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Emissions of nitrogen dioxide in the northeast U.S. during the 2020 COVID-19 lockdown

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A B S T R A C T
We have quantified the emissions of Nitrogen dioxide (NO2) in the Northeast megalopolis of the United States during the COVID-19 lockdown. The measurement of NO2 emission serves as the indicator for the emission of the group of nitrogen oxides (NOx). Approximately 56% of NOx emissions in the US are from mobile sources, and the remainder is from stationary sources. Since 2002, clean air regulations have resulted in approximately 5% compound annual reduction of NOx emissions in the US (8.2% in the study area). Therefore, when studying the impact of sporadic events like an epidemic on emissions, it is necessary to account for the persistent reduction of emissions due to policy driven emission reduction measures. Using spaceborne sensors, ground monitors, National Emission Inventory data, and the US Motor Vehicle Emission Simulator, we quantified the reduction of total NOx emissions, distinguishing stationary sources from on-road mobile sources (trucks and automobiles). When considering total NOx emissions (stationary and mobile combined), we find that the pandemic restrictions resulted in 3.4% reduction of total NOx emissions in the study area in 2020. This is compared to (and in addition to) the expected 8.2% policy driven reduction of NOx emissions in 2020. This somewhat low reduction of emissions is because most stationary sources (factories, power plants, etc.) were operational during the pandemic. Truck traffic, a significant source of mobile emissions, also did not decline significantly (average 4.8% monthly truck traffic reduction in the study area between March and August 2020), as they were delivering goods during the lockdown. On the other hand, automobile traffic, responsible for 24% of total NOx emissions, dropped significantly, 52% in April, returning to near normal after 5 months. While the reduction of automobile traffic was significant, especially in the early months of the pandemic, its effect on emissions was relatively insignificant.

1. Introduction

Nitrogen dioxide (NO2), a gaseous air pollutant, has been shown to cause cardiovascular and respiratory diseases (Andersen et al., 2011; Liu et al., 2017) and serve as a catalyst to greenhouse gases, including tropospheric ozone (O3) and nitrous oxide (N2O) (Ehnhalt et al., 2001; Lammel and Grajil, 1995). The combustion of fossil fuels by vehicles and power plants is considered the primary source of NO2 (American Lung Association, 2020). In the first quarter of 2020, during the first peak of COVID-19, many parts of the world enforced travel restrictions and closed non-essential businesses in order to curb the spread of the virus, prompting the decrease of ambient NO2 concentrations globally (Addas and Maghrabi, 2021). It has been estimated that NO2 emission was reduced by around 20% globally due to the worldwide lockdown (Hoang et al., 2021). In the Northeast region of the United States, New York City (NYC) reported its first confirmed case of COVID-19 on March 1st, 2020 (Goldstein and McKinley, 2020). From mid-March, the tri-state area (New Jersey, New York, Connecticut), which is the area we report on here, experienced complete lockdown, resulting in an unprecedented number of residents staying indoors (Azad and Ghandehari, 2021b; Hogan et al., 2020). As we embarked on studying the effect of these lockdowns, including their effect on emissions, we encountered large variability in what others have found regarding the effect of the 2020 lockdown on emission in various regions around the world.

In the United States, the nationwide reduction of NO2 concentration after the onset of the first wave of the pandemic was quantified as 25.5% due to the pandemic-induced travel restrictions (Berman and Ebisu, 2020). One study reported that emissions in major cities of the northeastern U.S., such as New York City and Philadelphia, dropped by 28% and 24% NO2, respectively, where emissions in the rural areas in the

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same region dropped far more (around 40%) (Bauwens et al., 2020). This result contradicts another study, which found that the magnitude of NO₂ reduction is positively associated with population density, and urban areas in the U.S. experienced greater reduction of emissions than the suburbs (Chen et al., 2020). Another study reported that the ambient NO₂ concentration in New York City was reduced by 51% shortly after the lockdown (Zangari et al., 2020). On the west coast, the tropospheric NO₂ declined by 40% in Los Angeles, 38% in Fresno, and about 20% in Bakersfield and San Francisco (Naeg and Murphy, 2020). The continent of Europe witnessed an average of 30% reduction in NO₂ (Crowe et al., 2020). Italy, France, and Spain imposed stringent travel restrictions and experienced a 50% decrease in emissions. On the other hand, there was only a 15% reduction of NO₂ concentration in Sweden, where no lockdown was in place (Guevara et al., 2021). Another study found lower reductions in NO₂ concentration in west European countries, only 30% in France and Spain and 20% in Germany and Belgium (Bauwens et al., 2020). Metropolitan cities like Milan reduced 31%, whereas Madrid, London, and Paris reduced 27%, 30%, and 46%, respectively (Bar et al., 2021; Sanz-nigrasri et al., 2021). Other studies found the reductions were much higher in these cities; 64.7% in Milan, 62% in Madrid and 71% in London, 66% in Paris (Baldasano, 2020a; Collivignarelli et al., 2021; Zoran et al., 2020). Different cities in China have shown diverse levels of pollution reduction during the first peak of the pandemic. Large cities such as Wuhan, Shanghai, and Nanjing were seen to reduce 25% more NO₂ during the lockdown compared to the year before (Q. Wang and Su, 2020). Another study found a much larger (55%) reduction in NO₂ concentrations in Wuhan (X. Shi and Brasseur, 2020). Analyzing air quality before and during the lockdown in 336 cities across China found the average NO₂ concentrations decreased by 54% (Y. Wang et al., 2020). Another study determined the overall reduction of NO₂ in China was around 21% (F. Liu et al., 2020). The big cities in India have reduced between 40% and 60% NO₂ after the lockdown (Jain and Sharma, 2020; Mahato et al., 2020). Megacities, such as Delhi and Kolkata reduced 60%, Bangalore 70%, Mumbai 75%, and Chennai 25% of NO₂ (Jain and Sharma, 2020; Misra et al., 2021). Surprisingly, one study has reported a 92% reduction of NO₂ in Delhi (Kotnala et al., 2020).

Although a wealth of knowledge has already been established, we find significant inconsistencies in the research outcomes and conclusions among the aforementioned studies. These are most likely due to the variation in data sources and techniques used in studies. For example, many studies leveraged data from space-borne sensors (Hoang et al., 2021), others used air quality data only from ground monitors (Jain and Sharma, 2020), and a few studies used data from both sources (Bar et al., 2021). Variation in data sources could be a leading cause of the inconsistency in results across studies. In addition, different studies used diverse calculation techniques to quantify the pandemic effect on the ambient NO₂. One approach was to subtract the NO₂ concentration level between the same period of 2019 and 2020 (Baldasano, 2020a; Biswal et al., 2020; Chu et al., 2021; Corpus-Mendoza et al., 2021; Oo et al., 2021). Some studies quantified the lockdown-induced reduction by subtracting the NO₂ concentration of the consecutive months before and during lockdown (Hashim et al., 2021). Other studies utilized a baseline scenario of NO₂ by averaging the concentration over the past few years before COVID-19 and compared the baseline with the NO₂ concentration during the pandemic lockdown to quantify the pandemic-driven NO₂ reduction (Sathe et al., 2021; Wang et al., 2020). Studies also used forecast models, such as GEM-MACH (Global Emission Model for Meteorology) and Meteorology-Chemistry), SARIMA (Seasonal Autoregressive Integrated Moving Average), and so on and quantified the reduction in NO₂ by comparing the observed concentration with predictive values generated by the model during the pandemic lockdown (Dey et al., 2021; Griffin et al., 2020; Mashayekhi et al., 2021). One study utilized all three techniques mentioned above and demonstrated that the different methods produce different results of NO₂ reduction without much detail on the causes of discrepancies (Goldberg et al., 2020).

Clearly, the lockdown contributed to the decrease in NO₂ concentrations, but the estimated effect could be biased due to various factors. These include the effect of data sources utilized, the effect of existing reductions as a result of pollution prevention regulations, and seasonal effects such as ambient temperature. For example, due to high-frequency signal fluctuations (some natural and some by sensors response), daily observations from satellite images need to be averaged over space and time to arrive at useful quantities for analysis (Duncan et al., 2014). However, a few studies (Bassani et al., 2021; Oo et al., 2021) noted above, used daily satellite data without temporal aggregation to report the NO₂ reduction values after lockdown. Also, the comparison of pollutant levels of one year with the previous year assumes that the pollution level is constant over the years, which is often not the case. Over the last few years, many countries around the world have witnessed a continuous and steady decrease of NO₂ concentration every year, especially in countries where stringent clean air policies are in place (Geeddes et al., 2016; Georgoulas et al., 2019; Hilboll et al., 2013). Moreover, pollutants like NO₂ have strong seasonal dependencies, and the concentration varies significantly during different seasons, for example, as a function of temperature (Bijgi and Harrison, 2010). As a result, a direct comparison of NO₂ concentrations before and during lockdown could also be erroneous. A recent study found the effect of lockdown on NO₂ controlling weather-related variables using machine learning techniques, was not as large as expected (Shi et al., 2021). Many of the studies only report the cross-sectional value of the reduction percentage of NO₂ after imposing travel restrictions, lacking information on the longitudinal variability of concentrations.

Our study addresses the inconsistencies of the current body of knowledge by incorporating three novel steps. (1) Using the National Emission Inventory (NEI) report and MOVES simulator, we quantified the yearly rate of reduction of NO₂ in the study area due to pollution prevention regulations in order to quantify the NO₂ reduction caused only by the pandemic. (2) We determined that the first quarter of 2020 was warmer than 2019 and incorporated the effect of warmer temperatures when comparing the NO₂ concentration in those years. In other words, we introduced a temperature correction factor to adjust the NO₂ concentration level for all months analyzed. (3) We analyzed longitudinal changes in the volume of on-road automobiles and trucks to determine the association of ambient NO₂ concentration with the volume of different vehicle types. This step was not used in the emission analysis but as possible insight into sources that caused the observed changes of total emissions versus those by mobile sources.

2. Materials and methods

2.1. Approach

We investigated changes to ambient NO₂ concentration during the COVID-19 pandemic restrictions in the Northeast megalopolis of the United States. We collected monthly mean NO₂ concentrations for 2019 and 2020 from Sentinel 5P satellite (S5P), as well as roadside NO₂ monitors. We considered satellite data to quantify the total reduction of NO₂ versus roadside ground monitors in order to identify the mobility-induced NO₂ reductions during the pandemic restrictions. To quantify the NO₂ reduction due to the pandemic, first, we control the seasonal effect on NO₂ by subtracting the monthly concentration of 2019 and 2020. We identified that the first quarter of 2020 was warmer than 2019. We adjusted the NO₂ concentration for the temperature difference between 2019 and 2020. We used the NEI report and the MOVES simulator from the United States Environmental Protection Agency (U.S. EPA) in order to identify the compound annual reduction rate of total NO₂ and mobility-induced NO₂, respectively, due to pollution prevention regulations. These two data sources only report NO₂ while S5P and roadside monitors report NO₂ for consistency, we considered the percent change of NO₂ to correspond to the percent change of NO₂ and interchangeably used them in this study since NO₂ is a component of...
NO\textsubscript{x} (NO\textsubscript{x} = NO\textsubscript{2} + NO). Subsequently, we adjusted the monthly change of NO\textsubscript{x} in 2020 for the yearly NO\textsubscript{x} reduction by clean air regulations to achieve the effect of the pandemic restrictions. Later, we quantified the change dynamics of mobility in the study area using data collected by Apple Corporation (Apple mobility report). We adjusted the mobility data of the study area for the seasonal and spatial variability and compared the temporal change of on-road traffic with mobility-induced NO\textsubscript{x} reduction during COVID-19. We also used data from continuous vehicle count sensors to measure the change in volume of both automobiles and trucks during the pandemic. The flowchart in Fig. 1 shows our overall approach. We elaborate on the study area and data used for the analysis in the following subsections.

2.2. Study area

The study area includes a populous, well-developed region of the U.S. Northeast megalopolis, including major highways (Lin et al., 2013). The region of study consists of 68 counties from New Jersey, New York, Connecticut, and Pennsylvania, including New York City and Philadelphia, covering over 100,000 square kilometers. According to the U.S. census bureau’s urban and rural classification (US Census Bureau, 2019), 40% of the study area falls into the urban category. The total population of the study area is around 51 million people in 2020 (Center for International Earth Science Information Network - CIESIN - Columbia University, 2008). Fig. 2 (a) shows the extent of the study area. The region has several interstate highways, including I-95, one of the busiest highways in the country, which connects New York City with Washington DC. (U.S. DOT FHWA, 2013). The spatial distribution of population density for each county is shown in Fig. 2 (b).

2.3. Data and strategy

2.3.1. Measurement of NO\textsubscript{2} concentration

To measure NO\textsubscript{2} concentration before and after the pandemic, we used data from both NO\textsubscript{2} ground monitors and the SSP satellite. Ground monitors report NO\textsubscript{2} concentration in parts per billion (ppb), where the satellite reports it in column density in mole per square meter (mol/m\textsuperscript{2}). Fig. 2(c) shows the monthly average NO\textsubscript{2} concentration in the study area acquired by the SSP. The following subsections elaborate on the methods for NO\textsubscript{2} measurements.

2.3.1.1. Ground based monitoring of NO\textsubscript{2} concentration. In the United States, more than 4000 monitoring stations measure the ambient concentrations of pollutants across the country. These stations are owned and operated mainly by state environmental agencies, and they send hourly or daily measurements of the pollutants, including particulate matters (PM\textsubscript{2.5}, PM\textsubscript{10}), sulfur dioxide (SO\textsubscript{2}), carbon monoxide (CO), ozone (O\textsubscript{3}), nitrogen dioxide (NO\textsubscript{2}), and others, to EPA’s database Air Quality System (AQS) database (U.S. EPA, 2021a). The placement of these monitors is strategically determined by analyzing the intensities of emissions, terrains, meteorological conditions, and demographic attributes of the proposed deployment area (U.S. EPA, 2017b). The concentration of ground-level (roadside) pollution is affected by wind speed and direction. The highest concentrations of roadway pollutants occur on the downwind of a roadway, and the concentrations generally decrease to background levels within 500–600 feet (Brauer et al., 2012). In this regard, U.S. EPA requires air quality monitors to be placed near high-traffic roadways (U. S. EPA, 2014; U.S. EPA, 2015c). Fig. 2(a) shows the location of 26 ground monitors in the study area. It is clear from the map that the monitors are placed alongside the interstate highways. Undoubtedly, these roadside monitors should be highly sensitive to the vehicular emissions on the roads; however, may not

Fig. 1. Flow diagram demonstrating the study approach.
effectively capture the pollution level in neighborhoods located far from the roadway.

2.3.1.2. **NO\textsubscript{2} observations from space.** Several satellite missions have been launched to monitor the earth’s atmosphere, including airborne pollutants, from space. In 1995 European Space Agency (ESA) launched the ERS-2 satellite with the GOME spectrometer, which was successfully used to quantify global NO\textsubscript{2} column density (Konovalov et al., 2005). The successor of ERS-2 was the Envisat satellite, with one of its instruments called SCIAMACHY (SCanning Imaging Absorption spectroMeter for Atmospheric ChartographY), it performed global measurements of trace gases in the troposphere and the stratosphere between 2002 and 2012, providing NO\textsubscript{2} measurements globally every six days with 30 × 60 km\textsuperscript{2} spatial resolution (Boersma et al., 2008). In 2004, the AURA satellite was launched with an OMI sensor that mapped the NO\textsubscript{2} column density with high spatial resolution compared to its predecessors (13 × 24 km\textsuperscript{2}). This sensor has been operational for over 16 years, providing options to analyze the long-term trend of air quality, pollution, emission, solar irradiance, ozone, and ultraviolet radiation at a global scale (Levlt et al., 2018). In 2017, the S5P satellite was launched, equipped with the TROPOMI (TROPOspheric Monitoring Instrument) sensor. TROPOMI builds on the experience from previous polar-orbiting instruments such as the OMI (Ialongo et al., 2020). According to ESA, the TROPOMI instrument combines the strengths of SCIAMACHY and OMI. The performance of the TROPOMI sensor surpassed other instruments in terms of sensitivity, spectral, spatial, and temporal resolution (ESA. (n.d.). The TROPOMI spectrometer measures the backscattered solar radiation with ultraviolet (UV), visible (VIS), near-infrared (NIR), and shortwave infrared (SWIR). It observes the major atmospheric constituents, including ozone, nitrogen dioxide, carbon monoxide, sulfur dioxide, methane, formaldehyde, aerosols, and clouds (Veefkind et al., 2012). Using retrieval algorithms, the S5P one can derive the tropospheric NO\textsubscript{2} column density daily at about 5.5 × 3.5 km\textsuperscript{2} spatial resolution (7.5 × 3.5 km\textsuperscript{2} before August 6, 2019) with the solar radiation measured with 405–465 nm wavelength range (Copernicus, 2020; van Geffen et al., 2019).

![Figure 2](image-url)
We retrieved tropospheric NO\textsubscript{2} column density data from offline (OFFL) level-3 (L3) NO\textsubscript{2} daily global data product from Google Earth Engine (Gorelick et al., 2017). SSP data product comes with the quality flag (QA value), which can be used to measure the data quality. The QA value ranges between 0 and 1, where ‘0’ means the worst and ‘1’ refers to the best quality (Copernicus, 2020). The presence of cloud and aerosol particles deteriorates the quality of the data products, which can be identified with a low-quality flag value. This SSP-L3 data product is filtered to remove pixels with QA values less than 0.75. Fig. 2(c) shows the monthly average NO\textsubscript{2} concentration in the study area captured by the SSP satellite. The concentration is presented as tropospheric vertical column density with the unit in mole per square meter. In 2019 and 2020, we found the concentration drops every month from February, indicating the seasonal effect. In this regard, without adjusting this seasonal trend, a simple subtraction between NO\textsubscript{2} mean value of March 2020 and February 2020, to identify the reduction of NO\textsubscript{2} caused by the pandemic, would be inaccurate.

2.3.2. Pollution prevention regulations
Since 1970 the U.S. federal government has implemented legislation to curb air pollution. The 1970 Clean Air Act (CAA) authorizes the development of comprehensive federal and state regulations to limit both stationary and mobile emissions sources (US DOE, 2020). Since then, the combined emissions of criteria pollutants and their precursors have dropped by 77% (U.S. EPA, 2020a). In 1988, the Alternative Motor Fuels Act (AMFA) was introduced to enhance the fuel efficiency of motor vehicles (Public Law 100-494, 1988). Built on the 1970 Clean Air Act, the 1990 Clean Air Act Amendment (CAAA) was proposed with the aim to reduce four health and climate threats: urban air pollution, toxic air, acid rain, and stratospheric ozone depletion. It is reported that the economic benefit of the 1990 amendments reached two trillion dollars in 2020, along with preventing 230,000 premature deaths (U.S. EPA, 2020a). In 1991, congress passed the Intermodal Surface Transportation Efficiency Act (ISTEA) to bring transportation into the multi-modal arena. ISTEA established the Congestion Mitigation and Air Quality Improvement Program, administered by the Federal Highway Administration, to provide funding for projects and programs in air quality non-attainment and maintenance areas to reduce transportation-related emissions (US DOE, 2020; US DOT FHWFA, 2020). In October 1992, the Energy Policy Act of 1992 was enacted, aiming to reduce the country’s dependence on petroleum and improve the quality of air by addressing alternative fuel, renewable energy, and energy efficiency (US DOE, 2020). In 2000, EPA adopted stringent standards for heavy-duty vehicles requiring NO\textsubscript{x} exhaust control technology for all the on-road heavy-duty diesel engines by 2010 (MECA.., U.S. EPA, 2007). U. S. EPA launched a voluntary public-private program called SmartWay in 2004 to help companies move goods in the most energy-efficient way. It is reported that the SmartWay program reduced 150 million tons of air pollution (NO\textsubscript{x}, PM, and CO\textsubscript{2}) by saving 312 million barrels of oil (U.S. EPA, 2020c). Diesel Emission Reduction Act (DERA), which provides funding for owners to replace their diesel equipment sooner than legally required, cut 335,200 tons of NO\textsubscript{x} emission (EDF, 2020; U.S. EPA, 2021d). In addition to transportation or mobile emissions which constitute 56% of total U.S. NO\textsubscript{x} emissions, stationary sources are responsible for 44%, including power plants contributing 13% of total NO\textsubscript{x} generation in the U.S. The Clean Air Act Amendment of 1990 provided the first set of regulations to control emissions of toxic pollutants from power plants (U.S. EPA, 2021c). In 2011, U.S. EPA finalized the Cross-State Air Pollution Rule (CSAPR), replacing the Clear Air Interstate Rule (CAIR) of 2005, which requires certain states in the eastern half of the U.S. to reduce power plant emissions that cross state lines and affect the air quality in downwind states (U.S. EPA, 2021c). These regulations turned out to be a great success, and U.S. EPA reports an 87% reduction of NO\textsubscript{x} emission from power plants in 2020, compared to 1995 (U.S. EPA, 2021d).

Considering all the federal, state, and local level legislation and policies, the U.S. is reducing emissions every year. Fig. 3(a) shows the annual NO\textsubscript{x} emission and vehicular travel for the entire country. Here we used mobility data from the traffic volume trend reports by the U.S. Department of Transportation - Federal Highway Administration (US DOT FHWFA) and the country-wide yearly NO\textsubscript{x} measurements from EPA’s national annual emission trend data (U.S. DOT FHWFA, 2021; U.S. EPA, 2021b). Between 2002 and 2019, there was a 62% reduction of total NO\textsubscript{x} emissions nationwide, while vehicular travel increased by 14%, indicating the significance of legislation in curbing emissions. Using 2017 and 2019 values, we found that the country-wide compound yearly reduction rate for total emissions (from stationary and mobile sources) was 5%, while the reduction of NO\textsubscript{x} emissions by mobile sources only was 7.3%.

2.3.2.1. Motor Vehicle Emission Simulator (MOVES). Motor Vehicle Emission Simulator (MOVES) is a state-of-the-art emission modeling system developed by EPA. This can model mobile sources of air pollutants, greenhouse gases, and air toxins at three different spatial levels: national, county, and project (flexible geographic extent based on study area) (U.S. EPA, 2016). State and local agencies use MOVES to calculate vehicular emissions for state implementation plans and transportation conformity. To develop the emission simulation model, MOVES uses data from different sources. Vehicle regulatory class, fuel type, and age distribution categories are a few of the input variables in the MOVES simulation. To get this information at the national level, MOVES utilizes data from the VIUS (Vehicle Inventory and Use Survey), NPPV (National Vehicle Population Profile), and TIP (Transporting Industry Profile). MOVES also utilizes FHWA’s Highway Statistics to quantify vehicle miles traveled (VMT) and vehicle population. Vehicle fuel type distributions and the population of motor buses come from the National Transit Database (NTD) of the Federal Transit Administration (FTA). MOVES also incorporates data from school bus fleet factbook, transportation energy data book, motor-cycle industry council statistical annuals, annual energy outlook and national energy modeling systems, FHWA truck weight data, and so on (U.S. EPA, 2015b). Although MOVES algorithm and data is optimized for the United States, it is widely used in transport emission studies both for the inside and outside the country (Filigra et al., 2020; Romero et al., 2020; Wang et al., 2020). In this study, we used the most updated MOVES 2014b simulator, which can model air pollution on 1990 and 1999 through 2050 (U.S. EPA, 2018).

We simulated the on-road vehicular emission of NO\textsubscript{x} for 2017 and 2019 for the 68 counties in the study area. We found in 2017 mobile sources produced 210,000 U.S. tons of NO\textsubscript{x} in the study area, where the emission reduced to 166,395 U.S. tons in 2019. This reduction is the direct consequence of the pollution reduction regulations on fuel type and vehicle fuel efficiency. Using the concentration values of these two years, we found the compound rate of annual NO\textsubscript{x} reduction for on-road mobile sources in the Northeast U.S. is 10.9%, in contrast to the 7.3% nationwide annual reduction for the same period. Fig. 3(b) shows the spatial distribution of the MOVES simulated mobility-driven NO\textsubscript{x} emission in 2019 for each county.

2.3.2.2. National Emission Inventory (NEI). Every three years, U.S. EPA compiles a comprehensive summary of air emissions data known as the NEI report, in association with organizations, including state, tribal, and local air pollution control agencies, industry, and researchers. NEI is the most comprehensive report of national and regional estimates for criteria and hazardous air pollutants emissions from biogenic, fire, mobile, and stationary sources (U.S. EPA, 2017a). The latest NEI report was published for 2017, and the report for 2020 is expected to be published in 2022. In this study, we used NEI report 2014 and 2017 to compute the compound annual rate of total NO\textsubscript{x} decline in the study area due to pollution prevention policies. We found the 68 counties in our study area combined, reduced 135 thousand tons of total NO\textsubscript{x} in these three years (from 596,421 tons to 461,417 tons), with the
compound annual rate of reduction being 8.2%, compared to the nationwide 5% reduction for the same period. Assuming the same rate and extrapolating to 2019, the total NO\textsubscript{x} emission of 2019 would be 388,847 tons, used as a baseline for the pandemic-driven emission calculations for total NO\textsubscript{x}. The spatial distribution of the total NO\textsubscript{x} emission in 2019 is shown in Fig. 3(c). Fig. 3(d) shows the ratio of mobility-induced NO\textsubscript{x} to total NO\textsubscript{x} for each county in the study area. On average, in the study area, 66.8% of the total NO\textsubscript{x} is produced by mobile sources, where 40.6% is contributed by on-road mobile sources, such as motor vehicles, and the rest 26.2% comes from non-road mobile sources, like aircraft, marine vessels and so on. The share of on-road mobility-driven NO\textsubscript{x} is higher in northern New Jersey and upstate New York, between 50% and 75% and in some counties over 75%. In contrast, in New York City, Long Island, Philadelphia, and South Jersey the share of mobile source NO\textsubscript{x} emission versus total NO\textsubscript{x} is less than 50%, pointing to the role of higher population density and industrial emissions.

2.3.3. Mobility

In this study, we infer the mobility data from Apple mobility data and roadside continuous vehicle count sensors.

2.3.3.1. Apple mobility reports. We used Apple mobility data to observe the temporal trend of overall mobility in the study area before and during the pandemic. The data is publicly available and covers all major cities in 63 countries around the world. For U.S. cities, the mobility trend includes driving, transit, and walking. However, at the county level, the data only provide the temporal driving trend. Apple released the mobility trend in percent values, considering January 13, 2020 as the baseline. The data is generated by counting the number of requests made to Apple Maps for directions (Apple, 2020). Studies have already used Apple mobility data to model social distancing during the pandemic lockdown (Cot et al., 2021; Huang et al., 2021) and model COVID-19 virus spread (Bergman and Fishman, 2020; Kurita et al., 2021; Nouvellet et al., 2021). Here, we collected mobility data for all 68 counties in the study area between 1st February and August 30, 2020. Fig. 4 (a) shows a sample of the Apple mobility data for New York County (Manhattan).

2.3.3.2. Continuous vehicle count sensors. We also used traffic sensor data to identify changes to the volume of automobiles and trucks before and after the pandemic restrictions. Every year state-level transportation agencies prepare annual average daily traffic (AADT) report for all public roads, which is delivered to FHWA (U.S. DOT FHWA, 2018). In this regard, transportation agencies use automated traffic sensors and count the number of vehicles that pass a road segment for a period of either 48 h or less (known as short count) or continuously over the year (known as continuous count) (U.S. DOT FHWA, 2014). These continuous count monitors report hourly numbers with total vehicle volume according to vehicle categories. To measure the change in volume for automobiles and trucks, we used data from three continuous count monitors (Fig. 2(a)), located in Gowanus Expressway I-278 (station number = 020,011), interstate highway I-84 (station number = 840,008), and state highway NY-8 (station number = 930,070). Fig. 4 (b) shows the average daily percent volume of automobiles and trucks, considering the median daily volume of February as a baseline.
3. Analysis

3.1. MOVES weighted mobility trends for the study area

We collected daily mobility data for 68 counties in the study area from the Apple mobility report. The daily percent mobility in the study area can be calculated by averaging the mobility values of 68 counties. Fig. 4 (c) shows the mean Apple mobility for the study area taking 1st February as baseline (100%). The figure shows the mobility dropped to 40% during the early stage of the pandemic lockdown and returned back to 100% at the beginning of June. However, the counties in the study area are a mixture of urban and rural. As a result, the average of percent values is not a proper representation of the actual mobility trend as it failed to represent the change dynamic of the vehicular volume of different counties. In rural areas, where vehicular volume is low, a slight increase in vehicle volume on the road can lead to a significant percentage increase in mobility. The opposite scenario would likely occur in the urban areas. Therefore, to calculate the daily percent mobility for the study area, instead of doing a simple average, we performed a weighted average of percent mobility of 68 counties, where the weight is the MOVES simulated mobility driven NO\textsubscript{2} values for each county in 2019.

As MOVES simulated NO\textsubscript{2} corresponds to vehicular volume (U.S. EPA, 2015a), the NO\textsubscript{2} emission in 2019 by mobile sources is used as a surrogate measure of baseline vehicular volume for different counties in 2020. So, the MOVES adjusted mobility can be written as follows,

$$\text{daily MOVES adjusted mobility} = \frac{\sum_{i=1}^{n} w_i X_i}{\sum_{i=1}^{n} w_i} \quad (1)$$

where 
- \( w_i \) = MOVES mobility driven NO\textsubscript{2} for county \( i \).
- \( X_i \) = mobility percent value reported by Apple inc.

\( n \) = number of counties.

MOVES weighted mobility trend in the study area is shown in Fig. 4 (d). Again, we found a seasonal variability in mobility from FHWA nationwide Vehicle Mile Travel dataset, with high mobility in summer and low in winter (U.S. DOT FHWA, 2021). In Fig. 4 (d), the dashed line shows the average percent monthly mobility for 2019 by taking February as 100%. It is clear from the figure that the nationwide average mobility in February was lower than the following months. The highest mobility was observed in July 2019, which is 18% higher than the mobility of February. We used the 2019 national trend to adjust the seasonal effect of the MOVES adjusted mobility calculated with equation (1). In Fig. 4 (d), the solid line shows the MOVES and seasonality-adjusted mobility for the study area. After MOVES and seasonal correction, we found the mobility in the study area dropped 80% immediately after the lockdown, and it came back to its original state in late August 2020, corresponding to a 32% average monthly reduction between March and August.

3.2. Adjusted percent NO\textsubscript{2} observed from satellite and ground sensors

We used data of NO\textsubscript{2} ground monitors for calculation of changes to the mobility induced NO\textsubscript{2} emission, while we used SSP satellite to quantify the total NO\textsubscript{2} emission reduction (mobile and stationary sources) in the study area. The ground-level NO\textsubscript{2} data was obtained from the EPA AQPS ground-based monitors. From Fig. 2(a), it is noted that the ground monitors are placed by the major interstate highways and are concentrated in the population centers like New York City and Philadelphia; monitors are not present in the northern part of the study area where population density is low. We used the monthly mean NO\textsubscript{2} measurements of all twenty-six ground monitors located in the region to
quantify changes in NO$_2$ emissions by mobile sources, and we used the monthly mean of satellite S5P NO$_2$ column density value to calculate the total NO$_2$ emission reduction in the area.

There is strong seasonal effect of NO$_2$ concentration with high values in winter and low values in summer. The seasonal variation of NO$_2$ concentration is due to photochemical atmospheric reactions. In the summer, at high-temperature, NO$_2$ engages in photochemical reactions and creates ozone, resulting in lower NO$_2$ levels in the atmosphere (Cichowicz et al., 2017; Hagenbjörk et al., 2017). In the winter season, lower temperature inhibits ozone, which triggers NO$_2$ levels in the air (Roberts-Semple et al., 2012). Fig. 5 (a, b) shows the seven-day rolling average of daily NO$_2$ measurements from satellite sensors and ground monitors, along with daily temperature data. We collected the daily mean temperature of 33 weather stations in the study area from the National Oceanic and Atmospheric Administration (NOAA) local climatological data portal (LCD) (NOAA, n.d.). We calculated the mean value at the 33 stations to quantify the mean daily temperature of the study area.

The seasonal variation of NO$_2$ concentration needs to be corrected to quantify the actual pandemic effect; this can be achieved by taking the difference between 2019 and 2020. However, meteorological factors like aerosol, solar radiation, temperature, precipitation, humidity, wind speed, wind direction, and others can also influence the NO$_2$ concentration (Plaisance et al., 2004). The effect of these factors may not be identical over two consecutive years. As a result, the straight difference between these two years without considering other co-factors would give biased estimations of pandemic-driven NO$_2$ reduction. To adjust for these co-factors, first, we computed the relative percent NO$_2$ concentration of all months of a given year by taking the concentration of February as 100% (baseline). Then we subtracted the monthly relative concentration of 2019 and 2020 to identify the effect of NO$_2$ during pandemic restriction. The algebraic notation can be written as follows,

\[
\%\text{NO}_2(\text{x, 2019}) = \left( \frac{C_{\text{x, 2019}}}{C_{\text{Feb, 2019}}} \right) \times 100
\]

\[
\%\text{NO}_2(\text{x, 2020}) = \left( \frac{C_{\text{x, 2020}}}{C_{\text{Feb, 2020}}} \right) \times 100
\]

Here, %NO$_2$(x, 2019) and %NO$_2$(x, 2019) are the relative percent NO$_2$ concentrations for months ‘x’ in 2019 and 2020, respectively. $C_{\text{x, 2019}}$ and $C_{\text{x, 2020}}$ are the NO$_2$ concentration of month ‘x’ in 2019 and 2020, where $C_{\text{Feb, 2019}}$ and $C_{\text{Feb, 2020}}$ are the NO$_2$ concentration of February in 2019 and 2020, respectively.

This approach has two benefits; (1) the random errors and uncertainties for each monthly concentration will be referenced to February of that year. So, random errors will be minimized when quantifying the difference of year-to-year monthly concentration, (2) this will eliminate the effect of policy-driven annual reduction in the calculation of pandemic effect.

### 3.3. Calibration for ambient temperature

We found the first quarter of 2020 was warmer than 2019. For instance, the monthly mean temperature in March 2019 was 38 °F, whereas, for 2020, the mean temperature for the same month was 44.6 °F. Fig. 5 (c) shows the mean monthly temperature for 2019 and 2020 in the study area. The temperature variation between these two years needs to be controlled to quantify the actual effect of the pandemic on NO$_2$ concentration.

We performed Ordinary Least Square (OLS) linear regression to identify the change in relative monthly percent NO$_2$ for both remote and ground observations with the change in monthly average temperature. In Fig. 5(d), every point represents the relative monthly percent values for NO$_2$ with the corresponding monthly average temperature between

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Fig. 5. (a) Seven-day rolling average of daily NO$_2$ column density measured from satellite (primary y-axis) and daily temperature (secondary y-axis). (b) Seven-day rolling average of daily NO$_2$ measured from ground sensors (primary y-axis) and daily temperature (secondary y-axis). (c) Monthly mean temperature of 2019 and 2020 shows temperature differences in the identical month of these two years. (d) Scatter plot and separate regression line of remote and ground NO$_2$ measurements with temperature. The slope of the lines corresponds to the temperature correction factor remote and ground measurements, respectively.
February and December 2019. Relative monthly percent concentration of each month of a year is quantified considering the NO$_2$ value for February is considered 100%, similar to the concept introduced in the last section. In Fig. 5(d), the dots and lines show the ground observations and the corresponding regression line, respectively. The slope of the regression line is the correction factor for temperature. It is clear from the figure that the slope of the regression line for ground observations (~0.79) is less steep than the slope of remote observations (~1.31). So, every single degree Fahrenheit increase in temperature corresponds to a 0.79% decrease in ground monitored NO$_2$ and a 1.3% decrease in remotely monitored NO$_2$ relative percent concentrations. These indicate that the remote observations are more sensitive to temperature variations than the ground observations. As mentioned earlier, the ground NO$_2$ monitors are placed by the busy roads and are more susceptible to the change in mobility. Therefore, they are relatively less sensitive to ambient temperature.

4. Results and discussion

Before taking the difference of NO$_2$ relative monthly concentration of 2020 and 2019, calculated with equations (2) and (3), we adjusted the observed values with the temperature correction factor. Fig. 6 (left) shows the monthly percent values of remote and ground sensors without temperature correction. The solid and hashed bars depict the relative percent values of NO$_2$ in 2019 and 2020, respectively. First, we calculated the difference of percent NO$_2$ values for the identical months of two years before applying the temperature correction factor. For instance, Fig. 6 (left) shows the difference of remote NO$_2$ measurement for March 2019 and 2020 is 36.6%. Fig. 5 (c) indicates the temperature difference in March of these two years is 6.6-degree Fahrenheit. According to the regression coefficient, the correction factor for remote observation is ~1.3% for each degree increase in temperature. As a result, with temperature correction for remote observation, the drop of NO$_2$ in March 2020 is 28%. The algebraic notation of temperature adjusted NO$_2$ can be written as follows.

Adjusted \( \% \text{NO}_2 \) \(_{(x, 2020)} \) = \( \% \text{NO}_2 \) \(_{(x, 2019)} \) \( - \% \text{NO}_2 \) \(_{(x, 2020)} \) + \( \hat{\lambda} \) \( (T_{(x, 2019)} - T_{(x, 2020)}) \) + 100 \(_{(4)}\)

Here, \( \% \text{NO}_2 \) \(_{(x, 2019)} \) and \( \% \text{NO}_2 \) \(_{(x, 2020)} \) is the relative percent NO$_2$ calculated in equations (2) and (3), where \( \hat{\lambda} \) is the temperature correction factor, and \( T_{(x, 2019)} \) and \( T_{(x, 2020)} \) is the mean temperature of month ‘x’ in 2019 and 2020 respectively. Fig. 6 (right) shows the temperature corrected relative percent NO$_2$ concentration in 2020 for both remote and ground observations.

We compared the adjusted NO$_2$ percent value of 2020 with seasonality adjusted mobility drop in the study area. Fig. 6 (right) shows the NO$_2$ measured from ground sensors follow a similar temporal trend to mobility. We used the Pearson’s correlation coefficient (r) to identify the association between factors (Azad and Ghandehari, 2021a). The coefficient between monthly mobility and monthly ground NO$_2$ measurements indicates a very strong correlation with \( r = 0.91 \). However, NO$_2$ measured by satellite has a relatively weak correlation (r = 0.59). As discussed earlier the roadside NO$_2$ monitors are sensitive to mobility, where the satellite sensor can capture the emissions equally from both the mobile and the stationary sources. Similar to other studies (Bassani et al., 2021; Bechle et al., 2013; Virgilieanu et al., 2020), we also found a strong correlation between remote and ground NO$_2$ observations (r = 0.63). Ground monitors are strategically placed along the roadside to observe the pollution emitted by vehicular traffic. Inspecting the spatial distribution (Fig. 2(a)), we also found the roadside monitors are concentrated in cities, which are only 40% of the study area. On the other hand, the NO$_2$ value from satellite sensors shows the mean percent NO$_2$ change for the entire region regardless of urban and rural. In this regard, we used observations from the remote sensor to measure the total NO$_2$ reduction in the area during the pandemic lockdown, and ground monitors to quantify the mobility-driven NO$_2$ reduction. With the NEI report, we estimated the total NO$_2$ emission in 2019 in the study area as 388,847 tons (section 2.3.2.2). With 8.2% regulation-driven reduction, the NO$_2$ emission for 2020 without pandemic lockdown would have been 357,000 tons, which corresponds to around 30,000 tons of average monthly NO$_2$ emission in 2020. From the observations of SSP, we found the lockdown reduced 28% NO$_2$ in March, 14% in April, and 2% in May (Fig. 6 (right)). If we consider the percent change of NO$_2$ corresponds to the percent change of NO$_2$ (Reevers et al., 2012), we can claim that the COVID-19 lockdown was responsible for 13,200 tons (\( \sum \%_{30000 \text{t}} \text{i} \) = monthly percent reduction) of total NO$_2$ reduction in the study area. So, the pandemic lockdown was responsible for 3.4% reduction (13,200/388,847) of total (from mobility and stationary sources combined) NO$_2$ concentration in the study area in 2020. We found earlier (section 2.3.2.2) that clean air regulations result in 8.2% reduction of NO$_2$ emissions in the region every year. So, the pandemic-induced total NO$_2$ reduction is equivalent to about five months’ worth of policy-driven reduction in the region.

Regarding vehicular emissions, with the MOVES simulation, we found 166,395 tons of mobility-induced NO$_2$ emission in 2019. We also calculated the compound annual rate of reduction of mobility-driven emission to be 10.9% (section 2.3.2.1), which estimates 148,257 tons (12,354 tons per month) of mobility induced NO$_2$ emission in 2020 if there were no pandemic restrictions. Due to the pandemic, the mobility-driven NO$_2$ emission was reduced 13.6% in March, 18.5% in April, 16.2% in May, 6.6% in June, 3.7% in July. With a weighted sum (\( \sum 12354 \text{i} \) = monthly percent reduction), we found 7239 tons of mobility-induced NO$_2$ reduction due to the pandemic lockdown.

![Fig. 6. (left) Monthly percent NO$_2$ from satellite (blue) and ground (green) measurements of 2019 and 2020. (right) seasonality and temperature corrected NO$_2$ change during the pandemic for remote (blue symbol) and ground (black dots) measurements with daily mobility. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)](image)
Therefore, the pandemic triggered 5% (7239/148,257) more annual mobility-induced NOx reduction on top of the 10.9% policy-driven reduction in 2020. This COVID-19 restriction driven reduction is equivalent to around 5.5 (5%/10.9%) months of policy-driven reduction.

From March to August 2020, there was 32% average monthly reduction of mobility (using Apple mobility data). The continuous vehicle counting sensors indicated that the mean monthly reduction of automobiles and trucks is 22.5% and 4.8%, respectively. The above mismatch between the reduction of mobility derived from Apple mobility and roadside sensors is primarily caused by the limitations of the data. Apple mobility data only accounts for Apple users, so it may not unbiasedly estimate the mobility patterns for the entire population. Regarding roadside sensors, due to data unavailability, we used a sample of only three continuous vehicles count sensors to measure the change dynamics of automobiles and trucks. While this may be a reliable representative sample for temporal analysis, one would have to prematurely assume that the observed temporal trend is spatially uniform.

According to the NEI report of 2017, in the U.S. Northeast, stationary sources generate 33.2% of NOx emissions, including 10.6% by residences, 13.8% by industrial and commercial sources, and 7% by electricity generation and waste disposal. Mobile sources generate 66.8% of the region’s NOx emissions, including 16.4% by heavy-duty vehicles, 24.2% by light-duty vehicles, and 26.2% by non-road mobile sources such as aircraft, marine vessels, locomotives, and so on. We do not count on much reduction of NOx emissions from stationary and non-road mobile sources during pandemic travel restrictions since most of those were operational as usual. Looking back at the reduction of truck volume during the pandemic restriction (4.8%) versus the reduction of passenger vehicles (22.5%) and considering that trucks are a major source of on-road pollution (Wang et al., 2020), one can see why emissions by mobile sources did not decline significantly. Table 1 summarizes relevant statistics.

5. Conclusion

- In the U.S., averaging urban and rural areas, 56% of NOx emissions are from mobile sources (on-road and non-road mobile sources combined) and 44% from stationary sources. Pollution prevention policies in the U.S. have resulted in a steady decrease in NOx emissions since the passing of the clean air act in 1970, on average 5% per year for the U.S.
- In 2020, the U.S. Northeast megalopolis (NYC Metro to Baltimore Metro) experienced an 11.6% annual reduction of total NOx (stationary and mobile combined) emissions compared to the prior year. 8.2% was due to the persistent decline of NOx emission as the result of pollution prevention regulations in the U.S.; the remainder 3.4% reduction was caused by the 2020 COVID-19 pandemic lockdown. As such, the pandemic-driven NOx reduction is equivalent to approximately five months of regulation-driven emission reductions. The most significant reduction of emissions in 2020 occurred in March (28%) and April (14%) compared to the same months in the year before the pandemic.
- When considering NOx emissions from mobile sources only, the annual NOx emissions in 2020 was 15.9% less than in 2019, where 10.9% of the reduction was contributed by pollution prevention regulations, and 5% was the result of pandemic travel restrictions.
- Looking at counts of all mobile sources in the northeast corridor, the average monthly reduction of automobiles is around 22.5% (between March and August 2020), where the decrease of trucks is only 4.8%. In other words, while citizens were locked down, goods were still being delivered.
- The 3.4% annual reduction of total NOx and the 5% annual reduction of mobile NOx emissions in the study area seem insignificant. However, consider that stationary sources (residents, factories, etc.) and non-road mobile sources (marine vessels, locomotives, etc.), responsible for more than half of all NOx emissions in the region, were not particularly locked down. Additionally, truck traffic, a significant source of mobile NOx emissions, declined marginally when compared to automobiles. Although automobile traffic dropped notably during the pandemic lockdown, its effect on emissions was relatively insignificant, resulting in the observed 3.4% reduction of total NOx and 5% reduction of mobile NOx emission in the study area.

Credit author statement

Shams Azad: Conceptualization, Methodology, Formal analysis, Data curation, Investigation, Visualization, Writing – original draft.
Masoud Ghandehari: Conceptualization, Methodology, Formal analysis, Investigation, Visualization, Writing – review & editing.

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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Table 1

| Total NOx reduction (%) | Mobility induced NOx reduction (%) | Reduction in automobile mobility (%) | Reduction in autos by sensors (%) | Reduction in trucks by sensors (%) |
|------------------------|-----------------------------------|-------------------------------------|----------------------------------|----------------------------------|
| March 28%               | 13.6%                             | 39%                                 | 24%                              | 1%                               |
| April 14%              | 18.5%                             | 64%                                 | 52%                              | 18%                              |
| May 2%                 | 16.2%                             | 45%                                 | 32%                              | 10%                              |
| June 0%                | 6.6%                              | 28%                                 | 15%                              | 0%                               |
| July 0%                | 3.7%                              | 12%                                 | 8%                               | 0%                               |
| August 0%              | 4%                                | 8%                                  | 4%                               | 0%                               |
| Mean 7.3%              | 9.7%                              | 32.0%                               | 22.5%                            | 4.8%                             |

In all cases, the mean value of February is considered as baseline (100%).
S. Azad and M. Ghandehari

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