation of NO_2 emissions across the TPPs may be attributed to the plant's age, its maintenance standard, capacity utilization of the various TPP, and lesser performance efficiency of the burner compared to the other units of the same category. Based on the capacity, functioning year, and the estimated emission of NO_2 , we have identified that two (Panipat and Harduaganj) out of the nine TPPs are operating at <50% efficiency (i.e., the ratio of the capacity of the plant capacity to the estimated emission).

3.2. Reduction in NO_2 emissions during the COVID-19 lockdown

India implemented a strict lockdown to curb the spread of COVID-19 from March 25 – May 31, 2020. We apply the same methodology to estimate NO_2 emission from these nine TPPs during the lockdown period

from March 25, 2020, to April 30, 2020, and compare them with the data for the same period of the previous year 2019 (Fig. 4).

In seven out of the nine TPPs, NO₂ emission significantly ($p < 0.05$) decreased during the lockdown period (Table 3). Among these TPPs, the largest (290%) and the smallest (41%) declines are observed for the Indira Gandhi TPP in Jhajjar and Talwandi Sabo TPP, respectively. While it slightly increased (by 10% and 24.68%) for the Guru Hargovind Singh TPP and Rajiv Gandhi TPP, respectively. During the lockdown, the NO₂ in the city outflow was significantly reduced due to restrictions on traffic movement, and therefore, the post-lockdown estimates of TPP emission are more accurate than the pre-lockdown estimates. This issue needs further attention in the future based on in-situ data.

During the lockdown, the TPPs operated at a reduced capacity (folk.uio.no/roberan/t/POSOCO.shtml). Unfortunately, data from the individual TPP is not available to understand the observed heterogeneity in emission reduction. Overall, NO₂ emissions from these TPPs reduced from 41% to 290% during the COVID-19 (Fig. 4).

4. Discussion and conclusions

In this work, we demonstrate the application of TROPOMI NO₂ data in tracking emissions from the TPPs. We note that the retrieval accuracy may get impacted due to the presence of clouds, the accuracy of the wind data, and the presence of other NO₂ emission sources like brick kilns, industrial complexes, and high traffic density (Liu et al., 2016) in the vicinity of the TPPs.

All TPPs in India are now mandated to comply with the strict emission norms to control air pollution. In India, the meteorological condition is highly conducive for rapid conversion of the precursor gases (NO₂ and SO₂) to secondary PM_{2.5} (Gani et al., 2019). Hence, to control PM_{2.5}, the emission of the precursor gases is necessary. Even though some of the TPPs monitor emissions in real-time, either the data are not made available, or the data are not adequately quality-controlled. Our method provides an alternative to resolve this issue; therefore, it is crucial in India's battle against air pollution.

Ghude et al. (2008) estimated NO₂ emissions from the Indian power sector for the years 1996–2006 (during a period of power scarcity and frequent load shedding) with the help of top-down satellite observations, and found a linear relationship between the installed capacity and the NO₂ columnar density over the plants. On the contrary, our study shows (Table 1) a clear disconnect between the plant capacity and emission fluxes, indicating that perhaps the system has transitioned into a power surplus condition where the TPPs are operating at a load lower than their corresponding full load or idling for some time periods. This issue can only be resolved if the actual operating capacity data are made available.

A common assumption in India is uniform emissions from the TPPs across the seasons. However, our data demonstrate otherwise, implying that any bottom-up estimates require a clear understanding of the merit dispatch order, existing power purchasing agreements, and their tenure, as well as of the competition between renewables and storage technology and coal to come up with future plant load factors.

The source apportionment of PM_{2.5}, taking the contribution of secondary components into account, is indeed important. Under the NCAP, source apportionment of PM_{2.5} and emission inventories are being conducted for various non-attainment cities. The method presented here can be extended to other TPPs, particularly those located upwind of the non-attainment cities, to provide independent estimates of emissions. Further, emissions of other trace gases like SO₂ can be estimated using the TROPOMI product. The key conclusions of this work are as follows:

1. The nine TPPs in the vicinity of the world's most polluted megacity Delhi emitted NO₂ in the range 8.00–30.56 Kt in 2019.
2. The NO₂ emission varies seasonally and is not uniform throughout the year.

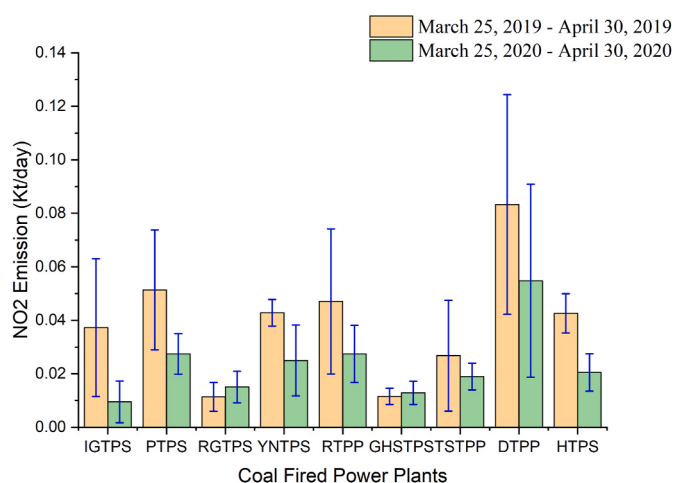


Fig. 4. Estimated NO₂ emission (in Kt per day) from the nine TPPs during the lockdown period (March 25, 2020–April 30, 2020) and the same period of the previous year 2019 (March 25, 2019–April 30, 2019). The error bars represent $\pm 1\sigma$.

Table 3

Tropospheric NO₂ concentration (in mol/m²) within a 20-km buffer of the TPPs.

	During Lockdown 2020 (mol/m ²)	Same period of previous year 2019 (mol/m ²)	Difference (2019–2020) (%)
IGTPP	0.46	0.77	40.26
PTPP	0.61	1.04	41.35
RGTPP	0.45	0.56	19.64
YNTPP	0.57	0.78	26.92
RTPP	0.47	0.78	39.74
GHSTPP	0.47	0.61	22.95
TSTPP	0.44	0.79	44.30
DTTP	0.77	1.77	56.50
HTPP	0.63	0.93	32.26

3. The NO₂ emission reduced significantly (in a range 41%–290%) during the COVID-19 lockdown period from March 25, 2020, to April 30, 2020, compared to the same period in 2019 due to the reduced operating capacity of the plants.

CRediT authorship contribution statement

Gautam Kumar Saw: Formal analysis. **Sagnik Dey:** Conceptualization, Writing – original draft. **Hemant Kaushal:** Writing – original draft. **Kanhaiya Lal:** Writing – original draft, All authors contributed to the interpretation of the results and the final versions of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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