Disentangling the impact of the COVID-19 lockdowns on urban
NO2 from natural variability

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Abstract

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Disentangling the impact of the COVID-19 lockdowns on urban NO₂ from natural variability

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Abstract

Satellite data show substantial drops in nitrogen dioxide (NO₂) during COVID-19 physical distancing. To attribute NO₂ changes to NOₓ emissions changes over short timescales, one must account for meteorological effects. We find that meteorological patterns were especially favorable for low NO₂ in much of the U.S. in spring 2020, complicating comparisons with spring 2019. Meteorological variations between years can cause column NO₂ differences of ~15% over monthly timescales. After accounting for sun angle and meteorological considerations, we calculate that NO₂ drops ranged between 9.2 – 43.4% among twenty cities in North America, with a median of 21.6%. Of the studied cities, largest NO₂ drops (>30%) were in San Jose, Los Angeles, and Toronto, and smallest drops (<12%) were in Miami, Minneapolis, and Dallas. These normalized NO₂ changes can be used to highlight locations with greater activity changes and better understand the sources contributing to adverse air quality in each city.

Plain-Language Summary

The current paradigm of disentangling emissions from meteorological influences on air pollution by averaging over many months has insufficient temporal granularity to quantify short-term emission changes. We developed two novel methods to account for weather impacts on daily pollution levels during COVID-19 precautions. Once we accounted for favorable weather conditions that in some cases kept air pollution low independent of tail-pipe emissions, calculated air pollutant emission reductions varied dramatically (9 – 43%) among twenty North American cities. Results can be used to understand factors contributing to inconsistent NO₂ changes during physical distancing, which can inform the effectiveness of COVID-19 protocols and aid future policy development. These methodologies will allow us to respond more quickly in future unintended experiments when emissions change suddenly.
Nitrogen dioxide (NO\textsubscript{2}) is unique due to its relatively short photochemical lifetime which varies from 2-6 h during the summer daytime (Beirle et al., 2011; de Foy et al., 2014; Laughner & Cohen, 2019; Valin et al., 2013) to 12-24 h during winter (Beirle et al., 2003; Shah et al., 2020). As a result, tropospheric NO\textsubscript{2} concentrations are strongly correlated with local NO\textsubscript{X} emissions, which are often anthropogenic in origin. However, due to the effects of meteorology and sun angle on the NO\textsubscript{2} abundance, NO\textsubscript{2} can vary by a factor of two simply due to seasonal changes (Pope et al., 2015; Wang et al., 2019). Therefore, satellite data are typically averaged over long timeframes (~seasonal/annual) to assess changes in NO\textsubscript{X} emissions (Duncan et al., 2016; Geddes et al., 2016; Georgoulias et al., 2019; Hilboll et al., 2013, 2017; Kim et al., 2009; Krotkov et al., 2016; Lamsal et al., 2015; McLinden et al., 2016; VanDerA et al., 2008).

With the COVID-19 crisis, there is now broad interest in rapid assessments of NO\textsubscript{X} emission changes on short timescales in locations that have implemented stay-at-home orders or other physical distancing measures. Using satellite data in this instance can be advantageous due to its global coverage at immediate timescales. However, current methods of averaging satellite NO\textsubscript{2} data over many months to minimize random daily effects of weather will not provide the temporal granularity needed to quantify short-lived NO\textsubscript{X} emission changes. Preliminary satellite-based studies indicate that NO\textsubscript{2} dropped substantially in China following stringent COVID-19 physical distancing actions (F. Liu et al., 2020; Zhang et al., 2020). Similar declines have also been seen over northern Italy (ESA, 2020b) and India (ESA, 2020a). Although lockdown measures – and adherence to them – have been looser in the U.S. than in China, India, and Italy, preliminary analyses show that NO\textsubscript{2} amounts are declining across U.S. cities as well (NASA, 2020). These declines have, in some cases in the media (Holcombe & O’Key, 2020; Plumer & Popovich, 2020), been attributed to the emission changes during lockdowns, without accounting for the potentially substantial influences of meteorology and seasonality. Accounting for natural NO\textsubscript{2} fluctuations are especially important during spring, a time when the NO\textsubscript{2} concentrations and lifetimes are quickly changing due to transitioning meteorology, sun angle, and snow cover.

Understanding how NO\textsubscript{X} emissions have changed in response to physical distancing measures requires new methods to account for sun angle and meteorological conditions over very short
time scales (days/weeks), as opposed to the traditional method of averaging over seasons and
years. Here, we use three different methods to assess the NO$_2$ decreases associated with COVID-
19 lockdowns. We combine TROPOMI NO$_2$ data with ERA5 re-analysis and a regional
chemical transport model to determine the effects of the sun angle and meteorological factors –
such as wind speed and wind direction – on NO$_2$ column amounts. The NO$_2$ changes after this
“normalization” are more likely to represent the NOx emissions changes due to COVID-19.

2. Methods

2.1 TROPOMI NO$_2$

TROPOMI was launched by the European Space Agency (ESA) for the European Union’s
Copernicus Sentinel 5 Precursor (S5p) satellite mission on October 13, 2017. The satellite
follows a sun-synchronous, low-earth (825 km) orbit with a daily equator overpass time of
approximately 13:30 local solar time (VanGeffen et al., 2019). TROPOMI measures total
column amounts of several trace gases in the Ultraviolet-Visible-Near Infrared-Shortwave
Infrared spectral regions (Veefkind et al., 2012). At nadir, pixel sizes are 3.5 × 7 km$^2$ (reduced
to 3.5 × 5.6 km$^2$ on August 6, 2019) with little variation in pixel sizes across the 2600 km swath.

Using a differential optical absorption spectroscopy (DOAS) technique on the radiance
measurements in the 405 – 465 nm spectral window, the top-of-atmosphere spectral radiances
can be converted into slant column amounts of NO$_2$ between the sensor and the Earth’s surface
(Boersma et al., 2018). In two additional steps, the slant column quantity can be converted into a
tropospheric vertical column content, which is the quantity used most often to further our
understanding of NO$_2$ in the atmosphere (Beirle et al., 2019; Dix et al., 2020; Goldberg et al.,
2019; Griffin et al., 2019; Ialongo et al., 2020; Reuter et al., 2019; Zhao et al., 2020).

2.2 Meteorological Dataset

We use ERA5 meteorology((C3S), 2017) for the wind speed and direction in our analysis. When
filtering the data based on wind, we use the average 100-m winds during 16 – 21 UTC, which
approximately corresponds to the TROPOMI overpass time over North America. To downscale
the ERA5 re-analysis, which is provided at 0.25° × 0.25°, we spatially interpolate daily averaged
winds to 0.01° × 0.01° using bilinear interpolation. Due to our dependence on 0.25° × 0.25°
meteorology, any microscale features (e.g., sea breezes) will not be accounted for, but these
effects should be minor for our particular analysis.

2.3 Calculation of NO\textsubscript{2} Changes

We calculate the NO\textsubscript{2} changes using three different methods. In Method 1, we compare an
average of March 15, 2020 – April 30, 2020 to the same timeframe of 2019; this year-over-year
comparison is used most often in satellite studies quantifying long-term changes in NO\textsubscript{X}
emissions. In Method 2, we develop a strategy to account for varying weather patterns without
the use of a chemical transport model. In this method, we normalize each day’s NO\textsubscript{2} observation
to a day with “standard” meteorology – similar to standard temperature and pressure (STP)
conditions in a laboratory setting. We do this by accounting for four different day-varying
effects; these are sun angle, wind speed, wind direction, and day-of-week. In all cases, we
normalize city-specific conditions to those that are climatological on April 15\textsuperscript{th}. Finally, in
Method 3, we infer a TROPOMI NO\textsubscript{2} column amount under normal circumstances using the
GEM-MACH regional chemical transport model, and then compare the actual TROPOMI
columns to the theoretical columns. Methods 2 & 3, both account for year-varying meteorology,
while Methods 1 does not. A detailed description of Methods 2 & 3 can be found in the
Supplemental.
3. Results

3.1 Sun Angle & Meteorological Relationships

In the top row of Figure 1, we show 2019 NO₂ column densities during the low sun-angle “cold” season (January – March, October – December) and high sun-angle “warm” season (May – September) in the continental United States and southern Canada.

Column NO₂ is larger during the cold season than during the warm season over the majority of our domain, despite NOₓ emissions generally peaking during the middle of the warm season due to a heavy air conditioning load (Abel et al., 2017; He et al., 2013). The larger NO₂ concentrations during the winter are instead due to the longer NO₂ lifetime during the cold season, primarily due to slower photolysis rates. When NOₓ is emitted during the warm season,
it is transformed into other chemical species, such as O₃ and HNO₃, more quickly than during the
winter. We find that in most near-urban locations column NO₂ amounts are 1.5 – 3 times larger
during the winter than during the summer, and can vary substantially between city.

In a next step, we account for wind speed and wind direction in the spatiotemporal variation of
NO₂ columns. In the middle and bottom panels of Figure 1, we demonstrate the effects of wind
speed and wind direction on the NO₂ in our domain. Increases in wind speed yield NO₂
decreases due to quicker dispersion away from the city centers. For example, in New York City,
Washington DC, Atlanta, and Chicago, all cities with relatively flat topography and located in
the eastern United States, increasing wind speeds from nearly stagnant to > 8 m/s decreases NO₂
by 30 – 60%. Conversely, in Denver and Los Angeles, cities with more heterogeneous
topography and with general isolation from an agglomeration of cities, show a stronger
dependence on wind speed; increasing wind speeds from nearly stagnant to > 8 m/s decreases
NO₂ by 70 – 85%. In both instances, these examples show the strong dependence of wind speed
on local NO₂ amounts.

Similarly, wind direction has a large role in the local NO₂ amounts, although the effects of wind
direction are non-linear. Generally, northwest winds yield the cleanest conditions in most U.S.
cities, but the effects of other wind directions are more nuanced. For example, southwesternly
winds yield the worst air quality in New York City, while northeasterly winds yield the largest
NO₂ in Washington, D.C. This is due to the fact that the other city lies upwind in each opposing
scenario. Changes in wind direction, given the same wind speed, can yield differences in NO₂ in
major cities by up to 70%, and must be accounted for if properly attributing NO₂ changes to NOₓ
emissions. Climatological patterns for all cities are shown in the Supplemental Material (Figures
S1-S3).

While 2-m air temperature and boundary layer depth may be affecting the NO₂ concentrations,
these are not independent of the aforementioned factors: sun angle, wind speed and wind
direction. In fact, sun angle, wind speed, and wind direction are by themselves highly skilled
predictors of near-surface temperatures and boundary layer depth in most instances. Since we
are focused on mostly clear-sky days, clouds have limited effects here. Previous day’s
precipitation may also be a contributing factor to daily NO₂ amounts, but in many areas, the wind
direction will partially account for this, since northwest winds usually follow large rain events in most areas.

### 3.2 Effects of COVID-19 physical distancing on NO₂

In order to quantify rapid changes in NO\textsubscript{X} due to COVID-19 physical distancing, we calculate NO\textsubscript{2} changes in North American cities using three different methods and a reference method.

The results for all cities are shown in Table 1.

**Table 1.** Percentage drop in column NO\textsubscript{2} as observed by TROPOMI. Cities are listed by largest to smallest reduction as determined by the median of all three methods.

| City Name      | Reference case | Account for sun-angle only | Account for sun-angle & meteorology | Mean of Methods 1-3 | Median of Methods 1-3 |
|----------------|----------------|---------------------------|-----------------------------------|---------------------|------------------------|
|                | Δ between months 2020 only (Jan-Feb vs. Mar 15 - Apr 30) | Δ between years 2019 vs. 2020 (Mar 15 - Apr 30) | Using ERA5 analogs to account for meteorology 2019 vs. 2020 (Mar 15 - Apr 30) | Using GEM-MACH to infer NO\textsubscript{2} 2020 only (Mar 15 - Apr 30) |                          |
| San Jose       | 65.2%           | 43.4%                     | 40.7%                             | 43.5%               | 42.5%                   | 43.4%                   |
| Los Angeles    | 66.1%           | 32.6%                     | 32.5%                             | 38.6%               | 34.6%                   | 32.6%                   |
| Toronto        | 60.4%           | 30.0%                     | 17.0%                             | 42.0%               | 30.0%                   | 31.0%                   |
| Philadelphia   | 50.3%           | 36.6%                     | 30.7%                             | 22.1%               | 29.8%                   | 30.7%                   |
| Denver         | 25.8%           | 29.2%                     | 23.4%                             | 39.1%               | 30.6%                   | 29.2%                   |
| Atlanta        | 39.6%           | 35.2%                     | 27.4%                             | 20.2%               | 27.6%                   | 27.4%                   |
| Detroit        | 35.5%           | 29.9%                     | 22.8%                             | 15.6%               | 22.8%                   | 22.8%                   |
| Boston         | 40.3%           | 22.8%                     | 23.5%                             | 17.8%               | 21.4%                   | 22.8%                   |
| Washington DC  | 42.9%           | 31.4%                     | 21.2%                             | 6.7%                | 19.8%                   | 21.2%                   |
| Montreal       | 12.5%           | 3.3%                      | 20.9%                             | 30.2%               | 18.1%                   | 20.9%                   |
| New York City  | 32.7%           | 20.2%                     | 20.0%                             | 17.9%               | 19.4%                   | 20.0%                   |
| New Orleans    | 41.7%           | 13.5%                     | 19.6%                             | 22.5%               | 18.5%                   | 19.6%                   |
| Las Vegas      | 66.7%           | 9.5%                      | 18.4%                             | 42.0%               | 23.3%                   | 18.4%                   |
| Houston        | 38.9%           | 26.3%                     | 15.6%                             | 1.9%                | 14.6%                   | 15.6%                   |
| Chicago        | 31.0%           | 23.6%                     | 14.9%                             | 3.5%                | 14.0%                   | 14.9%                   |
| Phoenix        | 43.9%           | 12.8%                     | 14.8%                             | 35.4%               | 21.0%                   | 14.8%                   |
| Austin         | 34.3%           | 14.5%                     | 9.4%                              | 16.1%               | 13.3%                   | 14.5%                   |
| Dallas         | 41.9%           | 11.9%                     | 3.6%                              | 16.7%               | 10.7%                   | 11.9%                   |
| Miami          | 27.9%           | 16.1%                     | -1.6%                             | 11.0%               | 8.5%                    | 11.0%                   |
| Minneapolis    | 0.1%            | 14.3%                     | 9.2%                              | 8.1%                | 10.5%                   | 9.2%                    |
| Mean of each method | 39.9%           | 22.9%                     | 19.2%                             | 22.5%               | 21.6%                   | 21.6%                   |

The reference method, Method 0, compares the pre-lockdown and post-lockdown periods and represents the “true” NO\textsubscript{2} change; however, this method does not account for seasonal changes and, thus, is not considered in the medians/means.

In Method 1, we compare an average of March 15, 2020 – April 30, 2020 to the same timeframe of 2019. In Figure 2, we show difference and ratio plots between these two years (i.e., Method
1. The largest decreases in NO$_2$ are near the major cities in North America. We also find regional decreases in the eastern North America. Conversely, the central and northwestern United States have seen little change between years, which is likely due to the high fraction of NO$_2$ attributed to biogenic sources and long-range transport. We also observe substantial decreases near retired electricity generating units in the western U.S. (Storrow, 2019)

Figure 2. TROPOMI NO$_2$ differences between 2019 & 2020, using March 15 – April 30, 2020 as the post-COVID-19 period. Plots are showing (a) the absolute difference and (b) the ratio between years.

In Figure 3, we demonstrate Method 2. Here, we show the 2019 and 2020 28-day running TROPOMI NO$_2$ medians after accounting for sun angle and meteorology. In this figure, the January values are uniformly lower than their true values (Figure S4) because we are normalizing to April meteorological conditions (i.e., sun angle is higher in April as compared to January). In New York City, we calculate a 20.0% drop in NO$_2$ due to COVID-19 precautions. We find that there is no difference between Method 2 – which accounts for meteorology – and Method 1 – which only accounts for sun angle. This suggests that varying meteorological conditions in New York City, while different between years, may not have had a strong biasing effect. However, in Washington D.C. we find favorable conditions in 2020 as compared to 2019 because we observe substantially different NO$_2$ drops before (31.4%) and after (21.2%) correcting for the meteorology. These results are corroborated by the wind speed and direction (Figure S5). In 2019, winds were on average southwesterly, while in 2020, winds had more of a northwesterly and therefore cleaner component. Of all cities analyzed, we find that Miami had the most favorable conditions for low NO$_2$ in 2020 as compared to 2019; in 2020, winds were
stronger from the south – in this case a cleaner air mass – than in 2019, which had relatively stagnant winds. Conversely, in Montreal, New Orleans, and Las Vegas, meteorological conditions appeared to be unfavorable in 2020 as compared to 2019.

**Figure 3.** Trends in TROPOMI NO\(_2\) since January 1 in 2019 and 2020 after accounting for meteorological variability and sun angle. The lines represent the 28-day rolling median value (50\(^{th}\) percentile) in a 0.4° × 0.4° box centered on the city center for the largest cities (New York City, Los Angeles, Chicago, Toronto, Houston) and 0.2° × 0.2° box in all other cities.

In Figure 4, we demonstrate Method 3, in which we account for meteorology and chemical interactions using a chemical transport model. We create a theoretical TROPOMI column NO\(_2\) using ECCC’s regional operational air quality forecast model (Moran et al., 2009; Pendlebury et al., 2018), which accounts for typical seasonal emission changes but not for any impacts due to the COVID-19 lockdowns; this helps provide expected NO\(_2\) levels with a business as usual scenario. Around mid-March there is often a divergence between the expected and observed NO\(_2\) in the major cities. Using this method, largest NO\(_2\) reductions due to COVID-19 precautions are in Toronto, San Jose, and Las Vegas. Similar to Method 2, we find that NO\(_2\) changes are generally smaller in the Northeastern U.S. and Florida as compared to Method 1 after accounting for meteorology. In fifteen of the twenty studied cities, we find that Methods 2 & 3, which utilize independent meteorological datasets, show similar biasing effects of meteorology (favorable vs. unfavorable) when compared to Method 1.
Figure 4. Trends in TROPOMI NO$_2$ since January 1, 2020. The actual observed columns are shown in black, while the “expected” columns - using GEM-MACH to infer NO$_2$ in the absence of lockdowns – is shown in blue. The lines represent the 28-day rolling median value (50$^{th}$ percentile) in a 0.4° × 0.4° box centered on the city center for the largest cities (New York City, Los Angeles, Chicago, Toronto, Houston) and 0.2° × 0.2° box in all other cities.

4. Discussion

Here we demonstrate two methodologies, Methods 2 & 3, to account for time-varying effects of meteorology on NO$_2$ concentrations. There are two main advantages for using Methods 2 & 3 to assess rapid changes in NO$_X$ as compared to a year-to-year comparison of the same month or seasonal period. Year-over-year technological improvements in the United States are generally causing NO$_X$ emissions to decrease over time, although we find a statistically insignificant NO$_2$ increase of 0.6% in our cities between 2019 and 2020 in the January – February average. Accounting for year-over-year changes would be more important if comparing 2020 values to years preceding 2019.

Perhaps more importantly, there are often different seasonal patterns between years, even when averaged over the entire season. Many longer-term meteorological patterns in North America can be attributed to the El Nino South Oscillation (ENSO) or the North Atlantic Oscillation.
In particular relevance to this analysis, the January – March 2019 period had a persistently negative NAO (https://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/month_nao_index.shtml) which allowed Arctic air to more readily intrude into the northern US than during more typical winters (https://www.ncdc.noaa.gov/sotc/national/201902). In January – March 2020, there was a consistently positive NAO which limited the influence of cold and relatively clean Arctic air in eastern North America, but instead yielded cloudier and wetter conditions. Similarly, ENSO can affect air quality in cities (Edwards et al., 2019; Shen & Mickley, 2017), but this had a minor effect between 2019 (Oceanic Niño Index: +0.8) and 2020 (Oceanic Niño Index: +0.5).

5. Conclusions

We estimate that NOx emissions temporarily dropped between 9 – 43% in North American cities due to COVID-19 precautions, with a median drop of 21.6% before and after COVID-19 physical distancing. If the sun angle is not accounted for, then the median NO2 drop is 39.9%; this represents the true change of NO2 in cities, but is not analogous to a change in NOx emissions. Our reported median drop of 21.6% is marginally lower than the 22.9% in a simple year-to-year comparison, which suggests that 2020 meteorology was slightly favorable for lower NO2, although these effects are most pronounced in the Northeastern United States and Florida.

A deficiency of our method is our reliance on a single satellite instrument and algorithm. It is known that the operational TROPOMI NO2 algorithm underestimates tropospheric vertical column NO2 in urban areas due to its reliance on a global model to provide shape profiles for the air mass factor (AMF); investigating the effects of the AMF bias on trends will be the subject of future work. Also, there may be a clear-sky bias (Geddes et al., 2012) associated with TROPOMI retrievals, but the results presented here are generally consistent with studies using ground monitors over the coincident region (Bekbulat et al., 2020) and the reported CO2 emissions reductions due to COVID-19 precautions (Le Quéré et al., 2020).

The estimates of NO2 changes using our Methods appear to be reasonable given a quick bottom-up emissions calculation. Assuming that passenger vehicles traffic dropped by ~50%, and that all other sources only dropped modestly ~10 – 25%, NOx reductions between 10 – 35% would be expected. San Jose, Los Angeles and Toronto appear to have reductions at the high end of this range, while Miami, Minneapolis, and Dallas have values near the lowest end; further work
will look into why these cities have reductions on the ends of the spectrum. Rapid assessments of NO₂ changes – after normalized for seasonal and meteorological factors – can be used to highlight locations with greater changes in activity and better understand the sources contributing to adverse air quality in each city.
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TROPOMI NO$_2$ data can be freely downloaded from the European Space Agency Copernicus Open Access Hub or the NASA EarthData Portal (http://doi.org/10.5270/S5P-s4ljq54). ERA5 can be freely downloaded from the Copernicus Climate Change (C3S) climate data store (CDS) (https://cds.climate.copernicus.eu/#!/search?text=ERA5&type=dataset). The submitted manuscript has been created by UChicago Argonne, LLC, Operator of Argonne National Laboratory (“Argonne”). Argonne, a US Department of Energy Office of Science laboratory, is operated under contract no. DE-AC02-06CH11357.

Author Contributions

DLG drafted the concept, wrote the manuscript, and performed much of the analysis. SCA jointly drafted the concept and edited the manuscript. DG and CAM provided the regional chemical model data and related analysis, and edited the manuscript. ZL jointly drafted the concept, helped to process the TROPOMI NO$_2$ data, and edited the manuscript. DGS edited the manuscript.
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Supporting Information for:

**Disentangling the impact of the COVID-19 lockdowns on urban NO$_2$ from natural variability**

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This PDF file includes:

Further description of TROPOMI NO$_2$ processing technique and associated uncertainties
Further description of methodologies using to calculate NO$_2$ drops during COVID-19
Figures S1 to S5
Table S1
1. TROPOMI NO\textsubscript{2}

1.1 Air Mass Factors and Uncertainty Estimates

The slant tropospheric column is converted to a vertical column using a quantity known as the air mass factor (Palmer et al., 2001). The air mass factor is the most uncertain quantity in the retrieval algorithm (Lorente et al., 2017), and is a function of the surface reflectance, the NO\textsubscript{2} vertical profile, and scattering in the atmosphere among other factors (Lamsal et al., 2014). Using accurate and high-resolution data (spatially and temporally) as inputs in calculating the air mass factor can significantly reduce the overall errors of the air mass factor (Choi et al., 2019; Goldberg et al., 2017; Laughner et al., 2016, 2019; Lin et al., 2015; Liu et al., 2019; Russell et al., 2011; Zhao et al., 2020) and thus the tropospheric vertical column content.

Operationally, the TM5-MP model (1 × 1° resolution) (Williams et al., 2017) is used to provide the NO\textsubscript{2} vertical shape profile and the climatological Lambertian Equivalent Reflectivity (0.5 × 0.5° resolution) (Kleipool et al., 2008) is used to provide the surface reflectivities. The operational air mass factor calculation does not explicitly account for aerosol absorption effects, which are accounted for in the effective cloud radiance fraction. While the operational product does have larger uncertainties in the tropospheric column contents than a product with higher spatial resolution inputs, we limit our analysis to relative trends, which dramatically reduces this uncertainty. The uncertainty in any daily measurement in the operational slant column data has been assigned to be approximately 5.7 × 10^{14} molecules-cm\textsuperscript{-2} (van Geffen et al., 2020). This equates to roughly a 5-10% uncertainty over polluted areas. However, because we are averaging over many days (~20-40), we assume that random errors will cancel due to the large number of observations used. This leaves only the systematic errors. Here, we assign the AMFs and tropospheric vertical column contents a systematic uncertainty of 20% in the trends (McLinden et al., 2014). This systematic uncertainty may be largest over areas with changing snow cover, such as Minneapolis, Chicago, Toronto, and Montreal. We calculate total uncertainty as the quadrature of the uncertainty associated with this potential systematic bias and the standard deviation of the three Methods. These are listed in Table S1.
1.2 Re-gridding of TROPOMI NO$_2$

For our analysis we re-grid the operational TROPOMI tropospheric vertical column NO$_2$, with native pixels of approximately 3.5 × 7 km$^2$, to a newly defined 0.01° × 0.01° grid (approximately 1 × 1 km$^2$) centered over the continental United States (CONUS; corner points: SW: 24.5° N, 124.75° W; NE: 49.5° N, 66.75° W). Before re-gridding, the data are filtered so as to use only the highest quality measurements (quality assurance flag (QA_flag) > 0.75).

2. Description of Methodologies 2 & 3

2.1 Method 2: Normalization of Daily TROPOMI NO$_2$ using ERA5

We use TROPOMI NO$_2$ data from 2018 – 2019 as analog data to normalize 2020 data. Essentially, our method is searching through the 2018 – 2019 archive to find a meteorological analog to the current conditions and then adjusting the current day’s conditions based off that analog.

For each day of the record, we modify the original observed TROPOMI NO$_2$ based on its value compared to a "baseline" which we set as a weekday in April with 3 m/s southwest winds. For each day, $n$, and each city, $i$, the normalized NO$_2$, $\overline{NO}_2$, is calculated as follows:

$$\overline{NO}_2 = \frac{NO_{2n,i}}{f_{\text{total}_{n,i}}}$$

The subscript $i$ represents a city-specific average within a 0.4° × 0.4° box (i.e., ~20 km radius) surrounding the city center.

The four adjustment factors are: sun angle, wind speed, wind-direction, and day-of-week. While other conditions affect NO$_2$ amounts they are either interrelated to the aforementioned factors or can be considered secondary. Each of the four individual factors are multiplied together to get a "total adjustment factor". The “total adjustment factor”, $f_{\text{total}_{n,i}}$ is calculated for each day, $n$, and each city, $i$, as follows:

$$f_{\text{total}_{n,i}} = [f_{\text{sun-angle}}]_n [f_{\text{day-of-week}}]_n [f_{\text{wind-speed}}]_{n,i} [f_{\text{wind-dir}}]_{n,i}$$
For the sun angle factor, we calculate this using a cosine fit. For each julian date, \( n \), the sun angle factor \( (f_{\text{sun-angle}}) \) can be calculated as follows:

\[
f_{\text{sun-angle}} = \frac{0.75 + 0.25 \times \cos \left[ \frac{2\pi}{365} \left( \frac{n + 11}{365} \right) \right]}{0.75 + 0.25 \times \cos \left[ \frac{2\pi}{365} \left( \frac{n_d + 11}{365} \right) \right]}
\]

At the winter solstice, December 21\textsuperscript{st} \((n = -11 \text{ or } n = 354)\) the numerator value is 1 and at the summer solstice, June 21\textsuperscript{st} \((n = 171)\) the numerator value is 0.5. The variable \( n_d \) represents the normalization day, in this case April 15\textsuperscript{th} \((n_d = 105)\). The aforementioned equation is only valid for locations north of the Tropic of Cancer \((23.4^\circ \text{N})\).

For the wind speed factor, we fit a third-order polynomial using analog winds speeds from the 2018 – 2019 TROPOMI time frame. Wind speeds of 5 m/s would yield a correction factor of 1. Values larger than 1 represent winds slower than 5 m/s and values smaller than 1 represent winds faster than 5 m/s. This fit allows us to calculate a correction factor given any city-specific wind speed.

For the wind direction factor, we calculate a correction factor normalized to southwest winds. Wind directions are grouped into the following categories: 0 – 90° are southwest, 90 – 180° are northwest, 180 – 270° are northeast, and 270 – 360° are southeast. Once the wind speed is grouped into a specific category, the factor is defined based on its relation to the climatological wind direction; northwest for New York City and Washington D.C., and northeast for Los Angeles. Daily winds which are typical of the climatological wind direction yield a correction factor of 1.

Lastly, for the day-of-week factor, we assume 15% lower values on Saturdays and 30% lower values on Sundays. We assume all weekdays have similar emissions rates to each other. Weekdays have a factor of 1, Saturdays a factor of 0.85 and Sundays a factor of 0.70. These assumptions are broadly consistent with literature demonstrating day-of-week NO\textsubscript{X} emissions patterns.
As an example, a stagnant day in January may be lowered by a factor of ~2 to "normalize" to a 5 m/s April weekday, whereas a very windy weekend day in April might be increased by a factor of 1.5 to account for the faster than normal winds and the weekend effect.

**Method 3: Normalization of Daily TROPOMI NO$_2$ using a CTM**

We infer expected NO$_2$ columns ($V_{ex}$) during the lock-down period ($t_{covid}$) using the output from the GEM-MACH model (Moran et al., 2009; Pendlebury et al., 2018). The operational version of the model, used in this study, has a $10 \times 10$ km$^2$ grid cell size with 80 vertical levels (from the surface to about 0.1 hPa), provides hourly output, and includes emissions, chemistry, dispersion, and removal processes of 41 gaseous and eight particle species. The emissions used in the model are processed using the Sparse Matrix Operator Kernel Emissions (SMOKE) (Coats, n.d.) and account for seasonal changes; changes in emissions due to the COVID-10 lock-downs are not considered in the model framework.

In a first step the GEM-MACH NO$_2$ vertical levels in the boundary layer (up to approximately 2 km) are summed to a column amount using the model’s pressure and temperature profile (Côté et al., 1998). Since the GEM-MACH model currently does not contain any NO$_x$ sources in the free troposphere (such as aircraft or lightning emissions), the NO$_2$ model concentrations decrease to 0 above the planetary boundary layer (PBL). A free tropospheric column (from 2 km to 12 km) is added to the GEM-MACH PBL vertical column densities (VCDs) using a monthly GEOS-Chem run (0.5x0.67° resolution, version v8-03-01; [http://www.geos-chem.org](http://www.geos-chem.org)) (Bey et al., 2001; McLinden et al., 2014). The model VCDs are then mapped in space and time to the TROPOMI observations, and treated like the observations, where data with $qa < 0.75$ are filtered and averaged over the city center using a 28-day running mean.

The expected VCDs ($V_{ex}$) are the 28-day running means of the modelled VCDs ($V_M$) during the lockdown period ($t_{covid}$). $V_{ex}$ is scaled to remove any bias between the model and satellite ($V_T$) for the pre-lockdown period ($t_{pre}$, between February 1$^{st}$ and March 1$^{st}$ 2020):

$$V_{ex}(t_{covid}) = V_M(t_{covid}) \cdot mean\left(\frac{V_T(t_{pre})}{V_M(t_{pre})}\right).$$
Depending on the city, some dates within the $t_{pre}$ time period may not be considered for the scaling, if there is a strong divergence between the model and the observations.

The estimated NO$_2$ drop is the average of the difference between the expected VCDs, $V_{ex}(t_{covid})$, and the observed TROPOMI VCDs, $V_{T}(t_{covid})$, between March 28$^{th}$ and April 16$^{th}$, 2020 using the daily 28-day running means as shown in Figure 4.
3. Supplemental Figures

**Figure S1.** Frequency of daily maximum 2-m temperature within each bin, according to the ERA5 re-analysis. Each bar is a different city as noted by list in top left.

**Figure S2.** Frequency of 100-m afternoon (16Z-21Z) wind speed within each bin, according to the ERA5 re-analysis. Each bar is a different city as noted by list in top left.
**Figure S3.** Frequency of 100-m afternoon (16Z-21Z) wind direction within each bin, according to the ERA5 re-analysis. Each bar is a different city as noted by list in top left.

**Figure S4.** Trends in TROPOMI NO$_2$ since January 1 in 2019 and 2020. The lines represent the 28-day rolling median value (50th percentile) in a $0.4^\circ \times 0.4^\circ$ box centered on the city center for the largest cities (New York City, Los Angeles, Chicago, Toronto, Houston) and $0.2^\circ \times 0.2^\circ$ box in all other cities.
Figure S5. Average 100-m afternoon (16Z-21Z) wind speed and direction for March 15 – April 30 in (left) 2019, (center) 2020, (right) difference between the two years, according to the ERA5 re-analysis.

4. Supplemental Table

Table S1. Uncertainties associated with our methodology. Uncertainties are calculated as the quadrature of any potential systematic bias (20%) and the standard deviation of Methods 1 – 3.

| City Name     | Uncertainty |
|---------------|-------------|
| San Jose      | 20.1%       |
| Toronto       | 20.3%       |
| Los Angeles   | 23.6%       |
| Philadelphia  | 21.3%       |
| Atlanta       | 21.5%       |
| Detroit       | 21.4%       |
| Denver        | 21.2%       |
| Montreal      | 20.2%       |
| Boston        | 23.5%       |
| Washington DC | 24.2%       |
| New York City | 20.0%       |
| New Orleans   | 20.5%       |
| Las Vegas     | 26.1%       |
| Phoenix       | 23.4%       |
| Chicago       | 22.4%       |
| Houston       | 23.6%       |
| Austin        | 20.3%       |
| Dallas        | 21.1%       |
| Miami         | 22.0%       |
| Minneapolis   | 20.3%       |
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