



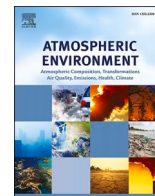
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## Impacts of the COVID-19 economic slowdown on ozone pollution in the U.S.

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### HIGHLIGHTS

- Observations and chemical transport modeling are used to quantify COVID-19 lockdown impacts on ozone pollution in the U.S.
- Widespread emissions decreases lead to widespread ozone decreases in rural regions, but local increases in urban regions.
- There is considerable spatiotemporal variability for the 2020 ozone changes compared to the previous five years.

### ARTICLE INFO

#### Keywords:

COVID-19 economic slowdown  
Ozone pollution in the U.S.  
CMAQ Model  
National Air Quality Forecast Capability

### ABSTRACT

In this work, we use observations and experimental emissions in a version of NOAA's National Air Quality Forecasting Capability to show that the COVID-19 economic slowdown led to disproportionate impacts on near-surface ozone concentrations across the contiguous U.S. (CONUS). The data-fusion methodology used here includes both U.S. EPA Air Quality System ground and the NASA Aura satellite Ozone Monitoring Instrument (OMI) NO<sub>2</sub> observations to infer the representative emissions changes due to the COVID-19 economic slowdown in the U.S. Results show that there were widespread decreases in anthropogenic (e.g., NO<sub>x</sub>) emissions in the U.S. during March–June 2020, which led to widespread decreases in ozone concentrations in the rural regions that are NO<sub>x</sub>-limited, but also some localized increases near urban centers that are VOC-limited. Later in June–September, there were smaller decreases, and potentially some relative increases in NO<sub>x</sub> emissions for many areas of the U.S. (e.g., south-southeast) that led to more extensive increases in ozone concentrations that are partly in agreement with observations. The widespread NO<sub>x</sub> emissions changes also alters the O<sub>3</sub> photochemical formation regimes, most notably the NO<sub>x</sub> emissions decreases in March–April, which can enhance (mitigate) the NO<sub>x</sub>-limited (VOC-limited) regimes in different regions of CONUS. The average of all AirNow hourly O<sub>3</sub> changes for 2020–2019 range from about +1 to −4 ppb during March–September, and are associated with predominantly urban monitoring sites that demonstrate considerable spatiotemporal variability for the 2020 ozone changes compared to the previous five years individually (2015–2019). The simulated maximum values of the average O<sub>3</sub> changes for March–September range from about +8 to −4 ppb (or +40 to −10%). Results of this work have implications for the use of widespread controls of anthropogenic emissions, particularly those from mobile sources, used to curb ozone pollution under the current meteorological and climate conditions in the U.S.

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<https://doi.org/10.1016/j.atmosenv.2021.118713>

Received 22 January 2021; Received in revised form 2 August 2021; Accepted 2 September 2021

Available online 4 September 2021

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## 1. Introduction

The global confinement due to rising COVID-19 cases, in particular, travel restrictions and quarantining shelter-in-place orders are associated with significant decreases in surface transportation activity by about 50% globally (Le Quééré et al., 2020). Consequently, the COVID-19 economic slowdown led to a “natural air pollution control experiment” due to widespread anthropogenic emissions reductions for atmospheric pollutants and their precursor gases, such as decreased oxides of nitrogen ( $\text{NO}_x = \text{NO} + \text{NO}_2$ ) emissions of up to  $\sim 50\%$  (Zhang et al., 2020; EEA, 2020; U.S. EIA, 2020). The COVID-19 impacts on air pollution occurred on a scale impossible to reproduce outside of such a global health emergency.

The emission reductions during the lockdown measures led to varying changes in air quality conditions across the world. During February–March 2020 in China, surface fine particulate matter ( $\text{PM}_{2.5}$ ) and carbon monoxide (CO) concentrations decreased by about 25% and 17%, respectively (Yue et al., 2020). It was approximated that although air pollutant emissions decreased by 40% in the Northern China Plain, there were high levels of  $\text{PM}_{2.5}$  (hourly levels  $>200 \mu\text{g m}^{-3}$ ) that persisted from late January to mid-February, while surface ozone ( $\text{O}_3$ ) also increased sharply by 84% (Li et al., 2020). In other cities, there were substantial decreases in  $\text{NO}_x$  (56%) and  $\text{PM}_{2.5}$  (42% in Wuhan and 8% in Europe), but surface ozone ( $\text{O}_3$ ) increased in all cities (36% in Wuhan and 17% in China) (Sicard et al., 2020). In fact, analyses of COVID-19 related air pollution changes show that ground level  $\text{O}_3$  increased by 2–30% for 11 cities globally (Shi et al., 2021). Ground-level  $\text{O}_3$  is formed by chemical reactions of volatile organic compounds (VOCs) and  $\text{NO}_x$  in the presence of sunlight, and its production rate can be altered via different chemical regimes and environments around the world (Sillman et al., 1990; Sillman 1995, 1999; Pusede et al., 2012; Jin et al., 2013; Walaszek et al., 2018; Li et al., 2019). High  $\text{O}_3$  concentrations can lead to decreased lung function and cause impaired respiratory symptoms, which are particularly dangerous for young children, the elderly, and those with preexisting conditions including asthma, chronic obstructive pulmonary disease (COPD), lung cancer, and respiratory infection (Kar Kurt et al., 2016).

The COVID-19 economic slowdown and related traffic decreases that reached up to  $\sim 50\%$  during March–May in the U.S. (INRIX; U.S. News, 2020) led to notable changes in pollutants in urban areas of the country, particularly for  $\text{NO}_2$  concentrations that declined significantly as recorded from both satellite- and ground-based observations. Ground-based monitors indicated statistically significant declines for  $\text{NO}_2$  of 26.0% or 5.4 ppb in urban counties (Berman et al., 2020), while the TROPOspheric Monitoring Instrument (TROPOMI) satellite observations showed that the  $\text{NO}_2$  decreases ranged between 9.2% and 43.4% among 20 cities in North America (Goldberg et al., 2020). Qu et al. (2021) finds that surface and satellite  $\text{NO}_2$  measurements at U.S. EPA ground based sites with the 5% highest concentrations show consistent reductions of 22–26% in March–April and 8–13% in May–June 2020 compared to the same months in 2019.

It was clear by mid-May in the U.S, however, that surface  $\text{O}_3$  levels had not fallen in coincidence with decreasing  $\text{NO}_x$  levels across much of the U.S. (NPR, 2020), where various analyses showed variable  $\text{O}_3$  changes across different U.S. regions (Arunachalam et al., 2020; Ivey et al., 2020; Kang et al., 2020; Van Haasen, 2020; Yang et al., 2020). The high spatial  $\text{O}_3$  variability may have been exacerbated by relaxed shelter-in-place orders for many U.S. states in early-to mid-June that led to rebounding anthropogenic emissions in some regions.

Motivated by the apparent COVID-19 related  $\text{O}_3$  variability in different global regions and in portions of the U.S., we hypothesize that there are regional differences in the impact of COVID-19 lockdowns on  $\text{O}_3$  formation across the U.S. This study combines the use of both ground and satellite-based observations of  $\text{NO}_2$  to infer changes in precursor emissions due to the COVID-19 economic slowdown, and then uses the derived emission changes and a chemical transport model to quantify

the related changes in  $\text{O}_3$  concentrations across the entire contiguous U.S. (CONUS). Here we focus on  $\text{O}_3$  as an indicator of pollution changes due to the COVID-19 economic slowdown in the U.S. because 1) changes in traffic  $\text{NO}_x$  emissions strongly impact  $\text{O}_3$  formation, 2)  $\text{O}_3$  is the dominating pollutant contributing to non-attainment zones in the warm summer months (Zhang et al., 2019; U.S. EPA, 2020), and 3) because  $\text{O}_3$  has well-defined health impacts (Anenberg et al., 2009; Fann et al., 2012).

## 2. Methodology

### 2.1. Model configuration and observations

The National Air Quality Forecasting Capability (NAQFC) used in this work is a well-documented and evaluated air quality modeling system (Eder et al., 2006, 2009; Mathur et al., 2008; Stajner et al., 2011; Lee et al., 2017). The NAQFC used in this work is based on the offline-coupled North American Mesoscale Model Forecast System on the B-Grid (NMMB) (Black, 1994; Janjic and Gall, 2012), which provides the driving weather data to the Community Multiscale Air Quality (CMAQ) model, version 5.0.2 (U.S. EPA, 2012). CMAQ simulates the formation, transport, and fate for a suite of atmospheric composition parameters. The NAQFC has provided real-time air quality forecast guidance over the past decade for different EPA-defined criteria pollutants, including near-surface  $\text{O}_3$  at a horizontal resolution of  $12 \times 12$  km centered over CONUS. The main chemical configurations for the NAQFC includes the CB05-TuCl/Aero6 gas-aerosol phase mechanism with simple aqueous phase chemistry reactions (see Lee et al., 2017 for further details). The NAQFC chemical initial conditions are started from a “warm-start” off of previous operational model output ending on March 01, 2020 and incur a two-week spin-up time (i.e., March 01–14 is removed from analyses). The time-dependent chemical lateral boundary conditions below 7 km altitude are provided by the Goddard Earth Observing System-Chemistry (GEOS-Chem; <http://acmg.seas.harvard.edu/geos/>) model output for 2006 that are mapped to appropriate CMAQ species and tuned for the operational NAQFC (Bey et al., 2001; Lam and Fu, 2009; Tang et al., 2009). We note that the version of the NAQFC used here has some slight differences compared to the operational NAQFC products (i.e., BASE simulation: see Section 2.2 below), which includes use of a single cycle 12Z forecast (as opposed to 4-cycle 00, 06, 12, and 18Z runs), and omission of wildfire emissions. These NAQFC configuration differences are not expected to make appreciable impacts on the  $\text{O}_3$  changes under the COVID-19 scenarios investigated here.

The U.S. EPA AirNow observation network data (<https://www.airnow.gov/>) are ideally suited for studying the ongoing impacts of the COVID-19 economic slowdown on  $\text{O}_3$  as they provide real-time air quality information across the U.S. for over 2,000 monitoring stations via the AirNow Application Programming Interface (<https://docs.airnow.wapi.org/>), while also maintaining a consistent historical data record and format to readily compare the average conditions of air pollution for different U.S. regions. The AirNow observation data are downloaded, processed/analyzed, and paired in space and time with the NAQFC simulation grid cells for the same hourly time periods using NOAA’s Model and Observation Evaluation Toolkit (MONET) (Baker and Pan, 2017). The AirNow observations are used to assess the spatial changes in  $\text{O}_3$  and to compare and evaluate the NAQFC simulations.

### 2.2. Emissions adjustment methodology and simulation design

The NAQFC 2020 simulations are based on the U.S. EPA National Emissions Inventory 2014v2 (NEI2014v2; U.S. EPA, 2018), and form the “BASE” case. We quantify the COVID-19 effect using the difference between a “business-as-usual” (BAU) and COVID-19 (C19) case, both based on the NEI2014v2 emissions (the BASE case). The BASE case is not projected into the forecast year, with the time lag being a

long-recognized issue in NAQFC (e.g., Tong et al., 2012). In both BAU and C19 cases, however, the emissions are projected from the BASE year (2014) to 2020. BAU and C19 use the same observation-based trend adjustment for the period of 2014–2019, with the only difference being the change from 2019 to 2020.

In the BAU case, the 2019 to 2020 emissions (mobile and area sectors) change is assumed the same as the 2014–2019 period, so the one-year change is the mean changing rate (% per year) from the pre-COVID-19 period. This is the best estimate if the COVID-19 pandemic did not happen. In the C19 case, the observed satellite and ground-based observed NO<sub>2</sub> changing rate from 2019 to 2020 is used to represent the actual emission progression under the pandemic. Compared to the annual emission changes in the pre-COVID-19 period, there was a much larger change from 2019 to 2020 in many states of the CONUS.

For both cases, we derive the NO<sub>2</sub> trend data using the approach developed by Tong et al. (2015, 2016). In this approach, the emission-changing rate for each state is derived according to the following equation:

$$AF = \frac{\Delta S \times N_s \times f_s + \Delta G \times N_G \times f_G}{N_s \times f_s + N_G \times f_G} \quad (1)$$

where AF is the emission adjustment factor (rate of emission change),  $\Delta S$  and  $N_s$  are the rate of change and the number of satellite data, respectively.  $\Delta G$  and  $N_G$  are the rate of change and the number of ground-based data, respectively.  $f_s$  and  $f_G$  are two weighting factors applied to the satellite and ground data, respectively. The values of  $\Delta S$  and  $\Delta G$  are calculated for each state using the vertical column density from the Ozone Monitoring Instrument (OMI) aboard the Aura satellite (Levelt et al., 2006, 2018), and the U.S. EPA Air Quality System (AQS) ground network (<https://www.epa.gov/aqs>), respectively. Here the value of  $f_s$  is set to be 1 and  $f_G$  to be 100 to place more weight in the ground-based AQS observations, and the OMI data is filtered with a low-value cutoff value ( $0.7 \times 10^{15}$ ) to further remove influence from retrieval noise and background sources of NO<sub>2</sub> (Tong et al., 2015, 2016). Furthermore, the AQS NO<sub>2</sub> changes are selected from the early morning rush hours (0600, 0700, and 0800 local time) that are more representative of transportation emission sector changes during the COVID-19 economic slowdown (Tong et al., 2016). Further details on the data processing and quality control procedures are provided in Tong et al. (2015). We use OMI as opposed to other newer satellite observations (e.g., TROPOMI) because of the well validated, and relatively long data record of OMI dating back to 2004 (Lamsal et al., 2020), which can more appropriately predict the emission trends used in deriving the BAU and COVID-19 cases.

The percent change in emission AFs between March–September (monthly averages) indicate widespread decreases in C19 emissions for March–May, with more states shifting to lesser decreases, or some relative increases by June–September (Fig. 1). The emission AFs are applied to all mobile and area source sectors and emission species, which impact their associated chemical species and consequential O<sub>3</sub> formation in the NAQFC simulations under each scenario. The difference

in the predicted O<sub>3</sub> concentrations between the BAU and C19 cases is attributed to the impact of the pandemic. Emissions from point/energy generating units are not adjusted in this study. The full simulation period analyzed in this study is March 01 – September 30, 2020 and is focused on the CONUS region.

### 3. Results

#### 3.1. Changes in anthropogenic emissions

The COVID-19 related economic slowdown generally led to decreased NO<sub>x</sub> emissions, but there is also state-to-state variability (Fig. 2).

Between March–June (Fig. 2a–c), many states in the east (e.g., New York) showed a relatively large decrease in NO<sub>x</sub> emissions (up to ~50–65%; Supporting Fig. S1), while states in the west experienced smaller decreases (<25%) and some increases (e.g., Montana and South Dakota). During May–June (Fig. 2c and d) and the following months, states in the east show progressively smaller emission decreases, with some states shifting to relative emission increases compared to BAU. Interestingly, some states in the west show larger emission decreases during and after June.

The calculated emission trends in the Central and Eastern U.S. mainly indicate lower NO<sub>x</sub> emissions for C19 compared to BAU for March–April, which then predominantly increase over time and become more similar to the BAU emissions by June–July. In fact, the C19 NO<sub>x</sub> emissions become higher than BAU for the Southeast and Upper Midwest U.S. in July (Fig. 3).

The regional and state-level variability in BAU and C19 emissions changes are impacted by differences in state-mandated shelter-in-place and partial recovery activities that occurred later in the spring and summer months during the pandemic, and largely from the impact that these protocols had on emissions from on-road passenger vehicles across the U.S. Mobility data from Apple Inc. (Apple Inc., 2020) indicates that there were widespread driving decreases and relatively high variability in March–May, which shifts to general driving increases and lower spatial variability in May–September (Supporting Fig. S2). This does not fully account for different transportation modes, and excludes much of the national and state-level truck traffic used in large-scale domestic shipping (i.e., Federal Highway Administration vehicle classes 5–13 or vehicle length >23 feet), which did not show similar trends (<https://www.ms2soft.com/traffic-dashboard/>).

Relative to passenger vehicle emissions, the emissions from commercial vehicles and electricity demand sources are relatively unchanged and impacts the changes in secondary air pollution formation during the COVID-19 lockdown (Archer et al., 2020). This affects the use of OMI-AQS NO<sub>2</sub> changes that are inclusive of all emission sector changes during COVID-19. Other emissions studies also agree with the timing of emissions changes estimated here and indicate that there were 13% decreases in transportation-related emissions early in March–May 2020 (Shilling et al., 2020), and then rebounding emission trends from May–July, particularly by mid-June through September when states

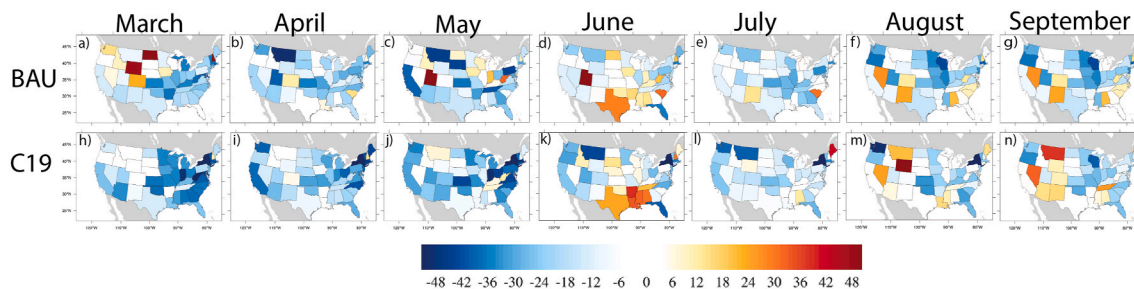


Fig. 1. Percent changes in monthly average emission adjustment factors (AFs) (based on Eq. (1)) for the a)–g) “Business-As-Usual” (BAU) and h)–n) COVID-19 (C19) cases.

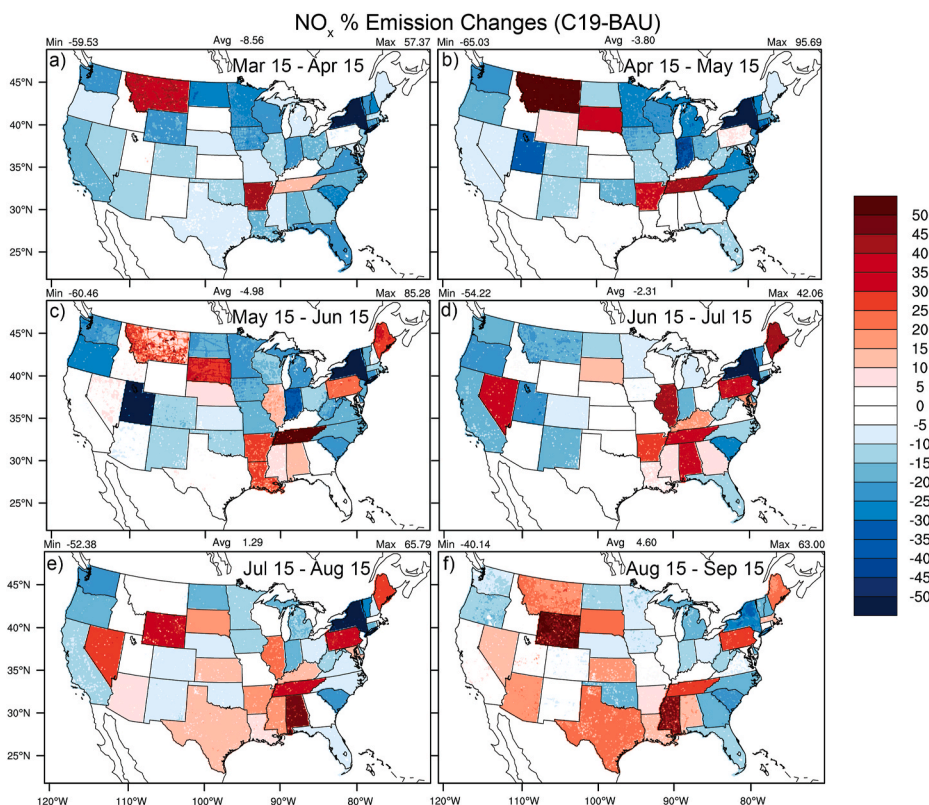


Fig. 2. Average percent changes for NO<sub>x</sub> emissions ( $[(C19-BAU)/BAU]*100\%$ ) between a) March 15 – April 15, b) April 15 – May 15, c) May 15 – June 15, d) June 15 – July 15, e) July 15 – August 15, and f) August 15 – September 15. The associated absolute changes in NO<sub>x</sub> emissions are found in Supporting Fig. S1.

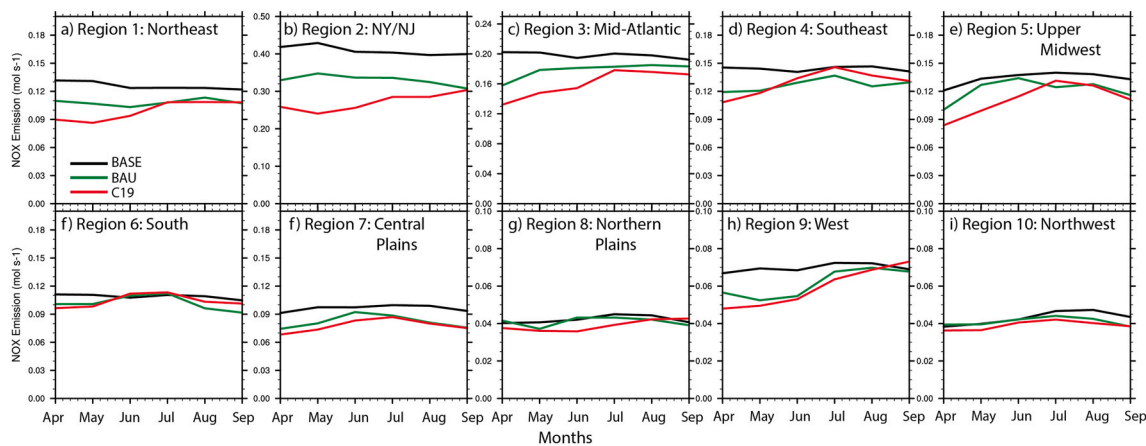


Fig. 3. Regional NO<sub>x</sub> emissions (mol s<sup>-1</sup>) trends ending on April 15 – September 15, 2020 for the BASE (black; NEI2014v2), “Business-As-Usual (BAU) (green), and COVID-19 (C19) (red) cases in the different U.S. EPA regions (<https://www.epa.gov/aboutepa/regional-and-geographic-offices>). Note the change in emissions scales on the y-axis. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

began lifting restrictions (Le Quéré et al., 2020). Furthermore, the shift to cleaner vehicle fleets in the BAU trend may also have led to fewer emissions compared to the C19 shift to more domestic, heavy-duty truck traffic (typically using diesel fuel) during the morning rush hours compared to less passenger traffic during the lockdown.

The shift to smaller decreases or increases for the OMI-AQS inferred NO<sub>x</sub> emissions in the summer months may also be impacted by an increasing background NO<sub>2</sub> concentration that partly limits the use of OMI observations in this work (discussed more below). The western U.S., which is characterized by relatively lower NO<sub>x</sub> emissions, indicates smaller decreases for C19 compared to BAU during all months, except September where C19 becomes slightly higher than BAU.

### 3.2. Comparisons of observed and modeled ozone concentrations

Evaluation of the BASE O<sub>3</sub> simulations (using NEI2014v2 emissions) against the U.S. EPA AirNow network for April–September 2020 shows that the NAQFC model performance is acceptable, while consistently falling within statistical criteria ranges for O<sub>3</sub> in Emery et al. (2017). The exceptions are a slightly high normalized mean bias (NMB) and low correlation coefficient (R) in the Northeast (Supporting Table S1a), and slightly high NMB in the Upper Midwest in May (Table S1e), Central Plains U.S. regions in May, and Northwest U.S. in April–May (Table S1j). The O<sub>3</sub> simulations for the BAU and C19 scenarios demonstrate mainly increases in the correlation, R, and Index of Agreement (IOA), and



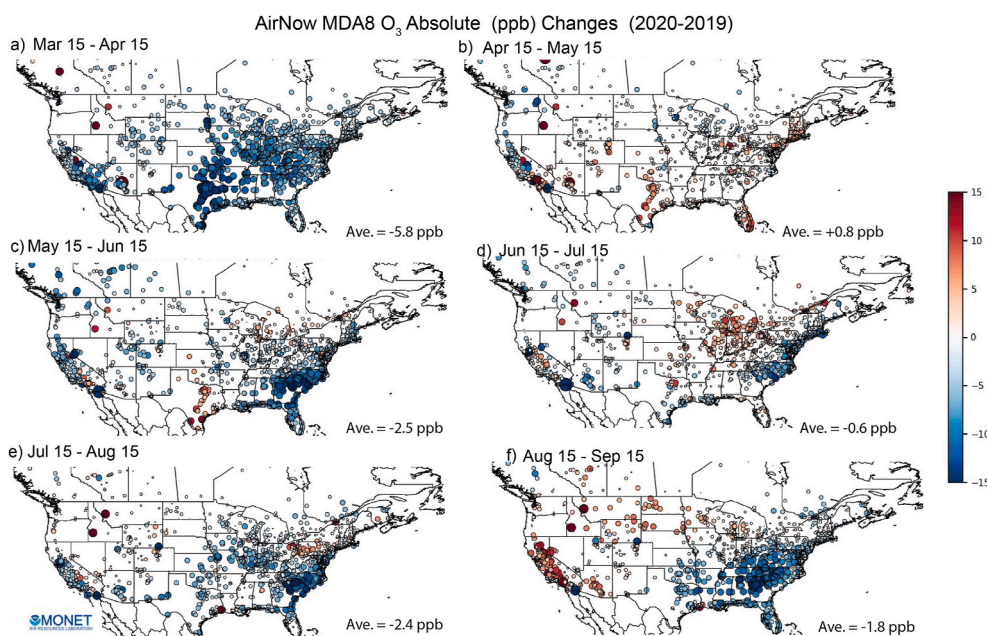


Fig. 5. Average absolute changes (2020–2019) for observed AirNow MDA8 O<sub>3</sub> (ppb) between a) March 15 – April 15, b) April 15 – May 15, c) May 15 – June 15, d) June 15 – July 15, e) July 15 – August 15, and f) August 15 – September 15. Average of all sites are shown in lower right corner of each panel. Supporting Fig. S4a shows the similar 2020–2019 spatial changes for hourly O<sub>3</sub>.

Table 1

Average of all AirNow site hourly (MDA8) O<sub>3</sub> changes in ppb for the 2020 COVID-19 economic slowdown periods compared to the previous five years (2015–2019).

Period	2020–2019	2020–2018	2020–2017	2020–2016	2020–2015	Average
Mar 15–Apr 15	−4.3 (−5.8)	−3.8 (−4.4)	−3.4 (−4.7)	−1.9 (−2.6)	−1.1 (−2.2)	−2.9 (−3.9)
Apr 15–May 15	+1.1 (+0.8)	−3.0 (−4.2)	+0.3 (−0.3)	+0.4 (−0.7)	−0.4 (−2.0)	−0.3 (−1.3)
May 15–Jun 15	−1.9 (−2.5)	−1.5 (−2.9)	−2.3 (−3.4)	−2.4 (−4.0)	−1.5 (−2.2)	−1.9 (−3.0)
Jun 15–Jul 15	−0.6 (−0.6)	−1.6 (−2.0)	−0.7 (−0.7)	−2.1 (−2.5)	+0.2 (+0.4)	−1.0 (−1.1)
Jul 15–Aug 15	−1.6 (−2.4)	−2.4 (−3.7)	−1.0 (−1.9)	−1.3 (−2.0)	−1.0 (−2.0)	−1.5 (−2.4)
Aug 15–Sep 15	−1.4 (−1.8)	−0.6 (−0.4)	−1.7 (−2.3)	−0.5 (−0.7)	−3.0 (−4.6)	−1.4 (−2.0)

Increases are shaded in red and decreases are shaded in blue.

occurred during March–April (Table 1; 5-yr average hourly/MDA8 O<sub>3</sub> ~ −3 ppb/−4 ppb). There are, however, year-to-year variability for the 2020 O<sub>3</sub> changes that demonstrates the role of non-linear formation from varying emissions and meteorological conditions. There are only a few instances of increased 2020 ozone, mostly during April–May, which demonstrated the smallest 5-year average AirNow observed decreases (~−0.3 ppb/−1.3 ppb). There are predominantly decreases in hourly (MDA8) O<sub>3</sub> during June–September that ranged from −1 to −1.5 ppb (−1.1 to −2.4 ppb) for 2020 compared to the 5-year average. The majority of AirNow sites are situated in highly populated, urban/city locations, and are not as representative of the surrounding rural regions in CONUS. Overall, the AirNow observed 2020 O<sub>3</sub> changes in Figs. 4 and 5 show significant spatiotemporal variability during the pandemic period of March–September compared to the previous 5 years (2015–2019), and thus the experimental NAQFC C19 and BAU simulations are further used to quantify the O<sub>3</sub> changes in both urban and rural areas throughout CONUS.

### 3.3.2. Simulated ozone changes

The differences in the NAQFC sensitivity simulations (C19-BAU) qualitatively agree with AirNow observations and show widespread decreases in monthly average absolute (Fig. 6) and percent O<sub>3</sub> changes (Fig. S6) due to the COVID-19-related mobility changes and reduced NO<sub>x</sub> emissions in March–June, which are strongly controlled by the NO<sub>x</sub>-limited photochemistry across the rural regions of the U.S.

The robust photochemical indicator O<sub>3</sub>/NO<sub>y</sub> (Sillman et al., 1997; Liang et al., 2006; Zhang et al., 2009; Campbell et al., 2015) is used here

to show the regions of NO<sub>x</sub>-limited and VOC-limited chemistry for the BAU and C19 cases in the U.S. (Supporting Figures S8a–S8b). In the major urban regions, there are increases in surface O<sub>3</sub> associated with the NO<sub>x</sub> emission decreases. There are also local enhancements in the ozone decreases near urban regions in states with increased NO<sub>x</sub> emissions. These regions are characterized by VOC-limited photochemistry, where the decreases (increases) in NO<sub>x</sub> emissions lead to increases (decreases) in O<sub>3</sub> formation, as the change in NO<sub>x</sub> emissions are in proportion to the change in VOC emissions (not shown). During June–September, there is a shift to more widespread, but relatively smaller increases in O<sub>3</sub> from the south and southeast to western parts of the U.S., which are associated with increases in NO<sub>x</sub> emissions across the rural, NO<sub>x</sub>-limited regions (Fig. 2), but not near the major urban centers that the model suggests are VOC-limited during this time. The areas of decreased C19 NO<sub>x</sub> emissions (more prolific in March–June) tend to enhance the NO<sub>x</sub>-limited conditions in the rural areas, and strongly mitigates the VOC-limited conditions in urban areas due to the additional increases in O<sub>3</sub>. The areas of increased C19 NO<sub>x</sub> emissions (more prolific in June–September) tends to mitigate NO<sub>x</sub>-limited conditions near the rural regions, and moderately enhances the already VOC-limited regions in urban regions (Supporting Fig. S8c). We note that uncertainties in the biogenic VOC emissions in the NAQFC simulations will affect the calculation of possible summertime shifts in more NO<sub>x</sub>-limited regimes in some locations, particularly in the southeast CONUS where there is significant vegetation.

These results are also in qualitative agreement with the AirNow observations that show more areas of increased O<sub>3</sub> during the summer

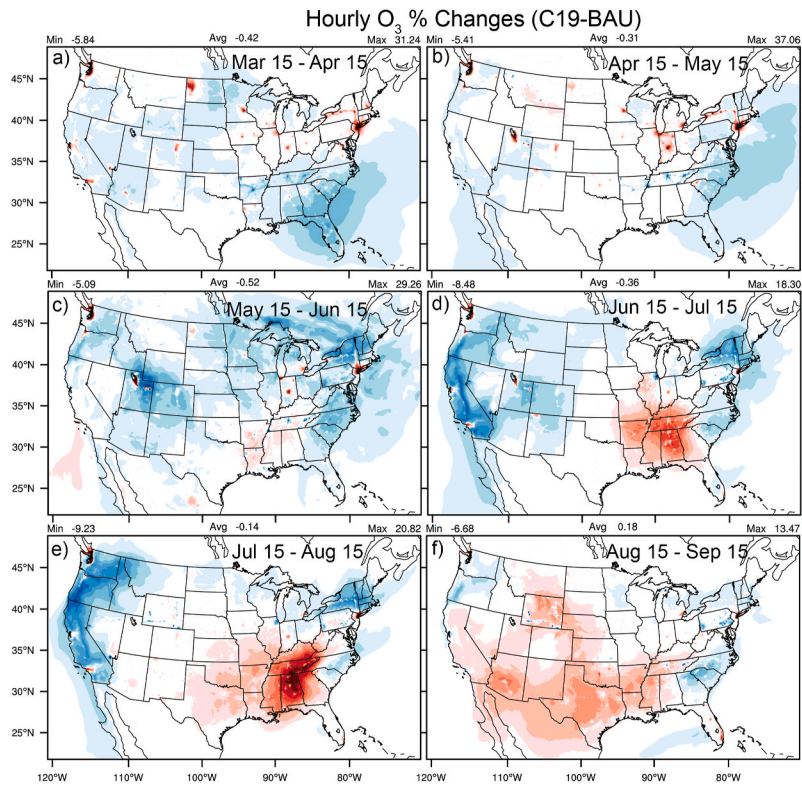


Fig. 6. Average absolute changes for simulated hourly O<sub>3</sub> (ppb) between a) March 15 – April 15, b) April 15 – May 15, c) May 15 – June 15, d) June 15 – July 15, e) July 15 – August 15, and f) August 15 – September 15.

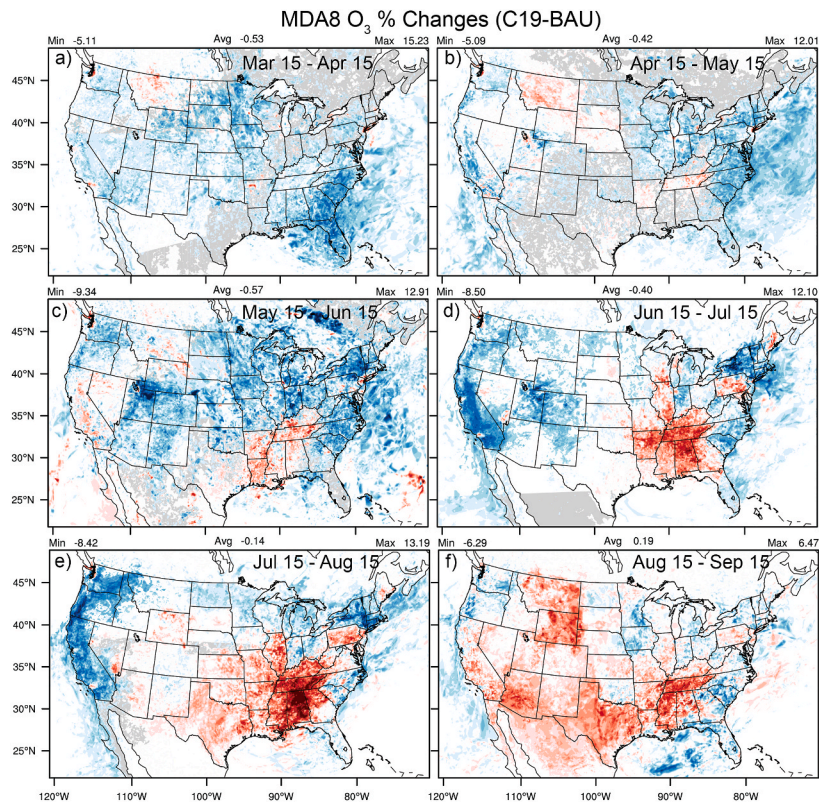


Fig. 7. Same as in Fig. 6, but for the median value of MDA8 O<sub>3</sub>.



months, particularly in the central and southern U.S. during June–August, and in California during August–September. The model agreement in the different CONUS regions tends to have dependence on the specific previous year compared to 2020 AirNow observations, where the simulated widespread enhanced ozone increases during summer has arguably the best spatial agreement with the observed 2020–2016 and 2020–2015 changes (Supporting Fig. 4d and e). The simulated shift to more widespread increases in O<sub>3</sub> across the southern U.S. also agrees with NASA's global atmospheric composition model (GEOS-CF) simulations of O<sub>3</sub> that used sustained reductions in global anthropogenic emissions of NO<sub>x</sub>, carbon monoxide (CO) and VOCs compared to a BAU scenario. This demonstrates the high non-linearity of O<sub>3</sub> chemistry, which leads to widespread O<sub>3</sub> increases in the southern portions of the U.S. in July–August (Keller et al., 2020). There are also localized increases in simulated ozone during all months in the urban coastline regions of the Long Island Sound (LIS) that span across the New York, New Jersey, and Connecticut state borders. This is in good agreement with the AirNow observations, where there are either hourly ozone increases or weaker decreases in the LIS region for the previous years compared to 2020 (Supporting Figs. S4a–4e).

The spatial patterns for the monthly median absolute (Fig. 7) and percent MDA8 O<sub>3</sub> changes (Supporting Fig. S7) are similar to hourly O<sub>3</sub>, but there are indications of larger decreases and increases for MDA8 O<sub>3</sub> in the enhancement regions.

Increases in the peak of daily O<sub>3</sub> values has consequence for the regions close to or in non-attainment for ozone standards. This is particularly true for the south-southeast states and other localized urban areas of the U.S. where increases in MDA8 O<sub>3</sub> of up to ~3–7 ppb may have affected the total number of O<sub>3</sub> exceedance days during the 2020 summer season.

There are also prominent decreases in MDA8 ozone in the northeast and western U.S., most notably in New York State during May–August, and in California, Oregon, and Washington during June–August. Decreases of up to ~3–5 ppb of MDA8 ozone are also important, and can result in alteration of the atmospheric oxidation capacity that can effectively change the production rate of secondary particles during the warm season (not shown). Co-impacts of O<sub>3</sub> and secondary particulate matter formation changes during the COVID-19 pandemic should be more closely studied in future work.

#### 4. Conclusions

Using both observations and NAQFC modeling (based on CMAQv5.0.2) we show that the COVID-19 lockdown caused variable impacts on anthropogenic emissions and both hourly and maximum daily (MDA8) ozone concentrations across the U.S. There were widespread decreases in NO<sub>x</sub> emissions in the U.S. during March–June 2020, which led to widespread decreases in O<sub>3</sub> concentrations in the rural regions that are NO<sub>x</sub>-limited, but also localized increases near some of the highly populated urban centers that are VOC-limited. Later in June–September 2020, the data-fused AQS and OMI NO<sub>2</sub> changes suggested that many areas in the U.S. showed relative increases in NO<sub>x</sub> emissions for the C19 compared to BAU scenarios, and consequently the simulations suggest widespread increases in O<sub>3</sub> concentrations. The widespread NO<sub>x</sub> emissions changes also alters O<sub>3</sub> photochemical formation regimes, most notably the NO<sub>x</sub> emissions decreases in March–April, which can enhance (mitigate) the NO<sub>x</sub>-limited (VOC-limited) regimes in different regions of CONUS.

The average of all AirNow hourly (MDA8) O<sub>3</sub> changes for 2020–2019 range from about +1 to –4 ppb (+1 to –6 ppb) during March–September, and are associated with predominantly urban monitoring sites that demonstrate considerable spatiotemporal variability for the 2020 ozone changes compared to the previous five years (2015–2019). The simulated maximum values of the average hourly (MDA8) O<sub>3</sub> changes for March–September range from about +8 to –4 ppb (+7 to –5 ppb), which correspond to relative changes that range from about

+40 to –10% (+15 to –10%). Overall, the variable spatial patterns in modeled ozone changes are in good agreement with the changes at the predominantly urban-limited AirNow sites; however, there are differences that vary depending on the specific previous year compared to 2020 during the COVID-19 pandemic.

To place our results into context, recent international results also show high spatiotemporal COVID-19 related O<sub>3</sub> changes both globally and regionally. Venter et al. (2020) showed that compared to the previous 3-year period, the COVID-19 lockdown led to marginal increases in observed O<sub>3</sub> of about 4% averaged across 34 countries during lockdown dates up until May 15, but that there were both increases and decreases at specific ground observation sites across the U.S. in January–May. This is in qualitative agreement with our results of spatial variability in the year-to-year changes for ground-site observations (Fig. 5 and S4-S5) and model-based results with both increased and decreased O<sub>3</sub> for different CONUS regions by May 15. Chossiere et al. (2021) found that of the 146 of the 252 regions analyzed showed O<sub>3</sub> decreases in response to the COVID-19 lockdowns, with 45 of those regions being statistically significant. However, they further indicate there was no statistically significant change in O<sub>3</sub> concentrations on average across in the U.S., with a range of –5.6 to 4% (mean ~ 0.8%). The contrasting results of Chossiere et al. with our work may be due to different analysis methods, and because we more closely analyzed model-grid cell (12 × 12 km) resolved MDA8 O<sub>3</sub> changes later in the U.S. ozone season, which showed relatively higher local O<sub>3</sub> changes (~–40 to +10%) due to the COVID-19 lockdown. Bray et al. (2021) showed widespread and rather prolific increases in observed ground level O<sub>3</sub> at AirNow ground-based sites during the peak March–April lockdown period in the U.S. The Bray et al. analysis is only in partial agreement with our results of observed AirNow changes in O<sub>3</sub> concentrations in some U.S. regions and specific year-to-year changes, particularly for the regions of increased O<sub>3</sub> in April–May (Table 1, Fig. 5, and Supporting Figs. S4-S5). Indeed, there are some discrepancies between studies for unknown reasons at this time. Our results here extend the quantitative analysis of COVID-19 driven O<sub>3</sub> impacts further into the warmer “ozone season” months in CONUS (i.e., May–September 2020), which have implications for widespread emission changes during the most prolific ozone non-attainment months in the U.S.

Use of the satellite and ground-based NO<sub>2</sub> observations to reflect the actual COVID-19 related emission changes in 2020 has some limitations. The ground-based changes in NO<sub>2</sub> are heavily weighted towards the predominantly urban site locations, where the meteorological conditions and natural NO<sub>2</sub> emission sources, i.e., natural variability, plays an important role in accurately attributing the observed NO<sub>2</sub> changes to NO<sub>x</sub> emissions and consequently the NAQFC simulated O<sub>3</sub> concentration changes. Goldberg et al. (2020) found that the NO<sub>2</sub> was relatively low in 2020 (compared to 2019) based on the meteorological conditions in many regions, particularly the prevailing wind directions that transported predominantly clean air masses to major cities areas such as Miami, FL, and Washington D.C. The numerous natural sources of NO<sub>2</sub> (e.g., lighting, soil, and wildfires) that heavily impact background concentrations further confound the use of OMI NO<sub>2</sub> observations to infer the actual COVID-19 related emissions changes, especially during the summer months (Qu et al., 2021).

The COVID-19 economic slowdown and natural experiment of widespread reductions in precursor emissions in different ozone formation regimes in the U.S. has implications for emission control strategies used to curb elevated pollution near major cities and remaining non-attainment areas in the U.S. The impact of the COVID-19 pandemic sheds further light onto the importance of significantly controlling VOC emissions in and around urban areas, such that widespread controls on NO<sub>x</sub> emissions are not efficient at reducing ozone levels in regions that experience similar reductions in VOC emissions. This suggests that VOC emission reductions may need to be even greater than NO<sub>x</sub> reductions in VOC-limited cities in the spring/summer.

This work shows that there were widespread reductions in ozone

levels during the initial period of COVID-19 lockdown, but there are indications of predominantly increased ozone near major cities and possibly more widespread increases later in the summer. It is these regions of elevated ozone that are of concern for those suffering with preexisting health issues, where the increased exposure to air pollution due to the COVID-19 related emissions changes may exacerbate the human susceptibility, health impacts, and spread of the COVID-19 virus itself (Chakrabarty et al., 2020; Wu et al., 2020). Undoubtedly, more research is needed on the interconnections between air quality, exposure and susceptibility, and public health management during widespread pandemics and the many unintended consequences that follow.

#### Data availability statement

For emissions adjustment factor preparation, the OMI/Aura satellite data are available at [https://aura.gesdisc.eosdis.nasa.gov/data/Aura\\_OMI\\_Level2/OMNO2.003/](https://aura.gesdisc.eosdis.nasa.gov/data/Aura_OMI_Level2/OMNO2.003/) and the U.S. EPA AQS ground observation data are available at the AQS Application Programming Interface (API) at [https://aqs.epa.gov/aqsweb/documents/data\\_api.html](https://aqs.epa.gov/aqsweb/documents/data_api.html). The U.S. EPA AirNow observations are also available via the AirNow API at <https://docs.airnowapi.org/>. The National Air Quality Forecasting Capability (NAQFC) code used in this work, which is based on CMAQv5.0.2, is published on Zenodo at <http://doi.org/10.5281/zenodo.1079888> and is also available for download on GitHub at <https://github.com/USEPA/CMAQ/tree/5.0.2>. The raw, gridded emissions and NAQFC simulation output are very large (multiple Terabytes) and are freely available in two different ways: (1) on the local NOAA/NCEP repositories that can be directly transferred via SFTP or SCP in pieces, or manually copied in their entirety and provided via external hard drives, and (2) on a publicly available repository/transfer in pieces or via another high-speed file transfer service such as Globus (<https://www.globus.org/datatransfer>).

#### Disclaimer

The scientific results and conclusions, as well as any views or opinions expressed herein, are those of the author(s) and do not necessarily reflect the views of NOAA or the Department of Commerce.

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#### 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.

#### Acknowledgments

This study was co-funded by the National Oceanic and Atmospheric Administration's (NOAA's) Weather Program Office (Grant/Contract Number NA19OAR4590082) and the NASA Health and Air Quality Program (Grant/Contract Number 80NSSC21K0512). Support for this work was also provided by NOAA's Office of Oceanic and Atmospheric

Research and the Cooperative Institute for Satellite Earth System Studies (CISESS).

#### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.atmosenv.2021.118713>.

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## Further reading

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