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REVIEW

# The global impacts of COVID-19 lockdowns on urban air pollution: A critical review and recommendations

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The coronavirus-19 (COVID-19) pandemic led to government interventions to limit the spread of the disease which are unprecedented in recent history; for example, stay at home orders led to sudden decreases in atmospheric emissions from the transportation sector. In this review article, the current understanding of the influence of emission reductions on atmospheric pollutant concentrations and air quality is summarized for nitrogen dioxide ($NO_2$), particulate matter ($PM_{2.5}$), ozone ($O_3$), ammonia, sulfur dioxide, black carbon, volatile organic compounds, and carbon monoxide (CO). In the first 7 months following the onset of the pandemic, more than 200 papers were accepted by peer-reviewed journals utilizing observations from ground-based and satellite instruments. Only about one-third of this literature incorporates a specific method for meteorological correction or normalization for comparing data from the lockdown period with prior reference observations despite the importance of doing so on the interpretation of results. We use the government stringency index (SI) as an indicator for the severity of lockdown measures and show how key air pollutants change as the SI increases. The observed decrease of $NO_2$ with increasing SI is in general agreement with emission inventories that account for the lockdown. Other compounds such as $O_3$, $PM_{2.5}$, and CO are also broadly covered. Due to the importance of atmospheric chemistry on $O_3$ and $PM_{2.5}$ concentrations, their responses may not be linear with respect to primary pollutants. At most sites, we found $O_3$ increased, whereas $PM_{2.5}$ decreased slightly, with increasing SI. Changes of other compounds are found to be understudied. We highlight future research needs for utilizing the emerging data sets as a preview of a future state of the atmosphere in a world with targeted permanent reductions of emissions. Finally, we emphasize the need to account for the effects of meteorology, emission trends, and atmospheric chemistry when determining the lockdown effects on pollutant concentrations.

**Keywords:** COVID-19 lockdown, Air quality, Urban pollution

## 1. Introduction

The global spread of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in early 2020 was an unprecedented, highly disruptive event. Lockdowns instituted to control the subsequent coronavirus disease 2019 (COVID-19) pandemic led to rapid, unforeseen decreases in economic and social activity and associated emissions of air pollutants and greenhouse gases worldwide. It has been suggested in a number of perspective articles and comments that this episode provides a unique scientific opportunity to detect, attribute, and understand the impacts of anthropogenic emissions on the Earth's atmosphere at all spatial scales, from regional to global (Forster et al., 2020; He et al., 2020; Kroll et al., 2020; Le Quéré et al., 2020; Liu et al., 2020d), and on the Earth System and climate generally (Diffenbaugh et al., 2020; Phillips et al., 2020; Raymond et al., 2020). Of particular interest have been shifts in regional air quality that have been documented by ground-level monitoring networks and spaceborne remote sensing instruments. Such changes, occurring to a varying extent on every continent except Antarctica, have been the subject of intense interest among the general public and within the scientific and regulatory communities charged with understanding the air quality impacts of anthropogenic emissions. These transient shifts within particular emissions sectors have the potential to test the efficacy of air pollution control strategies and may even provide a preview of the future state of the atmosphere in a world with more permanent reductions in emissions from certain sectors.

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**Table 1.** Overview of compounds of relevance for ambient air quality and the respective guideline values as stated in the 2005 global update of the World Health Organization (WHO) air quality guidelines. DOI: https://doi.org/10.1525/elementa.2021.00176.t1

| Compound | WHO Guideline Value ($\mu g/m^3$) or Comment | Additional Definition ($\mu g/m^3$) or Comment |
|---|---|---|
| $NO_2$ | $40^{/\text{annual mean}}$ | $200^{/\text{1-h mean}}$ |
| NMVOCs | | Some NMVOCs considered for indoor air guidelines |
| $SO_2$ | $20^{/\text{24-h mean}}$ | $500^{/\text{10-min mean}}$ |
| $NH_3$ | | Not defined |
| $O_3$ | $100^{/\text{8-h mean}}$ | No WHO guideline values for annual or 24-h mean exist |
| $PM_{2.5}$ | $10^{/\text{annual mean}}$ | $25^{/\text{24-h mean}}$ |
| $PM_{10}$ | $20^{/\text{annual mean}}$ | $50^{/\text{24-h mean}}$ |
| CO | Chinese guideline value | $4^{/\text{24-h mean}}$ mg m$^{-3}$, $10^{/\text{1-h mean}}$ mg m$^{-3}$ |
| | European guideline value | $10^{/\text{24-h mean}}$ mg m$^{-3}$ |
| | U.S. guideline value | $10^{/\text{8-h mean}}$ mg m$^{-3}$, $40^{/\text{1-h mean}}$ mg m$^{-3}$ |

NMVOC = nonmethane volatile organic compound; $NO_2$ = nitrogen dioxide; $SO_2$ = sulfur dioxide; $NH_3$ = ammonia; $O_3$ = ozone; PM = particulate matter; CO = carbon monoxide.

The concept of air quality acknowledges the health burden attributable to atmospheric pollutants (World Health Organization [WHO], 2019). The WHO assesses that air pollution is the number one environmental health risk globally, causing 7.1 million premature deaths per year, of which 4.2 million are attributable to outdoor air pollutants. The WHO defines guideline values for key air pollutants (see **Table 1**), yet national regulatory limit values vary widely and are often less stringent than the WHO guideline values. The air quality index (AQI) is a common term used by government agencies to define standards for the simultaneous presence of multiple pollutants. Individual pollutant concentrations are combined to derive the AQI and determine air quality levels. However, no agreed upon definition for AQI exists, with AQI determined in different ways for each country (Bishoi et al., 2009; Fareed et al., 2020).

In addition to emission and deposition processes, both sources and sinks of air quality relevant trace compounds are determined by atmospheric chemistry. Species that are emitted directly to the atmosphere are considered primary, whereas species formed through atmospheric chemical processes are referred to as secondary. The main species of concern for human health are particulate matter (PM) and tropospheric ozone ($O_3$; Gakidou et al., 2017). PM has both primary and secondary sources, while ozone is formed almost exclusively through atmospheric chemistry, that is, it is secondary in nature. Major pollutants that serve as precursors to $O_3$ and secondary PM include nitrogen oxides ($NO_x$ = NO + nitrogen dioxide [$NO_2$]), volatile organic compounds (VOCs), sulfur dioxide ($SO_2$), carbon monoxide (CO), and ammonia ($NH_3$; see **Figure 1**).

Observational and laboratory approaches to understand relevant atmospheric chemical processes are complemented by modeling approaches to determine atmospheric composition on regional and global scales. Atmospheric chemical transport models (CTMs) account for (1) emissions from anthropogenic and natural sources, (2) atmospheric chemistry, and (3) transport, dilution, and deposition processes. The ability of CTMs to correctly simulate atmospheric composition is traditionally verified through comparisons of model and observational outputs. Extreme events, such as volcanic eruptions (Kristiansen et al., 2016; Wilkins et al., 2016; Beckett et al., 2020), wildfires (Liu et al., 2010), and heatwaves (Churkina et al., 2017; Zhao et al., 2019), play a particularly important role in this regard, as such events can expose model biases or missing processes.

The various national, statewide, and municipal lockdowns and implementations of social distancing for pandemic control of COVID-19 offer an "extreme" real-world experiment in which various anthropogenic sector-specific emissions of air pollutants have been suddenly and significantly reduced. This link of changes in human behavior and reduced anthropogenic emissions is expected (Beirle et al., 2003). In particular, during the pandemic, emissions from the transportation sector were reduced as a consequence of stay-at-home orders, as revealed by mobility data sets (Forster et al., 2020; Venter et al., 2020), for example. Early reports of observed decreases in $NO_x$ and PM in various regions of the world are now complemented by data sets showing varied responses in the secondary pollutants $O_3$ and PM resulting from the nonlinear interactions involved in atmospheric chemistry (Seinfeld, 2006). The COVID-19 lockdowns, therefore, offer a unique opportunity to (1) verify emission inventories and (2) explore the sensitivity of secondary pollutants to emission changes. Several review articles have already been published as of the writing of this article. Shakil et al. (2020) used 23 publications through May 2020 to highlight the effects of lockdowns and environmental factors on air quality and recommended that future analyses include meteorological corrections. Srivastava et al. (2020) focused on the link between PM pollution and the

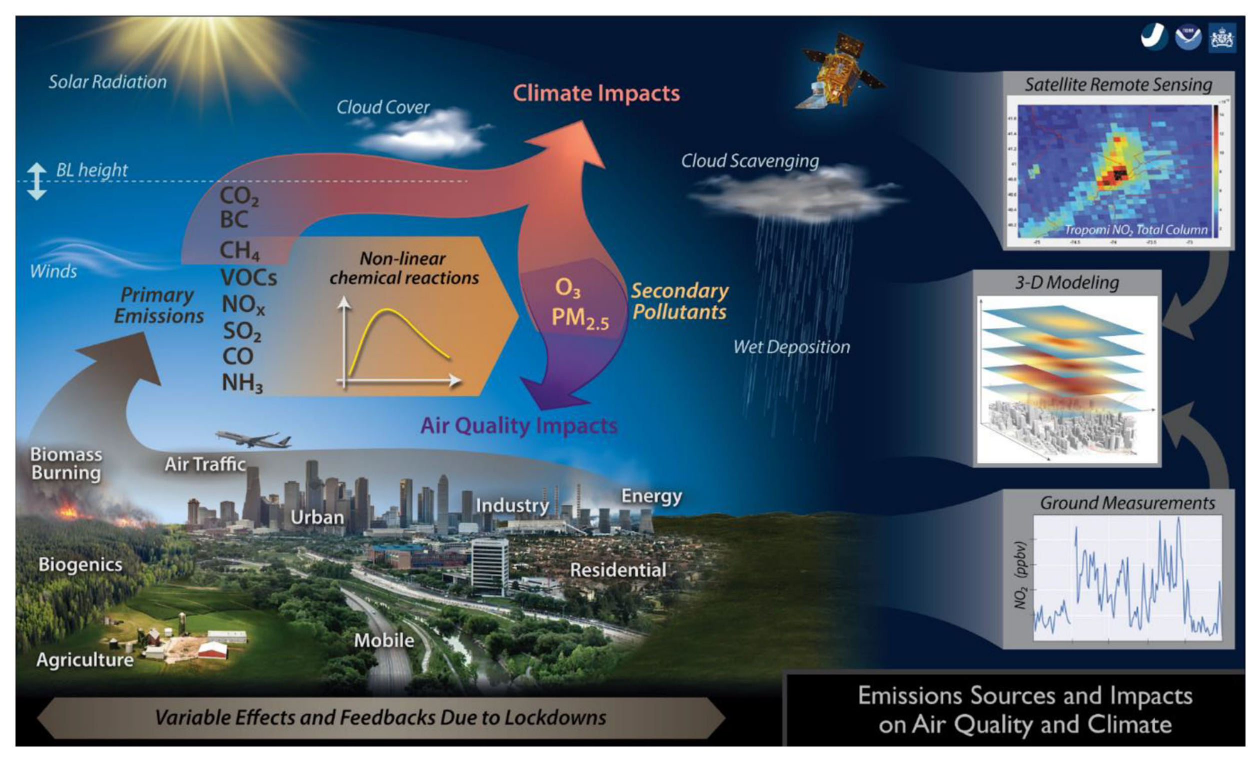


**Figure 1.** Schematic of major emission sectors and primary emissions, meteorological and chemical processes, impacts to air quality and climate, and measurement and analysis tools used to analyze the effects of emissions changes. DOI: https://doi.org/10.1525/elementa.2021.00176.f1

positive correlation to COVID-19 cases as well as the impact of weather on pollutant concentrations that affect morbidity and mortality. Kumar et al. (2020) highlighted the key findings of 28 publications on the effects of lockdowns on pollutant concentrations. Finally, Le et al. (2020b) discussed 16 publications related to PM concentration reductions during the pandemic.

In this review, we summarize the available literature through September 30, 2020, comprising more than 200 publications, and the approaches used to quantify changes in atmospheric pollutant levels. We focus on species that are of relevance as air pollutants and short-lived climate forcers, namely, $NO_2$, $PM_{2.5}$, $O_3$, $NH_3$, $SO_2$, black carbon (BC), VOCs, and CO. We further provide an outlook on the tools and analyses required to expand from individual case studies to a global framework of readily comparable results. To enhance the readability of the text, we present the references in tables, which allows for structured overviews of all references relevant to respective methods, regions, or compounds. With the pandemic, and hence lockdowns, ongoing as of this writing, this review intends to serve as a milestone in identifying and quantifying the overall impacts of emission reductions to air quality.

## 2. Methods

### *2.1. Literature review process*

Analysis of ground- and satellite-based observations of pollutants has received intense scientific focus in 2020. During the 7 months following the onset of the pandemic (March–September 2020), more than 200 manuscripts were accepted for publication in peer-reviewed journals. There are undoubtedly many others that are in preparation and review at the time of this writing or that have been published after October 2020. Subsequent reviews will be required to fully assess the breadth of this literature. The goal of this review is to provide an initial synthesis of this rapidly developing literature, as well as to provide some critical assessment of the state of the initial literature that may be useful for authors of manuscripts that follow.

To generate the database of peer-reviewed scientific articles used in this study, we utilized Google Scholar (Google, 2020) and searched the websites of prominent publishers of environmental scientific journals to find as many relevant and newly accepted papers as possible. We used the following search terms to query subject matter content: "COVID* AND air AND pollution" or "COVID* AND air AND quality." The wildcard "*" accounted for common iterations such as "COVID-19" and "COVID2019," while the Boolean operator AND was used to limit the results to studies related to air pollution or air quality topics. The first search was conducted in September 2020 and updated biweekly through October 30, 2020. We further limited the search results to papers that had undergone peer review, were accepted by September 30, 2020, and were published in English.

Each of the 219 papers that met the above criteria was examined by at least one coauthor to determine its overall relevance to the goals of this study. The papers were then added to our database and all pertinent information was manually cataloged. This included the author list, journal

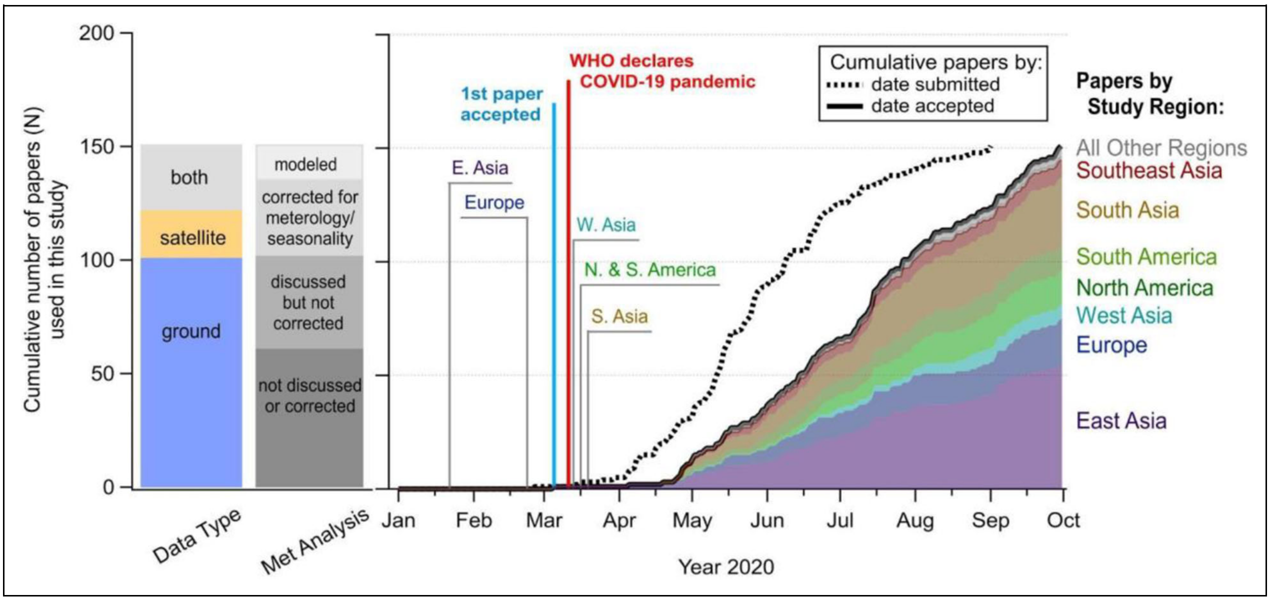


**Figure 2.** The cumulative number of papers for which we digitized data for this analysis. The papers are grouped by data type, treatment of meteorology/seasonality, and study region as a function of the manuscript acceptance date (also see **Tables 2**–4). The dates that the first country within each geographic region to undergo a strict lockdown (stringency index > 70) are included, starting with China on January 22, 2020. DOI: https://doi.org/10.1525/elementa.2021.00176.f2

name, dates of submission and acceptance, the region and time frames studied, the type of data set used (ground-based, satellite, or both), and whether the authors accounted for the effects of seasonality/meteorology and the year-to-year variability in atmospheric concentrations.

Furthermore, we manually digitized the findings from 150 papers relating to the observed percentage change and/or concentrations of the pollutants discussed in each study (see Table S1 for the nondigitized yet reviewed papers). **Figure 2** shows the cumulative number of papers by sample type, methodology, and region of study. This subset of our database comprises manuscripts published in 37 different scientific journals with a median submission to acceptance peer-review period of 35 days. There were 10 different geographic study regions, led by East Asia ($N = 54$ papers) and South Asia ($N = 28$ papers). These two regions were dominated by air quality studies in China ($N = 46$ papers) and India ($N = 27$ papers), respectively. The first COVID-related air quality manuscript was accepted on March 5, 2020 (Wang et al., 2020c) before the WHO declared COVID-19 a global pandemic on March 11, 2020.

Portions of our analysis rely on the stringency index (SI), a metric used to quantitatively compare lockdown measures for each country over time (Hale et al., 2020). The SI ranges from 0 (no lockdown) to 100 (strictest lockdown) based on a variety of measures meant to slow the spread of COVID-19 (see Section 3.2). We have not made explicit use of other common metrics of economic activity changes found in other papers, such as sector-specific mobility indices provided by Google or Apple (Forster et al., 2020) or traffic counts. The SI is convenient for the purpose of this article since its focus is appropriate for the continental and regional scales considered in the data synthesis presented here.

All data digitized for analysis in this review are available on the website https://covid-aqs.fz-juelich.de. This includes the observed percentage change in species concentration for $NO_2$, $NO_x$, CO, $PM_{2.5}$, $PM_{10}$, $O_3$, $SO_2$, $NH_3$, speciated nonmethane volatile organic compound (NMVOCs), aerosol optical depth (AOD), BC, and the AQI. Also, the absolute concentrations of $NO_2$, $PM_{2.5}$, $O_3$, and CO during the lockdown and reference periods are provided. Each data set is linked with the digital object identifier of the original publication, information on the corresponding author, region, country, city (where applicable), and the observational start and end times. This website is designed as a living version of this review, that is, as new literature emerges, authors of published papers are encouraged to upload their data to the database, thus complementing the data coverage in space, time, and compound dimensions. The data sets from the website are provided with free and unrestricted access for scientific (noncommercial) use including the option to generate targeted reference lists. Users of the database are requested to acknowledge the data source and reference this review in publications utilizing the data set.

### *2.2. Platforms used to measure pollutant concentrations*

#### 2.2.1. Ground-based

**Figure 2** shows that ground-based measurements comprise the largest fraction of the data used in the analysis of COVID-19 lockdowns to date. These data normally come from local, regional, or national air quality monitoring networks in various regions, as discussed in Section S1.1. Air quality monitoring networks include the U.S. Environmental Protection Agency (2020), the European Environment Agency EAA together with the European Monitoring and Evaluation Programme (2020), the China National Environmental Monitoring Center established by the Ministry of Ecology and Environment of China (Chu et al., 2021), and the Central Pollution Control Board in India managed by the Ministry of Environment, Forests, and Climate Change (Pant et al., 2020).

All these networks or infrastructures such as the Aerosols, Clouds and Trace gases Research Infrastructure and In-service Aircraft for a Global Observing System (Petzold et al., 2015) provide preliminary data in near real time, with final, quality-assured data updated either quarterly or biannually. Other data sources such as the OPEN-AQ data source (https://openaq.org/) compile network data into readily accessible, larger databases. However, the data quality assurance process is not always made clear in a given publication. For example, the OPEN-AQ platform explicitly makes no guarantee of quality assurance or assessment of accuracy. Data are uploaded in real time and not necessarily updated when quality assured (final) data are made available from a given air quality network. Papers published to date on COVID-19 lockdown effects using ground-based monitors generally specify the source of their data but commonly do not specify whether those data are preliminary or final. Given the speed with which these manuscripts were prepared, it is possible that many are based on data with no final quality control.

#### 2.2.2. Satellites

Roughly one-third of the publications discussed in this review make use of satellite observations. A large number of satellite data sets have been used, including:

- Sentinel-5P TROPOspheric Monitoring Instrument (TROPOMI) $NO_2$, CO, $SO_2$, and HCHO;
- AURA-OMI (Ozone Monitoring Instrument) $NO_2$, $SO_2$, and AOD;
- Terra and Aqua MODIS AOD, PM, and fire products; and
- Terra MOPITT CO and Aqua AIRS CO.

By far, the most used data set is the TROPOMI $NO_2$ tropospheric column product of Sentinel-5P, used in 41% of cases (calculated as the number of papers using TROPOMI $NO_2$ divided by the total number of satellite data sets used in the papers). The second most used data set is AURA-OMI $NO_2$, used in 27% of cases, followed by MODIS AOD, used in 14% of cases. All other data sets have been used sporadically (1–3 times). Of the papers reviewed herein that use satellite data, 61% used TROPOMI $NO_2$, 40% used OMI $NO_2$, and 21% used MODIS AOD (note that several papers used multiple satellite data sets for their analysis, on average 1.5 satellite data sets per paper). Taking the $NO_2$ data sets from OMI and TROPOMI together, 68% of the published satellite results on the COVID-19 impact on air quality were generated using these two data sets.

Note that satellite instruments like TROPOMI and OMI measure at one given overpass time (e.g., 13:30 local). As the diurnal profile of the emissions may have changed during the lockdowns, observed changes at a given overpass time may not be fully representative of the total changes. Also, TROPOMI and OMI tropospheric column $NO_2$ retrieval products contain detailed uncertainty estimates for each observation separately, typically ranging between 20% and 60% for polluted scenes. The use of averaging kernels in the data products is advised to remove the dependency on the retrieval a priori and reduce the associated uncertainties (see Section S1.2).

### *2.3. Methods used to determine lockdown effects on pollutants*

The atmospheric abundance of trace compounds is determined through the interplay of emissions, atmospheric chemistry, transport, and loss processes. To quantify the effect of changes in any of these, an analysis must isolate the influence of confounding parameters. The main focus of the literature reviewed here is the effect of emission changes on ambient mixing ratios of criteria pollutants. In general, three types of approaches are used: a comparison of observed concentrations to a reference period during which "business as usual" emissions prevailed (see Section 2.3.1), an analysis of observed concentrations when accounting for meteorological influences or atmospheric chemistry (e.g., photolysis frequencies, humidity, and temperature dependencies; Section 2.3.2), and a comparison of observed concentrations with the output of CTMs run to derive "business as usual" expected values (Section 2.3.3).

#### 2.3.1. Direct comparison to a reference period

Nearly two-thirds of the studies summarized here were a direct comparison of lockdown periods to a reference measurement period (**Table 2**). Two main approaches were used: (1) a comparison of pollutant concentrations directly before and/or after a lockdown, that is, data sets covering a relatively short time period or (2) a comparison of pollutant concentrations from seasonally similar time periods, that is, data sets that included 2019, and often several other previous years, for the same period of time as the 2020 lockdown. The main advantage of these approaches is the simplicity in identifying relative changes. For the first approach, uncertainties arise due to the unquantified effects of seasonality, meteorology, and atmospheric chemistry. Although the second approach generally covers meteorological effects, uncertainty may still arise from other processes that affect the abundance of atmospheric trace compounds, such as climatological variability and exceptional events. It is not possible to conclude generally whether the use of direct comparisons to reference periods bias the derived changes low or high, as this will be determined by the specific conditions prevailing in each studied region. Unambiguous quantification of emission changes is, therefore, not possible, although the correlation of observed changes with indicators of emission activity (e.g., traffic counts, fuel sales, mobility, electric power consumption) can be explored. Various studies included in this work highlight the importance of identifying the effects of meteorology, atmospheric chemistry, and emission trends in the observed

**Table 2.** Summary of studies that perform a direct comparison of the lockdown period to a reference period. DOI: https://doi.org/10.1525/elementa.2021.00176.t2

| Direct Comparison Publications | |
|---|---|
| East Asia | **China:** (Agarwal et al., 2020; Chauhan and Singh, 2020; Chen et al., 2020a; Chen et al., 2020c; Chen et al., 2020d; Fan et al., 2020; G Huang and Sun, 2020; Lian et al., 2020; Liu et al., 2020c; Miyazaki et al., 2020; Nichol et al., 2020; Pei et al., 2020; Shakoor et al., 2020; Shi and Brasseur, 2020; Silver et al., 2020; Wan et al., 2020; Wang et al., 2020a; Wang et al., 2020b; Wang et al., 2020f; Xu et al., 2020c; Zhang et al., 2020a; Yuan et al., 2021) |
| | **Other:** (Ghahremanloo et al., 2020; Han et al., 2020; Ju et al., 2020; Ma and Kang, 2020; Zhang et al., 2020b) |
| South Asia | **India:** (Bedi et al., 2020; Beig et al., 2020; Biswal et al., 2020; Chatterjee et al., 2020; Gautam et al., 2020; Harshita and Vivek, 2020; Jain and Sharma, 2020; Kant et al., 2020; Kumari and Toshniwal, 2020; Kumari et al., 2020; Mahato and Ghosh, 2020; Mahato et al., 2020; Panda et al., 2020; Ranjan et al., 2020; Selvam et al., 2020; Sharma et al., 2020a; Siddiqui et al., 2020; Singh and Chauhan, 2020; Singh et al., 2020; Vadrevu et al., 2020) |
| | **Other:** (Masum and Pal, 2020; Rodríguez-Urrego and Rodríguez-Urrego, 2020) |
| Southeast Asia | **Malaysia:** (Abdullah et al., 2020; Ash'aari et al., 2020; Kanniah et al., 2020; Mohd Nadzir et al., 2020; Suhaimi et al., 2020) |
| | **Other:** (Jiayu and Federico, 2020; Stratoulias and Nuthammachot, 2020) |
| West Asia | **Turkey:** (Aydın et al., 2020; Şahin, 2020) |
| | **Iran:** (Broomandi et al., 2020; Faridi et al., 2020) |
| | **Other:** (Anil and Alagha, 2020; Hashim et al., 2020) |
| North America | **United States:** (Bauwens et al., 2020; Berman and Ebisu, 2020; Chen et al., 2020b; Hudda et al., 2020; Pan et al., 2020; Son et al., 2020; Zangari et al., 2020; Zhang et al., 2020d; Liu et al., 2021b) |
| South America | **Brazil:** (Dantas et al., 2020; Krecl et al., 2020; Nakada and Urban, 2020; Siciliano et al., 2020a) |
| | **Other:** (Mendez-Espinosa et al., 2020; Pacheco et al., 2020; Zalakeviciute et al., 2020; Zambrano-Monserrate and Ruano, 2020) |
| Europe | **Multiple countries:** (Baldasano, 2020; Collivignarelli et al., 2020; Filippini et al., 2020; Gautam, 2020a; Giani et al., 2020; Gualtieri et al., 2020; Higham et al., 2020; Ljubenkov et al., 2020; Sicard et al., 2020; Tobías et al., 2020; Martorell-Marugán et al., 2021) |
| Oceania | **Australia:** (Fu et al., 2020) |
| | **New Zealand:** (Patel et al., 2020) |
| Africa | **Morocco:** (Ass et al., 2020; Otmani et al., 2020) |

This includes the "discussed but not corrected" and "not discussed or corrected" categories in **Figure 2.**

percentage emission changes and are discussed in the following section.

### 2.3.2. Accounting for effects of meteorology and emission trends

Meteorological factors have an important effect on atmospheric pollution levels (Shenfeld, 1970). Wind velocity, stability, and turbulence affect the dilution, transport, and dispersion of pollutants. Sunshine triggers the photochemical production of oxidants that form smog, whereas rainfall has a scavenging effect that washes out particles and some gases from the atmosphere. Furthermore, concentrations of various atmospheric pollutants can change due to decreasing trends of emissions in urban environments around the world (e.g., Warneke et al., 2012; Sun et al., 2018; Zheng et al., 2018). Changing pollutant concentrations can influence atmospheric chemistry by affecting the pollutant's chemical sources and sinks and therefore its lifetime (e.g., Shah et al., 2020). With atmospheric chemistry and pollutant distribution changing with season and location (e.g., summer vs. winter, urban vs. remote locations), all the above highlight the need to quantify the effects of meteorology, atmospheric chemistry, and emission trends on atmospheric pollutant concentrations when describing pollutant changes during the pandemic.

Several studies quantified the effects of meteorology and emission trends on the observed pollutant changes, as summarized in **Table 3.** Of the 32 studies listed, 16 studies focused on East Asia, six on Europe, six on North America, three on South Asia, two on South America, and two were global studies. Over 98% of the measurements presented in publications that were included in this review were from urban environments. Different statistical approaches were used to account for the above effects, which are summarized below.

#### *2.3.2.1. Statistical tools used for pollutant source apportionment*

Two approaches were utilized to apportion pollutant concentrations to different sectors and to elucidate the role of atmospheric chemistry and/or meteorology. One commonly used approach was positive matrix factorization

**Table 3.** Summary of studies controlling for effects of meteorology, atmospheric chemistry, and emission trends on air quality analysis. DOI: https://doi.org/10.1525/elementa.2021.00176.t3

| Type | Region | Study Period | Baseline Year(s) | Species | Meteorological Variables | Reference |
|---|---|---|---|---|---|---|
| Dilution corrected | East Asia | January 26–February 17 | 2016–2020 | $NO_2$, $SO_2$, CO, and $PM_{2.5}$ | PBLH | (Su et al., 2020) |
| Dilution corrected | North America | January 1–April 30 | 2019–2020 | $NO_2$ | SZA, WS, and WD | (Goldberg et al., 2020) |
| Dilution corrected with CO | East Asia | January 14–March 4 | 2020 | NR-$PM_1$ | – | (Xu et al., 2020a) |
| Tracer–tracer ratios | East Asia | January 1–March 31 | 2012–2019 | $PM_{2.5}$ | – | (Sun et al., 2020) |
| Benchmarking | North America | March 14–April 30 | 2019–2020 | CO, $NO_2$, and $PM_{2.5}$ | T and precip. | (Tanzer-Gruener et al., 2020) |
| Deseasonalize | North America | January 1–April 27 | 2015–2020 | $PM_{2.5}$, $NO_2$, $NO_x$, and $O_3$ | – | (Adams, 2020) |
| Deseasonalize | East Asia | January 1–May 31 | 2005–2020 | $NO_2$ and AOD | – | (Diamond and Wood, 2020) |
| Deseasonalize | South Asia and East Asia | January 1–April 30 | 2016–2019 | $NO_2$, $SO_2$, and CO | – | (Metya et al., 2020) |
| Dispersion indices | East Asia | January 26–February 25 | 2013–2020 | $PM_{.2.5}$, $PM_{10}$, $SO_2$, CO, $NO_2$, and $O_3$ | WS, wind shear, potential T, and RH | (Wang and Zhang, 2020) |
| Back-trajectory | East Asia | January 1–February 26 | 2019–2020 | $PM_{2.5}$ | HYSPLIT | (Chang et al., 2020) |
| Back-trajectory and PMF | East Asia | January 12–April 2 | 2020 | $PM_{2.5}$ | GDAS | (Cui et al., 2020) |
| Back-trajectory | South America | March 1–April 16 | 2020 | CO, $NO_2$, $O_3$, VOC, and $PM_{10}$ | HYSPLIT | (Siciliano et al., 2020b) |
| Back-trajectory and cluster analysis | East Asia | January 23–April 8 | 2020 | $PM_{2.5}$, $SO_2$, $NO_2$, CO, and $O_3$ | HYSPLIT | (Zhao et al., 2020a) |
| Back-trajectory analysis | East Asia | January 24–February 29 | 2000–2020 | AOD | HYSPLIT | (Shen et al., 2021) |
| Machine learning and PMF | East Asia | January 23–February 22 | 2019 | $PM_{2.5}$ | T, P, WS, RH, PBLH, and radiation | (Zheng et al., 2020) |
| Dispersion-normalized PMF | East Asia | January 1–February 15 | 2020 | $PM_{2.5}$ | T, WS, PBLH, and radiation | (Dai et al., 2020) |
| Cluster analysis | South Asia | March 25–May 15 | 2017–2020 | CO, $NO_2$, $SO_2$, $O_3$, $PM_{10}$, and $PM_{2.5}$ | T | (Bera et al., 2020) |
| Multivariate regression | East Asia | January 23–March 21 | 2019–2020 | $SO_2$, $PM_{2.5}$, $PM_{10}$, $NO_2$, and CO | WS, rain, and snow | (Bao and Zhang, 2020) |
| Multivariate regression | North America | March 25–May 4 | 2017–2020 | $PM_{2.5}$, $NO_2$, and $O_3$ | WS, T, and precip. | (Jia et al., 2020a) |
| Multivariate regression | Europe | January 1–March 27 | 2017–2020 | $NO_2$ and $PM_{10}$ | T, WS, and precip. | (Cameletti, 2020) |

*(continued)*

TABLE 3. *(continued)*

| Type | Region | Study Period | Baseline Year(s) | Species | Meteorological Variables | Reference |
|---|---|---|---|---|---|---|
| Multivariate regression | South America, North America, and Europe | March 1–March 31 | 2015–2020 | $PM_{2.5}$, CO, $NO_2$, and $O_3$ | T, RH, WS, and precip. | (Connerton et al., 2020) |
| Multivariate regression and machine learning | East Asia | February 5–February 20 | 2013–2018 | $PM_{2.5}$ and $O_3$ | Geopotential height, T, RH, dew point, stability, WS, and precip. | (Lei et al., 2020) |
| Multivariate regression | Global | January 1–May 15 | 2017–2020 | $NO_2$, $PM_{2.5}$, and $O_3$ | T, RH, precip., and WS | (Venter et al., 2020) |
| Multivariate regression | North America | February 17–May 31 | 2020 | BC, $PM_{2.5}$, NO, $NO_2$, $NO_x$, CO, and UFP | T, RH, precip., WS, and WD | (Xiang et al., 2020) |
| Machine learning | Europe | January 1–April 23 | 2013–2020 | $NO_2$ | T2, WS, U10, V10, P, cloud cover, radiation, UV, and PBLH | (Petetin et al., 2020) |
| Machine learning | East Asia | January 1–April 26 | 2020 | $NO_2$, $PM_{2.5}$, and $O_3$ | WS, WD, T, RH, and P | (Wang et al., 2020e) |
| Machine learning | Europe | March 1–May 31 | 2015–2019 | $NO_2$, $O_3$, $PM_{10}$, and $PM_{2.5}$ | WS, WD, P, RH, T, and radiation | (Wyche et al., 2020) |
| Difference-in-difference method | Global | January 1–July 7 | 2020 | $NO_2$, $PM_{10}$, $SO_2$, $PM_{2.5}$, CO, and $O_3$ | T, WS, and RH | (Liu et al., 2021a) |
| Difference-in-difference method | South Asia | March 25–May 3 | 2019–2020 | $PM_{2.5}$, $PM_{10}$, $NO_2$, CO, and $SO_2$ | T, WS, and RH | (Navinya et al., 2020) |
| Difference-in-difference method | East Asia | January 1–March 1 | 2019–2020 | Air quality index, $PM_{2.5}$, CO, $NO_2$, $PM_{10}$, $SO_2$, and $O_3$ | T, precip., and snow | (He et al., 2020) |
| Generalized additive model | Europe | March 15–April 30 | 2015–2019 | $NO_2$ and $O_3$ | T2, U10, V10, Z500, specific humidity, radiation, and precip. | (Ordóñez et al., 2020) |
| Generalized additive model | Europe | March 10–June 30 | 2015–2019 | NO, $NO_2$, $NO_x$, $O_3$, $PM_{10}$, and $PM_{2.5}$ | WS, WD, and T | (Ropkins and Tate, 2020) |

This includes the "corrected for meteorology/seasonality" category in **Figure 2.** PMF = positive matrix factorization; AOD = aerosol optical depth; BC = black carbon; VOC = volatile organic compound; $NO_2$ = nitrogen dioxide; $SO_2$ = sulfur dioxide; $O_3$ = ozone; PM = particulate matter; CO = carbon monoxide; $NO_x$ = nitrogen oxide.

(PMF), a widely used receptor model to resolve pollution sources and quantify the source contributions. Studies using PMF focused on the $PM_{2.5}$ chemical composition, and the sources of organic particulate pollution, in Beijing (Cui et al., 2020), Wuhan (Zheng et al., 2020), and Tianjin (Dai et al., 2020), China. Conventional PMF analysis may suffer from information loss due to nonlinear dilution variations. Dai et al. (2020) incorporated the ventilation coefficient into their dispersion-normalized PMF, which reduced the dilution effect. The advantages of using PMF were highlighted in all studies, and their findings supported the substantial contribution of secondary sources, as well as the influence of local primary sources, to PM pollution. Finally, a hierarchical cluster analysis and principal component analysis were used in one study in India to investigate the impact of changing temperatures on pollutant concentrations (Bera et al., 2020). However, although these approaches will more reliably quantify observed changes in the atmospheric abundance of pollutants as a response to emission changes, the effects of meteorology and atmospheric chemistry are not always fully disentangled.

##### *2.3.2.2. Statistical tools to account for the influence of meteorology and emission trends*

Several approaches were used to reduce the effects of meteorology on the interpretation of air quality. One approach is to examine tracer-tracer ratios (Homan et al., 2010; Borbon et al., 2013), for example, normalizing pollutants relative to a relatively long-lived species like CO. These ratios provide a simple way to account for dilution and are typically used to isolate the effects of secondary chemistry. A confounding factor is that many of the commonly used tracers in the denominator (e.g., CO) also changed significantly due to emission reductions related to COVID-19. Other studies performed dilution corrections by normalizing to meteorological variables such as planetary boundary layer height (Su et al., 2020) or satellite column data with solar zenith angle, wind speed, and wind direction (Goldberg et al., 2020). Another approach is to benchmark periods of similar meteorology in past years with meteorology experienced during lockdown periods (Tanzer-Gruener et al., 2020). Methods to deseasonalize lockdown periods with prelockdown periods or past years were also employed (Adams, 2020; Diamond and Wood, 2020; Metya et al., 2020). Finally, other approaches identified metrics to assess synoptic meteorological conditions conducive to air pollution episodes (Wang and Zhang, 2020) or performed back trajectory analysis, such as with the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model, to assess the origin of pollutants and long-range transport (Chang et al., 2020; Cui et al., 2020; Siciliano et al., 2020b; Zhao et al., 2020a; Shen et al., 2021).

A variety of more complex statistical approaches were also used to quantify the effects of meteorology, atmospheric chemistry, and emission trends. This included the following:

1. multivariate regression analysis methods, where two main data sets were used: the dependent/outcome variables describing the pollutant concentrations and the independent/exposure variables that adjusted for weather conditions (Bao and Zhang, 2020; Cameletti, 2020; Connerton et al., 2020; Jia et al., 2020a; Lei et al., 2020; Venter et al., 2020; Xiang et al., 2020);
2. machine-learning methods, where algorithms were trained on measurements of pollutants and meteorological parameters from previous years to predict the "business as usual" emission estimates for 2020 (Petetin et al., 2020; Wang et al., 2020e; Wyche et al., 2020; Zheng et al., 2020);
3. difference-in-difference methods, where the impact of lockdown measures on air quality were quantified through a fixed-effects ordinary least squares (OLS) approach with the key explanatory variable being the lockdown measures and weather variables used as vectors (Navinya et al., 2020; Liu et al., 2021a); and
4. generalized additive models that accounted for the additive effect of meteorology on the pollutant concentrations and their nonlinear relationships using the meteorological parameters as a model predictor input to derive the pollutant concentration (Ordóñez et al., 2020; Ropkins and Tate, 2020).

The majority of these studies included data sets from multiple years, thereby accounting not only for meteorological effects but also emission trends. Although each of these statistical tools has uncertainties associated with the representativeness of the input data sets, they constitute the best up-to-date published methods to quantify the effects of meteorology, and/or atmospheric chemistry, and/or long-range transport on pollutant concentrations.

#### 2.3.3. Air quality modeling and emission inventories constrained by observed changes

Chemical transport modeling provides a means for disentangling the effects of changes in emissions, chemistry, and meteorology on observed changes in air quality due to changing emissions. **Table 4** provides a summary of air quality or climate modeling studies published in the literature assessing the impacts of COVID-19. Of the 16 modeling studies listed, 14 are regional modeling studies: 12 of East Asia, one of Europe, and one of Europe and East Asia and two are global climate modeling studies. These modeling studies focused on lockdown measures in China and Europe, and the time period of study is limited to the winter of 2020. Studies of North America, South America,

**Table 4.** Summary of modeling studies assessing COVID-19 and air quality or climate impacts. DOI: https://doi.org/10.1525/elementa.2021.00176.t4

| Model | Type | Resolution | Baseline Inventory | Region | Emission Sectors Adjusted | Simulation Period | Lockdown Impact | Reference |
|---|---|---|---|---|---|---|---|---|
| WRF-CMAQ | Forward CTM | 27 · 27 km, 9 · 9 km, and 3 · 3 km | MICS-Asia + TEDS | East Asia | 50% reduction of all sectors | January 28, 2020–February 2, 2020 | $PM_{2.5}$ ↓ | (Griffith et al., 2020) |
| WRF-Chem | Forward CTM | 60 · 60 km and 20 · 20 km | MEIC | East Asia | Adjust mobile, power, and industry | December 1, 2019–March 5, 2020 | $PM_{2.5}$ ↑ and $O_3$ ↑ | (Huang et al., 2020) |
| WRF-Chem | Forward CTM | 12 · 12 km | INTEX-B | East Asia | 80% reduction of $NO_x$ | January 21, 2020–February 16, 2020 | $PM_{2.5}$ ↑ and $O_3$ ↑ | (Le et al., 2020a) |
| WRF-CAMx | Forward CTM | 36 · 36 km, 12 · 12 km, and 4 · 4 km | MEIC + MIX | East Asia | Adjust mobile, industry, dust, solvent, cooking, residential, and biomass burning | January 1, 2020–March 31, 2020 | $PM_{2.5}$ ↓, $NO_2$ ↓, $SO_2$ ↓, and $O_3$ ↑ | (Li et al., 2020a) |
| GEOS-GMI | Forward CTM | 0.25 · 0.25 | RCP 6.0 + EDGAR | East Asia | Constant emissions (to assess meteorology) | January 1, 2020–February 29, 2020 | $NO_2$ ↓ | (Liu et al., 2020a) |
| WRF-CMAQ | Forward CTM | 36 · 36 km | MEIC + MIX | East Asia | Adjust mobile, industry, and residential | January 1, 2020–February 12, 2020 | $PM_{2.5}$ ↓ | (Wang et al., 2020c) |
| WRF-GC | Top-down | 27 · 27 km | MEIC | East Asia | Derive $NO_x$ emissions from TROPOMI $NO_2$ | January 1, 2020–March 12, 2020 | $NO_x$ ↓ | (Zhang et al., 2020c) |
| WRF-CMAQ | Forward | 36 · 36 km | AiMa | East Asia | Constant emissions (to assess meteorology) | January 8, 2020–February 6, 2020 | $NO_2$ ↓, $SO_2$ ↓, CO ↓, $PM_{2.5}$ ↓, and $O_3$ ↑ | (Zhao et al., 2020b) |
| WRF-CMAQ | Forward CTM | 4 · 4 km | SAES | East Asia | Adjust mobile, power, and industry | December 29, 2019–February 29, 2020 | $PM_{2.5}$ ↓ and $O_3$ ↑ | (Liu et al., 2020b) |
| GEOS-Chem | Top-down | 0.5 · 0.625 | MIX + EDGAR | East Asia | Derive $NO_x$ emissions from TROPOMI $NO_2$ | January–March 2019<br>January–March 2020 | $NO_x$ ↓, $PM_{2.5}$ ↓, and $O_3$ ↑ | (Zhang et al., 2021) |
| GEOS-Chem | Forward CTM | 0.25 · 0.31 | MEIC | East Asia | 60% reduction of $NO_x$ and 30% reduction of VOC | January 1, 2020–February 15, 2020 | PAN ↑ | (Qiu et al., 2020) |
| CHIMERE | Top-down | 0.25 · 0.25 | Satellite-derived | East Asia | DESCO Inverse Algorithm | January 24, 2020–March 20, 2020 | $NO_2$ ↓ | (Ding et al., 2020) |
| WRF-Chem | Gaussian | 27 · 27 km | EDGAR | East Asia and Europe | Model 2016 to get spatial $PM_{2.5}$ gradient | 2016 | $PM_{2.5}$ ↓ | (Giani et al., 2020) |
| WRF-CHIMERE | Forward CTM | 60 · 60 km and 20 · 20 km | CAMS | Europe | Adjust mobile and industry | March 1, 2020–March 31, 2020 | $NO_2$ ↓, $O_3$ ↑↓, and $PM_{2.5}$ ↓ | (Menut et al., 2020) |
| CAM5 | Climate | 1.9 · 2.5 | CMIP6 + MEIC | Global | Adjust mobile, power, and industry | 2020 | T ↑ | (Yang et al., 2020) |
| FaIR | Climate | – | EDGAR | Global | Adjust mobile, industry, and buildings | 2020 | T ↓ | (Forster et al., 2020) |

This includes the "modeling" category in **Figure 2.** WRF-CMAQ = Weather Research Forecasting and Community Multiscale Air Quality; WRF-Chem = Weather Research Forecasting with Chemistry; WRF-CAMx = Weather Research Forecast with Comprehensive air quality model with extensions; GMI = Global Modeling Initiative; WRF-GC = Weather Research Forecast with GEOS-Chem; WRF-CHIMERE = Weather Research Forecast with CHIMERE chemistry-transport model; GEOS-Chem = Goddard Earth Observing System with Chemistry; CTM = chemical transport model; EDGAR = Emissions Database for Global Atmospheric Research; MEIC = Multi-resolution Emission Inventory for China; CAMS = Copernicus Atmosphere Monitoring Service; VOC = volatile organic compound; $NO_2$ = nitrogen dioxide; $SO_2$ = sulfur dioxide; $O_3$ = ozone; PM = particulate matter; CO = carbon monoxide; PAN = peroxyacetyl nitrate; $NO_x$ = nitrogen oxide.

and Africa are notably missing, although it is anticipated that modeling studies will be published in the future for these regions.

Most of the modeling studies listed in **Table 4** used a traditional forward Eulerian CTM, such as the Weather Research Forecasting and Community Multiscale Air Quality (Wong et al., 2012), Weather Research Forecasting with Chemistry (Grell et al., 2005), or Goddard Earth Observing System with Chemistry (Henze et al., 2007) models. All of the studies simulate business-as-usual conditions with a baseline emissions inventory. A variety of baseline inventories were used (**Table 4**), the most common being the global Emissions Database for Global Atmospheric Research (EDGAR) inventory (Crippa et al., 2020) and the Multi-resolution Emission Inventory for China (He, 2012). Many of the modeling studies adjusted their input emission inventories by scaling all emission sectors relative to changes in ambient or satellite observations (Griffith et al., 2020; Le et al., 2020a; Qiu et al., 2020; Zhang et al., 2020c; Zhang et al., 2021). Others have taken a sector-by-sector approach to scaling emission inventories (Forster et al., 2020; Huang et al., 2020; Le Quéré et al., 2020; Li et al., 2020a; Liu et al., 2020b; Menut et al., 2020; Wang et al., 2020d; Yang et al., 2020). For example, Forster et al. (2020) scaled mobile source emissions based on mobility and traffic count data, Huang et al. (2020) scaled industrial emissions based on economic and industrial activity data, and Le Quéré et al. (2020) scaled power generation emissions using energy statistics. Forster et al. have made publicly available a lockdown-adjusted daily inventory based on EDGAR emissions of $CO_2$, $CH_4$, $N_2O$, $SO_2$, BC, OC, CO, NMVOC, $NH_3$, and $NO_x$ for each country throughout the COVID-19 lockdown period.

In general, by modeling both baseline and COVID-19-perturbed emissions scenarios, the effects of meteorology can be isolated from those related to changes in emissions and can then be used to quantitatively assess the impacts of emission changes on the formation of secondary pollutants, such as $O_3$ and $PM_{2.5}$. Other studies have modeled constant or prepandemic emissions during the lockdown period to quantify the expected changes in atmospheric concentrations due to meteorology alone and thereby deduce the fraction of observed changes in air quality that are due to emission changes. Additionally, TROPOMI $NO_2$ vertical column densities were used to derive top-down scaling factors of $NO_x$ emission inventories (Zhang et al., 2020c; Zhang et al., 2021), which were then used to assess impacts on $O_3$ and $PM_{2.5}$ formation (Zhang et al., 2021). Ding et al. (2020) use an inverse modeling algorithm to derive top-down $NO_x$ emissions in China. Finally, climate models were used in some studies to assess COVID-19 perturbations in bottom-up emission inventories and their impacts on global radiative forcing (Forster et al., 2020; Yang et al., 2020). Although the number of modeling studies comprises <10% of the total number of studies analyzed here (**Figure 2**), they provide an explicit means by which to control the effects of meteorology on observed changes in primary and secondary pollutants.

## 3. Results and discussion

### *3.1. "Business as usual" emission inventory*

Worldwide lockdown measures strongly impacted the transportation sector (Forster et al., 2020; Le Quéré et al., 2020). To assess the impact that the transportation sector typically has on pollutant emissions for each country, a "business as usual" emission scenario was investigated using the 2015 EDGAR v5 (Crippa et al., 2020), which is the most recent year for which data are publicly available. **Figure 3** shows a world map colored by the largest source of $NO_x$ emissions for each country as well as characteristic examples of the contribution of different sectors to the $NO_x$, CO, and $PM_{2.5}$ emissions for various countries around the world. Emission sectors are separated into transportation, energy and manufacturing, industrial and other processes, building and miscellaneous, and agriculture by lumping IPCC emission categories (see Table S2). Following the IPCC guidelines, energy and manufacturing (IPCC 1.A.1, 1.A.2, 1.B.1, 1.B.2) is classified as fuel combustion activities associated with energy production and industry. All other industrial emissions are included under industrial and other processes. In the following, the contribution of the different sectors to $NO_x$, $PM_{2.5}$, and CO emissions is discussed and detailed differences for countries around the world are provided in Section S2. Pie charts in **Figure 3** are used to highlight differences in the contribution of the various pollutant sectors for countries representative of different regions of the world, with an emphasis on the countries listed in **Tables 5–10.** The category "building emissions" includes residential, commercial, and institutional combustion as well as other combustion sources, whereas "miscellaneous emissions" apply to all remaining emissions from fuel combustion that are not specified elsewhere. Note that agricultural and land-use change emissions, for example, of $NO_x$ from soil are not included in the EDGAR emission inventory, which likely results in an underestimation of the agricultural $NO_x$ emissions. Global annual $NO_x$ emissions based on the 2015 EDGAR inventory were 40 Tg of nitrogen with agriculture accounting for less than 1%. However, global soil $NO_x$ emissions are estimated to be around 5 Tg/year (Yan et al., 2005).

The global EDGAR inventory provides context for expected changes in air pollutant species due to the COVID-19 pandemic, especially those related to the transportation, energy, manufacturing, and industrial sectors. Globally, the median transportation contribution was 36% (15%–51%), 8% (3%–19%), and 30% (5%–70%) for the $NO_x$, primary $PM_{2.5}$, and CO emissions, respectively.

Countries were further divided into developed (Annex I) and developing (Annex II) categories based on the United Nations (2020) Climate Change framework to examine the contribution differences of the various emission sectors. The median transportation contribution for Annex I countries was 44% (36%–56%), 14% (8%–19%), and 25% (17%–44%) for the $NO_x$, primary $PM_{2.5}$, and CO emissions, respectively, whereas for Annex II countries, it was 29% (5%–49%), 9% (2%–42%), and 35% (1%–75%). Although the contribution of transportation emissions varied for the above pollutants, it is evident that

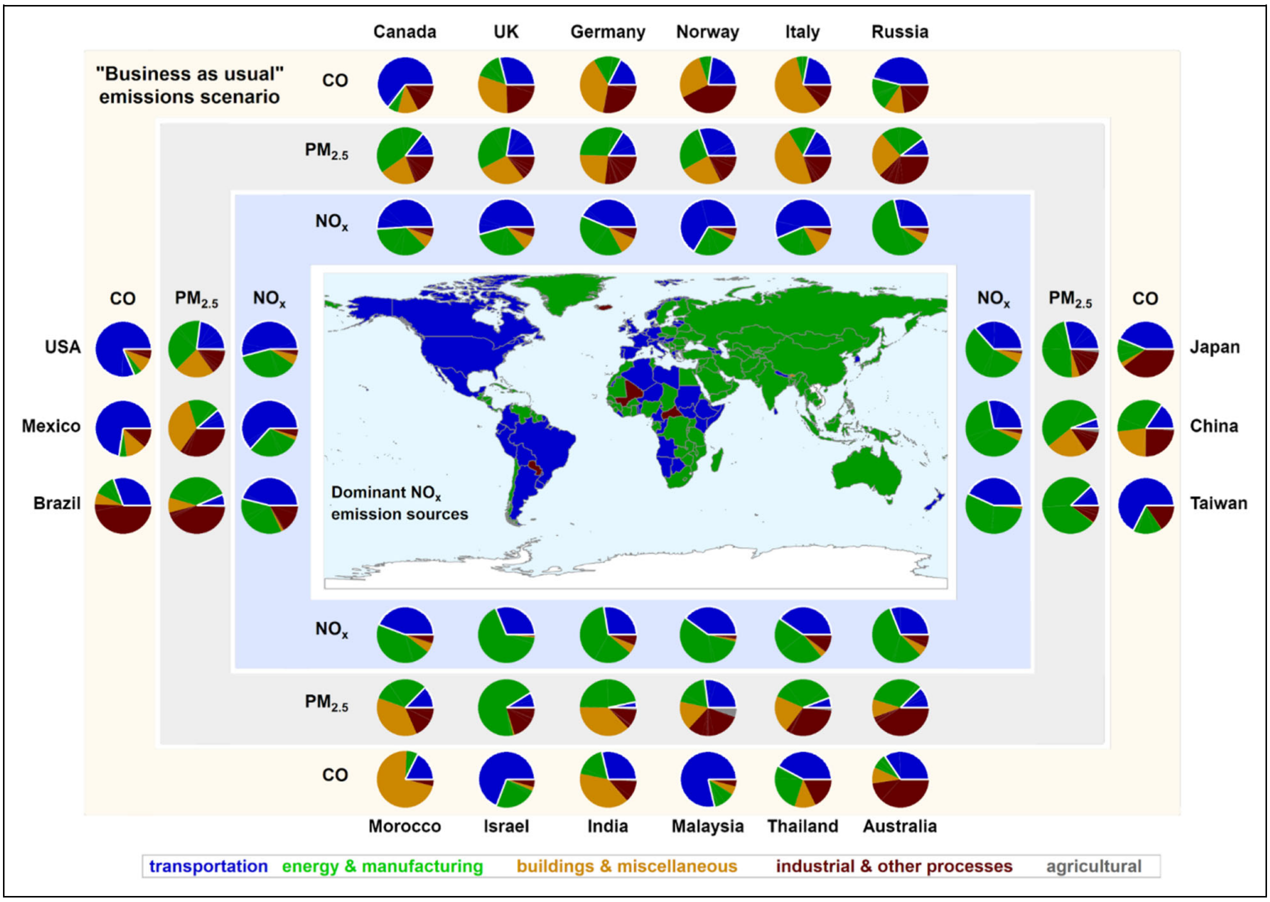


**Figure 3.** Distribution of emissions among different sectors (pie charts) based on the "business as usual" scenario using the 2015 Emissions Database for Global Atmospheric Research (EDGAR v5) for nitrogen oxide ($NO_x$), primary $PM_{2.5}$, and CO. Countries in the world map are colored by the dominant source of $NO_x$ emissions for each country. DOI: https://doi.org/10.1525/elementa.2021.00176.f3

**Table 5.** Nitrogen dioxide ($NO_2$) publications for the percentage change analysis and the absolute concentration change analysis. DOI: https://doi.org/10.1525/elementa.2021.00176.t5

| $NO_2$ | Country | Publications |
|---|---|---|
| East Asia | China | (Agarwal et al., 2020), (Bao and Zhang, 2020),[a] (Bauwens et al., 2020), (Chen et al., 2020c), (Diamond and Wood, 2020), (Forster et al., 2020), (Gautam, 2020a), (Griffith et al., 2020), (X Huang et al., 2020), (Le et al., 2020a),[a] (Lian et al., 2020)[a], (Liu et al., 2020a), (Ma and Kang, 2020),[a] (Metya et al., 2020), (Nichol et al., 2020),[a] (Pei et al., 2020),[a] (Shakoor et al., 2020),[a] (Shi and Brasseur, 2020),[a] (Silver et al., 2020), (Venter et al., 2020), (Wang et al., 2020b),[a] (Xu et al., 2020c),[a] (Zhang et al., 2020a),[a] (Zhang et al., 2020c), (Zhao et al., 2020b),[a] (Zheng et al., 2020), (Wang et al., 2020e),[a] (Fu et al., 2020), (Wang et al., 2020f),[a] (Wang et al., 2020a),[a] (Ding et al., 2020), (Chen et al., 2020d),[a] (Ghahremanloo et al., 2020), (Zhang et al., 2020d), (Fan et al., 2020),[a] (Wan et al., 2020),[a] (Xu et al., 2020c),[a] (Yuan et al., 2021),[a] (Zhang et al., 2021), (Liu et al., 2020b), (Liu et al., 2020c), (Wang et al., 2021),[a] (Su et al., 2020), (Miyazaki et al., 2020), (Huang and Sun, 2020), (Wang and Zhang, 2020), (Xu et al., 2020b),[a] (Park et al., 2020) |
| | Japan | (Ghahremanloo et al., 2020), (Ma and Kang, 2020),[a] (Fu et al., 2020) |
| | South Korea | (Fu et al., 2020), (Han et al., 2020),[a] (Ju et al., 2020),[a] (Bauwens et al., 2020), (Ma and Kang, 2020),[a] (Ghahremanloo et al., 2020) |
| | Taiwan | (Forster et al., 2020) |

*(continued)*

TABLE 5. *(continued)*

| $NO_2$ | Country | Publications |
|---|---|---|
| South Asia | India | (Agarwal et al., 2020), (Bera et al., 2020),[a] (Dhaka et al., 2020), (Forster et al., 2020), (Gautam, 2020a), (Jain and Sharma, 2020),[a] (Kumari and Toshniwal, 2020),[a] (Mahato et al., 2020),[a] (Metya et al., 2020), (Navinya et al., 2020), (Resmi et al., 2020),[a] (Selvam et al., 2020),[a] (Sharma et al., 2020b),[a] (Siddiqui et al., 2020), (Venter et al., 2020), (Fu et al., 2020), (Gautam et al., 2020),[a] (Biswal et al., 2020), (Mahato and Ghosh, 2020),[a] (Kant et al., 2020), (Zhang et al., 2020d), (Sharma et al., 2020a),[a] (Harshita and Vivek, 2020), (Singh et al., 2020),[a] (Kumari et al., 2020),[a] (Bedi et al., 2020),[a] (Beig et al., 2020),[a] (Naqvi et al., 2020), (Vadrevu et al., 2020) |
| | Nepal | (Venter et al., 2020) |
| | Bangladesh | (Masum and Pal, 2020)[a] |
| Southeast Asia | Malaysia | (Kanniah et al., 2020),[a] (Suhaimi et al., 2020), (Ash'aari et al., 2020)[a] |
| | Thailand | (Venter et al., 2020), (Stratoulias and Nuthammachot, 2020)[a] |
| | Singapore | (Jiayu and Federico, 2020)[a] |
| Central Asia | Kazakhstan | (Kerimray et al., 2020)[a] |
| West Asia | Turkey | (Fu et al., 2020), (Şahin, 2020)[a] |
| | Iran | (Bauwens et al., 2020), (Broomandi et al., 2020)[a] |
| | Iraq | (Hashim et al., 2020)[a] |
| | Saudi Arabia | (Anil and Alagha, 2020)[a] |
| North America | United States | (Bauwens et al., 2020), (Berman and Ebisu, 2020),[a] (Connerton et al., 2020),[a] (Forster et al., 2020), (Goldberg et al., 2020), (Jia et al., 2020a),[a] (Shakoor et al., 2020),[a] (Tanzer-Gruener et al., 2020),[a] (Venter et al., 2020), (Zangari et al., 2020),[a] (Fu et al., 2020), (Chen et al., 2020b), (Zhang et al., 2020d), (Hudda et al., 2020),[a] (Xiang et al., 2020), (Liu et al., 2021b), (Naeger and Murphy, 2020) |
| | Canada | (Adams, 2020),[a] (Forster et al., 2020), (Venter et al., 2020) |
| | Mexico | (Venter et al., 2020), (Fu et al., 2020) |
| South America | Brazil | (Connerton et al., 2020),[a] (Dantas et al., 2020),[a] (Nakada and Urban, 2020),[a] (Siciliano et al., 2020a),[a] (Fu et al., 2020), (Krecl et al., 2020), (Siciliano et al., 2020b) |
| | Ecuador | (Forster et al., 2020), (Zalakeviciute et al., 2020),[a] (Zambrano-Monserrate and Ruano, 2020),[a] (Parra and Espinoza, 2020),[a] (Pacheco et al., 2020) |
| | Chile | (Forster et al., 2020), (Venter et al., 2020) |
| | Peru | (Venter et al., 2020), (Fu et al., 2020) |
| | Colombia | (Mendez-Espinosa et al., 2020),[a] (Forster et al., 2020) |
| Europe | Multiple countries | (Baldasano, 2020),[a] (Bauwens et al., 2020), (Cameletti, 2020),[a] (Collivignarelli et al., 2020),[a] (Connerton et al., 2020),[a] (Forster et al., 2020), (Gautam, 2020a), (Menut et al., 2020), (Sicard et al., 2020),[a] (Tobías et al., 2020),[a] (Venter et al., 2020), (Higham et al., 2020),[a] (Fu et al., 2020), (Petetin et al., 2020), (Martorell-Marugán et al., 2021),[a] (Filippini et al., 2020), (Zhang et al., 2020d), (Gualtieri et al., 2020),[a] (Ordóñez et al., 2020), (Ropkins and Tate, 2020), (Wyche et al., 2020), (Ljubenkov et al., 2020), (Jakovljević et al., 2020)[a] |
| Oceania | Australia | (Forster et al., 2020), (Venter et al., 2020), (Fu et al., 2020) |
| | New Zealand | (Patel et al., 2020)[a] |
| Africa | Morocco | (Otmani et al., 2020),[a] (Ass et al., 2020)[a] |

[a]Publications that include absolute concentrations and relative changes.

transportation reduction measures during lockdowns are expected to consistently have a greater impact on CO and $NO_x$ emissions than for primary $PM_{2.5}$ worldwide.

### *3.2. Worldwide lockdown measures*

Next, we discuss the impact of policy actions designed to mitigate the COVID-19 pandemic and relate the stringency of lockdown measures with observed changes in the atmosphere. The onset and temporal evolution of SARS-CoV-2 infection rates have varied globally, as have the respective lockdown periods, resulting in emission reductions that are distributed over time and space. Although the onset of lockdown measures is well-defined on national or state levels, the transition to the

**Table 6.** $PM_{2.5}$ publications for the percentage change analysis and the absolute concentration change analysis. DOI: https://doi.org/10.1525/elementa.2021.00176.t6

| $PM_{2.5}$ | Country | Publications |
|---|---|---|
| East Asia | China | (Agarwal et al., 2020), (Bao and Zhang, 2020),[a] (Chauhan and Singh, 2020),[a] (Chen et al., 2020c),[a] (Huang et al., 2020), (Le et al., 2020a),[a] (Li et al., 2020a), (Li et al., 2020b),[a] (Lian et al., 2020),[a] (Ma and Kang, 2020),[a] (Nichol et al., 2020),[a] (Rodríguez-Urrego and Rodríguez-Urrego, 2020),[a] (Shakoor et al., 2020),[a] (Shi and Brasseur, 2020),[a] (Silver et al., 2020), (Venter et al., 2020), (Wang et al., 2020b),[a] (Wang et al., 2020c), (Xu et al., 2020c),[a] (Zhang et al., 2020a),[a] (Zhao et al., 2020b),[a] (Zheng et al., 2020),[a] (Wang et al., 2020e),[a] (Fu et al., 2020), (Wang et al., 2020f),[a] (Wang et al., 2020a),[a] (Chen et al., 2020a),[a] (Chen et al., 2020d),[a] (Zhang et al., 2020d), (Wan et al., 2020),[a] (Lei et al., 2020),[a] (Xu et al., 2020c),[a] (Giani et al., 2020), (Yuan et al., 2021),[a] (Zhang et al., 2021), (Liu et al., 2020b),[a] (Liu et al., 2020c),[a] (Su et al., 2020), (Xu et al., 2020a),[a] (Jia et al., 2020b) |
| | Japan | (Ma and Kang, 2020),[a] (Fu et al., 2020), (Rodríguez-Urrego and Rodríguez-Urrego, 2020),[a] (Wang and Zhang, 2020), (Xu et al., 2020b)[a] |
| | South Korea | (Ma and Kang, 2020),[a] (Fu et al., 2020), (Han et al., 2020),[a] (Ju et al., 2020)[a] |
| | Nepal, Mongolia | (Rodríguez-Urrego and Rodríguez-Urrego, 2020)[a] |
| | Taiwan | (Griffith et al., 2020) |
| South Asia | India | (Agarwal et al., 2020), (Bera et al., 2020),[a] (Chauhan and Singh, 2020),[a] (Jain and Sharma, 2020),[a] (Kumari and Toshniwal, 2020),[a] (Mahato et al., 2020),[a] (Navinya et al., 2020), (Resmi et al., 2020),[a] (Selvam et al., 2020),[a] (Sharma et al., 2020b),[a] (Singh and Chauhan, 2020), (Venter et al., 2020), (Fu et al., 2020), (Gautam et al., 2020),[a] (Mahato and Ghosh, 2020),[a] (Kant et al., 2020), (Zhang et al., 2020d), (Sharma et al., 2020a),[a] (Harshita and Vivek, 2020), (Singh et al., 2020),[a] (Kumari et al., 2020),[a] (Bedi et al., 2020),[a] (Rodríguez-Urrego and Rodríguez-Urrego, 2020),[a] (Beig et al., 2020)[a] |
| | Sri Lanka | (Rodríguez-Urrego and Rodríguez-Urrego, 2020)[a] |
| | Nepal | (Venter et al., 2020) |
| | Bangladesh | (Masum and Pal, 2020),[a] (Rodríguez-Urrego and Rodríguez-Urrego, 2020)[a] |
| Southeast Asia | Malaysia | (Abdullah et al., 2020),[a] (Kanniah et al., 2020),[a] (Mohd Nadzir et al., 2020),[a] (Suhaimi et al., 2020),[a] (Mohd Nadzir et al., 2020),[a] (Ash'aari et al., 2020)[a] |
| | Vietnam | (Rodríguez-Urrego and Rodríguez-Urrego, 2020)[a] |
| | Indonesia | (Rodríguez-Urrego and Rodríguez-Urrego, 2020),[a] (Venter et al., 2020) |
| | Thailand | (Rodríguez-Urrego and Rodríguez-Urrego, 2020),[a] (Stratoulias and Nuthammachot, 2020)[a] |
| | Singapore | (Rodríguez-Urrego and Rodríguez-Urrego, 2020),[a] (Jiayu and Federico, 2020)[a] |
| Central Asia | Kazakhstan | (Kerimray et al., 2020),[a] (Rodríguez-Urrego and Rodríguez-Urrego, 2020)[a] |
| | Uzbekistan | (Rodríguez-Urrego and Rodríguez-Urrego, 2020)[a] |
| | Afghanistan | (Rodríguez-Urrego and Rodríguez-Urrego, 2020)[a] |
| West Asia | Turkey | (Fu et al., 2020), (Aydın et al., 2020), (Şahin, 2020),[a] (Rodríguez-Urrego and Rodríguez-Urrego, 2020)[a] |
| | Iran | (Broomandi et al., 2020),[a] (Faridi et al., 2020),[a] (Rodríguez-Urrego and Rodríguez-Urrego, 2020)[a] |
| | Iraq | (Hashim et al., 2020)[a] |
| | United Arab Emirates | (Venter et al., 2020) |
| | Israel, and Kuwait | (Rodríguez-Urrego and Rodríguez-Urrego, 2020)[a] |
| North America | United States | (Berman and Ebisu, 2020),[a] (Bekbulat et al., 2021),[a] (Chauhan and Singh, 2020),[a] (Connerton et al., 2020),[a] (Jia et al., 2020a),[a] (Shakoor et al., 2020),[a] (Tanzer-Gruener et al., 2020),[a] (Venter et al., 2020), (Zangari et al., 2020),[a] (Fu et al., 2020), (Chen et al., 2020b), (Zhang et al., 2020d), (Pan et al., 2020),[a] (Son et al., 2020),[a] (Hudda et al., 2020),[a] (Xiang et al., 2020), (Liu et al., 2021b) |
| | Canada | (Adams, 2020),[a] (Venter et al., 2020) |
| | Mexico | (Rodríguez-Urrego and Rodríguez-Urrego, 2020),[a] (Venter et al., 2020), (Fu et al., 2020) |

*(continued)*

TABLE 6. *(continued)*

| $PM_{2.5}$ | Country | Publications |
|---|---|---|
| South America | Brazil | (Connerton et al., 2020),[a] (Nakada and Urban, 2020),[a] (Nakada and Urban, 2020),[a] (Fu et al., 2020) |
| | Ecuador | (Zalakeviciute et al., 2020),[a] (Zambrano-Monserrate and Ruano, 2020),[a] (Parra and Espinoza, 2020)[a] |
| | Chile | (Rodríguez-Urrego and Rodríguez-Urrego, 2020),[a] (Venter et al., 2020) |
| | Peru | (Rodríguez-Urrego and Rodríguez-Urrego, 2020),[a] (Venter et al., 2020), (Fu et al., 2020) |
| | Colombia | (Rodríguez-Urrego and Rodríguez-Urrego, 2020),[a] (Mendez-Espinosa et al., 2020)[a] |
| Europe | Multiple countries | (Cameletti, 2020), (Chauhan and Singh, 2020),[a] (Collivignarelli et al., 2020),[a] (Connerton et al., 2020),[a] (Menut et al., 2020), (Rodríguez-Urrego and Rodríguez-Urrego, 2020),[a] (Sicard et al., 2020),[a] (Venter et al., 2020), (Zoran et al., 2020),[a] (Higham et al., 2020),[a] (Fu et al., 2020), (Martorell-Marugán et al., 2021),[a] (Zhang et al., 2020d), (Giani et al., 2020), (Gualtieri et al., 2020),[a] (Ropkins and Tate, 2020), (Wyche et al., 2020), (Ljubenkov et al., 2020) |
| Oceania | Australia | (Venter et al., 2020), (Fu et al., 2020) |
| | New Zealand | (Patel et al., 2020)[a] |
| Africa | Uganda | (Rodríguez-Urrego and Rodríguez-Urrego, 2020)[a] |

PM = particulate matter.

[a]Publications that include absolute concentrations and relative changes.

**Table 7.** Ozone ($O_3$) publications for the percentage change analysis and the absolute concentration change analysis. DOI: https://doi.org/10.1525/elementa.2021.00176.t7

| $O_3$ | Country | Publications |
|---|---|---|
| East Asia | China | (Chen et al., 2020c), (Huang et al., 2020), (Le et al., 2020a),[a] (Li et al., 2020b),[a] (Lian et al., 2020),[a] (Shi and Brasseur, 2020), (Silver et al., 2020), (Venter et al., 2020), (Wang et al., 2020b),[a] (Xu et al., 2020c), (Zhang et al., 2020a),[a] (Zhao et al., 2020b),[a] (Wang et al., 2020e),[a] (Fu et al., 2020), (Wang et al., 2020f),[a] (Wang et al., 2020a),[a] (Zhang et al., 2020d), (Wan et al., 2020),[a] (Lei et al., 2020),[a] (Xu et al., 2020c),[a] (Yuan et al., 2021),[a] (Zhang et al., 2021), (Liu et al., 2020b),[a] (Liu et al., 2020c),[a] (Wang and Zhang, 2020), (Xu et al., 2020b)[a] |
| | Japan | (Fu et al., 2020) |
| | South Korea | (Han et al., 2020),[a] (Ju et al., 2020),[a] (Fu et al., 2020) |
| South Asia | India | (Bera et al., 2020),[a] (Jain and Sharma, 2020),[a] (Mahato et al., 2020),[a] (Resmi et al., 2020),[a] (Selvam et al., 2020),[a] (Sharma et al., 2020b),[a] (Venter et al., 2020), (Fu et al., 2020), (Gautam et al., 2020),[a] (Chatterjee et al., 2020),[a] (Mahato and Ghosh, 2020),[a] (Zhang et al., 2020d), (Panda et al., 2020),[a] (Sharma et al., 2020a),[a] (Harshita and Vivek, 2020), (Singh et al., 2020),[a] (Kumari et al., 2020),[a] (Bedi et al., 2020),[a] (Beig et al., 2020),[a] (Naqvi et al., 2020) |
| | Nepal | (Venter et al., 2020) |
| Southeast Asia | Thailand | (Venter et al., 2020), (Stratoulias and Nuthammachot, 2020)[a] |
| | Singapore | (Jiayu and Federico, 2020)[a] |
| Central Asia | Kazakhstan | (Kerimray et al., 2020)[a] |
| West Asia | Turkey | (Fu et al., 2020), (Aydın et al., 2020) |
| | Iran | (Broomandi et al., 2020)[a] |
| | Iraq | (Hashim et al., 2020)[a] |
| | United Arab Emirates | (Venter et al., 2020) |
| | Saudi Arabia | (Anil and Alagha, 2020)[a] |
| North America | United States | (Bekbulat et al., 2021),[a] (Jia et al., 2020a),[a] (Venter et al., 2020), (Fu et al., 2020), (Chen et al., 2020b), (Zhang et al., 2020d), (Pan et al., 2020),[a] (Liu et al., 2021b) |

*(continued)*

TABLE 7. *(continued)*

| $O_3$ | Country | Publications |
|---|---|---|
| | Canada | (Adams, 2020),[a] (Venter et al., 2020) |
| | Mexico | (Venter et al., 2020), (Fu et al., 2020) |
| South America | Brazil | (Dantas et al., 2020),[a] (Fu et al., 2020), (Nakada and Urban, 2020),[a] (Siciliano et al., 2020b) |
| | Ecuador | (Zambrano-Monserrate and Ruano, 2020),[a] (Parra and Espinoza, 2020)[a] |
| | Chile | (Venter et al., 2020) |
| | Peru | (Venter et al., 2020), (Fu et al., 2020) |
| Europe | Multiple countries | (Collivignarelli et al., 2020),[a] (Menut et al., 2020), (Sicard et al., 2020),[a] (Tobías et al., 2020),[a] (Venter et al., 2020), (Higham et al., 2020),[a] (Fu et al., 2020), (Martorell-Marugán et al., 2021),[a] (Zhang et al., 2020d), (Gualtieri et al., 2020),[a] (Ordóñez et al., 2020), (Ropkins and Tate, 2020), (Wyche et al., 2020) |
| Oceania | Australia | (Venter et al., 2020), (Fu et al., 2020) |
| | New Zealand | (Patel et al., 2020)[a] |
| Africa | Morocco | (Ass et al., 2020)[a] |

[a]Publications that include absolute concentrations and relative changes.

**Table 8.** Carbon monoxide (CO) publications for the percentage change analysis and the absolute concentration change analysis. DOI: https://doi.org/10.1525/elementa.2021.00176.t8

| CO | Country | Publications |
|---|---|---|
| East Asia | China | (Bao and Zhang, 2020),[a] (Chen et al., 2020c), (Lian et al., 2020), (Metya et al., 2020), (Shakoor et al., 2020), (Silver et al., 2020), (Wang et al., 2020b),[a] (Xu et al., 2020c),[a] (Zhang et al., 2020a),[a] (Zhao et al., 2020b),[a] (Wang et al., 2020e),[a] (Fu et al., 2020), (Wang et al., 2020f),[a] (Wang et al., 2020a),[a] (Chen et al., 2020a), (Chen et al., 2020d), (Ghahremanloo et al., 2020), (Zhang et al., 2020d), (Wan et al., 2020),[a] (Xu et al., 2020c),[a] (Yuan et al., 2021),[a] (Liu et al., 2020b), (Liu et al., 2020c), (Su et al., 2020), (Xu et al., 2020a), (Wang and Zhang, 2020), (Xu et al., 2020b),[a] (Park et al., 2020) |
| | Japan | (Fu et al., 2020), (Ghahremanloo et al., 2020) |
| | South Korea | (Han et al., 2020),[a] (Ju et al., 2020),[a] (Fu et al., 2020), (Ghahremanloo et al., 2020) |
| South Asia | India | (Bera et al., 2020),[a] (Jain and Sharma, 2020),[a] (Mahato et al., 2020),[a] (Navinya et al., 2020), (Resmi et al., 2020), (Selvam et al., 2020),[a] (Sharma et al., 2020b),[a] (Fu et al., 2020), (Gautam et al., 2020),[a] (Mahato and Ghosh, 2020),[a] (Zhang et al., 2020d), (Panda et al., 2020),[a] (Harshita and Vivek, 2020), (V Singh et al., 2020),[a] (Kumari et al., 2020),[a] (Bedi et al., 2020),[a] (Beig et al., 2020)[a] |
| Southeast Asia | Malaysia | (Kanniah et al., 2020),[a] (Mohd Nadzir et al., 2020),[a] (Suhaimi et al., 2020),[a] (Mohd Nadzir et al., 2020),[a] (Ash'aari et al., 2020)[a] |
| | Singapore | (Jiayu and Federico, 2020)[a] |
| Central Asia | Kazakhstan | (Kerimray et al., 2020)[a] |
| West Asia | Turkey | (Fu et al., 2020), (Şahin, 2020)[a] |
| | Iran | (Broomandi et al., 2020)[a] |
| | Saudi Arabia | (Anil and Alagha, 2020) |
| North America | United States | (Connerton et al., 2020),[a] (Shakoor et al., 2020), (Tanzer-Gruener et al., 2020),[a] (Fu et al., 2020), (Chen et al., 2020b), (Zhang et al., 2020d), (Xiang et al., 2020), (Liu et al., 2021b) |
| | Mexico | (Fu et al., 2020) |
| South America | Brazil | (Connerton et al., 2020),[a] (Dantas et al., 2020),[a] (Nakada and Urban, 2020),[a] (Siciliano et al., 2020a),[a] (Siciliano et al., 2020a),[a] (Fu et al., 2020), (Siciliano et al., 2020b) |
| | Ecuador | (Zalakeviciute et al., 2020),[a] (Parra and Espinoza, 2020)[a] |
| | Peru | (Fu et al., 2020) |
| Europe | Multiple countries | Italy: (Collivignarelli et al., 2020),[a] France: (Connerton et al., 2020),[a] Russia: (Fu et al., 2020), UK: (Fu et al., 2020), Spain: (Martorell-Marugán et al., 2021)[a] |
| Oceania | Australia | (Fu et al., 2020) |
| Africa | – | – |

[a]Publications that include absolute concentrations and relative changes.

**Table 9.** $PM_{10}$ publications for the percentage change analysis. DOI: https://doi.org/10.1525/elementa.2021.00176.t9

| $PM_{10}$ | Country | Publications |
|---|---|---|
| East Asia | China | (Bao and Zhang, 2020; Chen et al., 2020c; Chen et al., 2020d; Fu et al., 2020; Shakoor et al., 2020; Silver et al., 2020; Wan et al., 2020; Wang et al., 2020a; Wang et al., 2020b; Wang et al., 2020f; Xu et al., 2020a; Xu et al., 2020c; Zhang et al., 2020a; Zhao et al., 2020b; Zheng et al., 2020; Yuan et al., 2021), (Wang and Zhang, 2020), (Xu et al., 2020b) |
| | Japan | (Fu et al., 2020) |
| | South Korea | (Fu et al., 2020; Han et al., 2020; Ju et al., 2020) |
| South Asia | India | (Bedi et al., 2020; Bera et al., 2020; Fu et al., 2020; Gautam et al., 2020; Harshita and Vivek, 2020; Jain and Sharma, 2020; Kant et al., 2020; Kumari and Toshniwal, 2020; Kumari et al., 2020; Mahato and Ghosh, 2020; Mahato et al., 2020; Navinya et al., 2020; Resmi et al., 2020; Selvam et al., 2020; Sharma et al., 2020a; Sharma et al., 2020b; Singh et al., 2020) |
| | Bangladesh | (Masum and Pal, 2020) |
| Southeast Asia | Malaysia | (Kanniah et al., 2020; Mohd Nadzir et al., 2020) |
| | Thailand | (Stratoulias and Nuthammachot, 2020) |
| | Singapore | (Jiayu and Federico, 2020) |
| Central Asia | – | – |
| West Asia | Turkey | (Fu et al., 2020; Şahin, 2020) |
| | Iran | (Broomandi et al., 2020; Faridi et al., 2020; Hashim et al., 2020) |
| | Iraq | |
| | Saudi Arabia | (Anil and Alagha, 2020) |
| North America | United States | (Chen et al., 2020b; Fu et al., 2020; Shakoor et al., 2020; Liu et al., 2021b) |
| | Mexico | (Fu et al., 2020) |
| South America | Brazil | (Dantas et al., 2020; Fu et al., 2020; Nakada and Urban, 2020; Siciliano et al., 2020a), (Siciliano et al., 2020b) |
| | Peru | (Fu et al., 2020) |
| | Colombia | (Mendez-Espinosa et al., 2020) |
| Europe | Multiple countries | Italy: (Collivignarelli et al., 2020; Fu et al., 2020; Gualtieri et al., 2020; Sicard et al., 2020; Zoran et al., 2020), France: (Fu et al., 2020: Sicard et al., 2020, #5), Spain: (Fu et al., 2020; Tobías et al., 2020; Martorell-Marugán et al., 2021), United Kingdom: (Fu et al., 2020; Ropkins and Tate, 2020; Wyche et al., 2020), Germany, and Russia (Fu et al., 2020) |
| Oceania | Australia | (Fu et al., 2020) |
| | New Zealand | (Patel et al., 2020) |
| Africa | Morocco | (Otmani et al., 2020), (Ass et al., 2020) |

PM = particulate matter.

"new normal" after the initial containment of the disease still implies ongoing changes to anthropogenic emission sectors such as transportation. Emissions thus dropped rapidly at the beginning of the lockdown, but the increases after the initial lockdown are often much slower, and emissions may not return to their prepandemic levels, for example, due to changes in corporate policies for telecommuting, reduced business travel, and so on.

To better compare observations from different regions worldwide and at different times and stages of the pandemic, the government SI (Cameron-Blake et al., 2020; Petherick et al., 2020) is used. This index varies from 0 to 100 and takes into account available information on ordinal indicators of government responses to limit the spread of COVID-19. The index is available on national scales at a 1-day time resolution. The index provides a comparative measure only and is not designed to evaluate the effectiveness of a country's response. Categories that are included in the index are (1) the implementation and extent of school closures, (2) implementation and extent of workplace closures, (3) restrictions on public events, (4) restrictions on gatherings, (5) closure of public transport, (6) method of public information campaigns, for example, public officials urging caution or coordinated campaigns across traditional and social media, (7) extent of measures to enforce the lockdown, (8) restrictions on internal movement, (9) restrictions on international travel, (10) COVID-19 testing policy, and (11) contact tracing. As such, the index includes both measures that impact emissions and measures with no obvious consequence for emissions.

**Table 10.** Sulfur dioxide ($SO_2$) and other pollutant publications for the percentage change analysis. DOI: https://doi.org/10.1525/elementa.2021.00176.t10

| $SO_2$ | Country | Publications |
|---|---|---|
| East Asia | China | (Chen et al., 2020a; Chen et al., 2020c; Chen et al., 2020d; Fan et al., 2020; Fu et al., 2020; Ghahremanloo et al., 2020; Li et al., 2020a; Li et al., 2020b; Lian et al., 2020; Liu et al., 2020b; Liu et al., 2020c; Su et al., 2020; Wan et al., 2020; Wang et al., 2020a; Wang et al., 2020b; Wang et al., 2020f; Xu et al., 2020a; Xu et al., 2020c; Zhang et al., 2020a; Zhang et al., 2020d; Zhao et al., 2020b; Zheng et al., 2020; Yuan et al., 2021), (Wang and Zhang, 2020), (Xu et al., 2020b) |
| | Japan | (Fu et al., 2020; Ghahremanloo et al., 2020) |
| | South Korea | (Fu et al., 2020; Ghahremanloo et al., 2020; Han et al., 2020; Ju et al., 2020) |
| South Asia | India | (Bedi et al., 2020; Bera et al., 2020; Fu et al., 2020; Gautam et al., 2020; Harshita and Vivek, 2020; Kumari and Toshniwal, 2020; Kumari et al., 2020; Mahato et al., 2020; Metya et al., 2020; Navinya et al., 2020; Resmi et al., 2020; Selvam et al., 2020; Sharma et al., 2020a; Sharma et al., 2020b; Singh et al., 2020; Zhang et al., 2020d) |
| Southeast Asia | Malaysia | (Ash'aari et al., 2020; Kanniah et al., 2020; Suhaimi et al., 2020) |
| | Singapore | (Jiayu and Federico, 2020) |
| Central Asia | Kazakhstan | |
| West Asia | Turkey | (Fu et al., 2020; Şahin, 2020) |
| | Saudi Arabia | (Anil and Alagha, 2020) |
| North America | United States | (Zhang et al., 2020d) |
| | Mexico | (Fu et al., 2020) |
| South America | Brazil | (Nakada and Urban, 2020), (Fu et al., 2020) |
| | Ecuador | (Zalakeviciute et al., 2020) |
| Europe | Multiple countries | Italy: (Collivignarelli et al., 2020), (Zhang et al., 2020d), United Kingdom: (Higham et al., 2020), (Fu et al., 2020; Zhang et al., 2020d), Russia: (Fu et al., 2020), Italy: (Fu et al., 2020), France: (Fu et al., 2020), (Zhang et al., 2020d), Spain: (Fu et al., 2020), (Martorell-Marugán et al., 2021), (Zhang et al., 2020d), and Germany: (Zhang et al., 2020d) |
| Oceania | – | – |
| Africa | Morocco | (Otmani et al., 2020) |
| Other pollutants | | |
| $NO_x$ | China: (Chen et al., 2020a; Chen et al., 2020d; Jia et al., 2020b; Li et al., 2020a; Li et al., 2020b; Liu et al., 2020c; Qiu et al., 2020; Yuan et al., 2021), India: (Chatterjee et al., 2020; Panda et al., 2020), Italy: (Collivignarelli et al., 2020), United Kingdom: (Ropkins and Tate, 2020), Canada: (Adams, 2020), United States: (Xiang et al., 2020), and Brazil: (Nakada and Urban, 2020; Siciliano et al., 2020b) | |
| AOD | India: (Gautam, 2020b; Mahato and Ghosh, 2020; Ranjan et al., 2020; Zhang et al., 2020d), China (Diamond and Wood, 2020; Ghahremanloo et al., 2020; Zhang et al., 2020d; Shen et al., 2021), South Korea, and Japan (Ghahremanloo et al., 2020), North America, and Europe (Zhang et al., 2020d) | |
| NMVOCs | China: (Ghahremanloo et al., 2020; Jia et al., 2020b; Li et al., 2020a; Qiu et al., 2020), South Korea: (Ghahremanloo et al., 2020), Japan: (Ghahremanloo et al., 2020; Zhang et al., 2020b), India: (Beig et al., 2020; Resmi et al., 2020), Kazakhstan (Kerimray et al., 2020), Italy (Collivignarelli et al., 2020), Brazil (Siciliano et al., 2020b) | |
| $NH_3$ | India: (Bedi et al., 2020; Beig et al., 2020; Gautam et al., 2020; Mahato and Ghosh, 2020; Mahato et al., 2020) | |
| BC | India: (Panda et al., 2020), China: (Liu et al., 2020c; Wang et al., 2020a), Italy: (Collivignarelli et al., 2020), New Zealand: (Patel et al., 2020), United States: (Hudda et al., 2020; Xiang et al., 2020) | |
| AQI | Iraq: (Hashim et al., 2020), China: (Bao and Zhang, 2020; Chen et al., 2020c; He et al., 2020; Lian et al., 2020; Wan et al., 2020; Xu et al., 2020b; Xu et al., 2020c; Zhang et al., 2020a), India: (Gautam et al., 2020; Mahato and Ghosh, 2020; Mahato et al., 2020; Naqvi et al., 2020; Selvam et al., 2020; Sharma et al., 2020b; Siddiqui et al., 2020), Bangladesh: (Masum and Pal, 2020) | |

AOD = aerosol optical depth; BC = black carbon; NMVOC = nonmethane volatile organic compound; $NH_3$ = ammonia; AQI = air quality index; $NO_x$ = nitrogen oxide.

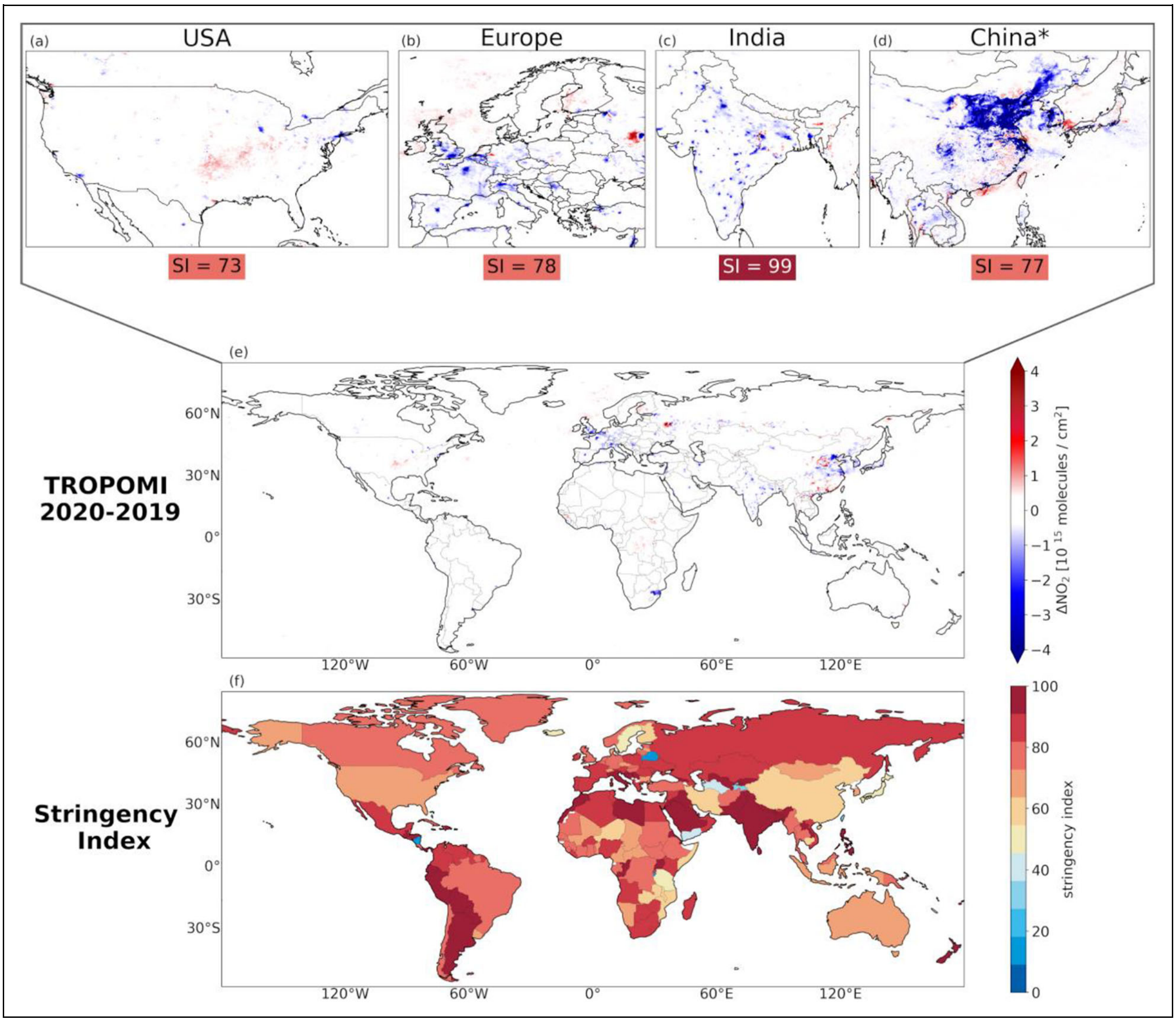


**Figure 4.** Meteorologically corrected TROPOMI $NO_2$ column difference between April 2020 and 2019 using the global Copernicus Atmosphere Monitoring Service-Integrated Forecasting System reanalysis in (a) the United States, (b) Europe, and (c) India at $0.1 \times 0.1$ resolution, as well as (d*) for the three post-Chinese New Year weeks in 2020 and 2019 in China at a $2 \times 2$ km resolution, (e) globally between April 2020 and 2019 at $0.4 \times 0.4$ resolution, and (f) the national stringency index as an indicator for the severity of lockdown averaged over April 2020. The corresponding stringency indices of the regions (a)–(d) are provided below the individual panels. DOI: https://doi.org/10.1525/elementa.2021.00176.f4

Here, we test the use of the government SI as an indicator for atmospheric composition change, with the data set (Cameron-Blake et al., 2020) as downloaded from the SI web page (Stringency Index, 2020). **Figure 4** shows the country-based SI averaged over April as a representative month for the most stringent conditions globally. China is an exception where lockdown measures were implemented in February–March and relaxed in April. Also shown is the April difference in $NO_2$ column concentrations based on TROPOMI measurements for 2020 compared to 2019. The high spatial resolution of TROPOMI is highlighted for the United States, Canada, Europe, India, and East Asia. Since China was the first country to undergo a lockdown at a time that coincided with the celebration of the Chinese New Year, the 3 post-Chinese New Year weeks in 2020 are compared to 2019 for the high spatial resolution map of China. Results in **Figure 4** are generated based on analysis performed as part of this work. The TROPOMI comparisons are only used qualitatively to show the effects of lockdowns in urban and industrialized environments around the world, and detailed analysis of emission reduction comparisons to stringency indices are the focus of future studies. The Copernicus Atmosphere Monitoring Service (CAMS) reanalysis results (Inness et al., 2019) were used to correct for variability of meteorology between the months of April 2019 and April 2020. The emissions used in the CAMS reanalysis were based on "business as usual" scenarios, unaffected by COVID-19 reductions. The CAMS 3-D $NO_2$ fields were interpolated to the location and time of all the individual TROPOMI observations used to construct the monthly mean. The averaging kernels were applied to obtain CAMS simulations of the TROPOMI observations. These data were averaged over the month of April, and the ratio 2020/2019 was applied to the TROPOMI monthly mean to correct for the expected meteorological impact on $NO_2$ between the 2 years.

Overall, densely populated regions around the world experienced $NO_2$ reductions, suggesting that the lockdowns and their consequent reduction in transportation and industrial activities influenced global $NO_2$ emissions. Specifically, various megacities shown in **Figure 4** had detectable $NO_2$ reductions including New Delhi, India; Beijing, China; New York City and Los Angeles, United States; Paris, France; and Sao Paulo, Brazil. A notable example highlighting the effect of lockdowns on emission reductions is India, the country with the most severe restrictions during April (SI = 98.6), which experienced $NO_2$ column concentration reductions for urban, industrial, and even remote regions across the country. Less densely populated regions around the world had no change, or sporadic increases, in $NO_2$ column densities (up to $10^{15}$ molecules $cm^{-2}$). Although measurements at remote sites are reported in this review, they represent the minority of the collected literature values (fewer than 5% of the reviewed data sets) because most studies focused on measurements observed predominantly in urban environments where emissions reductions were more evident.

### *3.3. Relative pollutant changes in different regions and their correlations with the SI*

**Figure 5** shows the relative changes in pollutant concentrations during the lockdown compared to reference periods for different continents and regions of the world. Pollutants include $NO_2$, $NO_x$, and CO, which have the largest expected contribution from transportation (see Section 3.1); $PM_{2.5}$ and $O_3$, secondary pollutants and the two most important pollutants for health impacts (Anderson et al., 2004); $SO_2$, $NH_3$, and NMVOCs, which are mostly related to primary gas-phase emissions; and $PM_{10}$, AOD, BC, and the AQI. For each region, ground-based measurements, satellite measurements, or modeling studies were performed for multiple countries, and often multiple cities within each country, using the different approaches discussed in the Methods section to determine the lockdown effects on pollutant concentrations. All results from these studies are combined in **Figure 5** to determine the broader impacts of lockdown measures and establish the variability of changes in atmospheric composition. Numbers in parentheses show the number of publications and the number of data sets considered to produce the respective distributions. A higher spatial resolution analysis is presented in the following sections. An overview of the literature associated with the respective compounds and regions is provided in **Tables 5–10**, and relative changes on a national level are further discussed in the Supplement (Section S3). All data are downloadable from the database (see Section 2.1).

$NO_2$ decreased for all continents and regions during lockdowns. The median reductions ranged from 20% to 54% (see **Figure 5**), except for Africa, where a 70% reduction was found based on two studies in Morocco (see **Table 5**, Section S3.1). The median reduction in $NO_x$ ranged from 26% to 67% (see Table 10 and Section S3.2). Note that the set of studies reporting $NO_x$ is considerably smaller than the literature on $NO_2$. The median reduction in CO ranged from 16% to 49%. Within one region, India had the largest variability of reported CO changes, ranging from decreases of 80% to increases of 60% (see **Table 8** and Section S3.3). Median reductions in $PM_{2.5}$ and $PM_{10}$ for all continents and regions ranged from 10% to 40% and 8% to 40%, respectively (see **Tables 6** and **9** and Sections S3.4 and S3.5). $PM_{2.5}$ measurements were widely used, whereas $PM_{10}$ measurements were limited to fewer studies. The median change in $O_3$ ranged from a decrease of 15% to an increase of 18% (see **Table 7** and Section S3.6). $O_3$ was the only pollutant that increased on a regional scale during the lockdowns, with a positive median change of 6.4% ($\pm$ 11%). The response of $O_3$ is complex and varies by season and region, as described further in Section 3.3.5. The median reduction in $SO_2$ for all continents and regions ranged from 5% to 49% (see **Table 10**and Section S3.7). For other pollutants, including AOD, NMVOCs, $NH_3$, BC, and the AQI, a much smaller number of publications for only a few regions were reported (see **Table 10** and Section S3.8).

#### 3.3.1. Importance of accounting for the effects of meteorology and emission trends

The literature summarized in this section lacks consistency in the analysis methodology or degree of meteorological normalization, which can confound the attribution of changes in ambient pollutant concentration changes to emissions reductions associated with COVID-19 lockdowns. Here, we compare reported changes, sorted by those that either do or do not correct for meteorology, to the SI in order to assess whether the changes in pollutant concentration correlate with metrics of lockdown intensity across a global scale. **Figure 6** shows box-and-whisker plots of $NO_2$, $PM_{2.5}$, and $O_3$ when combining data from all the countries around the globe and grouping them into different SI bins ranging from 20–40, 40–60, 60–80, and 80–100 (all bin ranges herein are defined as $\geq$ the lower number and $<$ the higher number). Measurements were further separated into direct comparisons of lockdown to reference periods as discussed in Section 2.3.1 and comparisons that were quantified and corrected for meteorological effects (see Sections 2.3.2 and 2.3.3).

For studies that performed a direct comparison of lockdown to reference periods without a meteorological correction, no significant trend in the median with increasing SI was found for $NO_2$, $PM_{2.5}$, or $O_3$. Rather, the changes were similar across SI bins, with average pollutant changes ($\pm$standard deviation) of –36% ($\pm$5%), –20% ($\pm$7%), and +6% ($\pm$ 1), respectively (**Figure 6**). Conversely, the binned SI did correlate with the change in $NO_2$ and $PM_{2.5}$ for studies that accounted for the effects of meteorology. The median change in $NO_2$ decreased from –13% to −48% and in $PM_{2.5}$ decreased from –10% to –33%, whereas the median change in $O_3$ increased from 0% to 4% with increasing SI. Studies performed in the 40–100 SI range were statistically significant for all pollutants, and

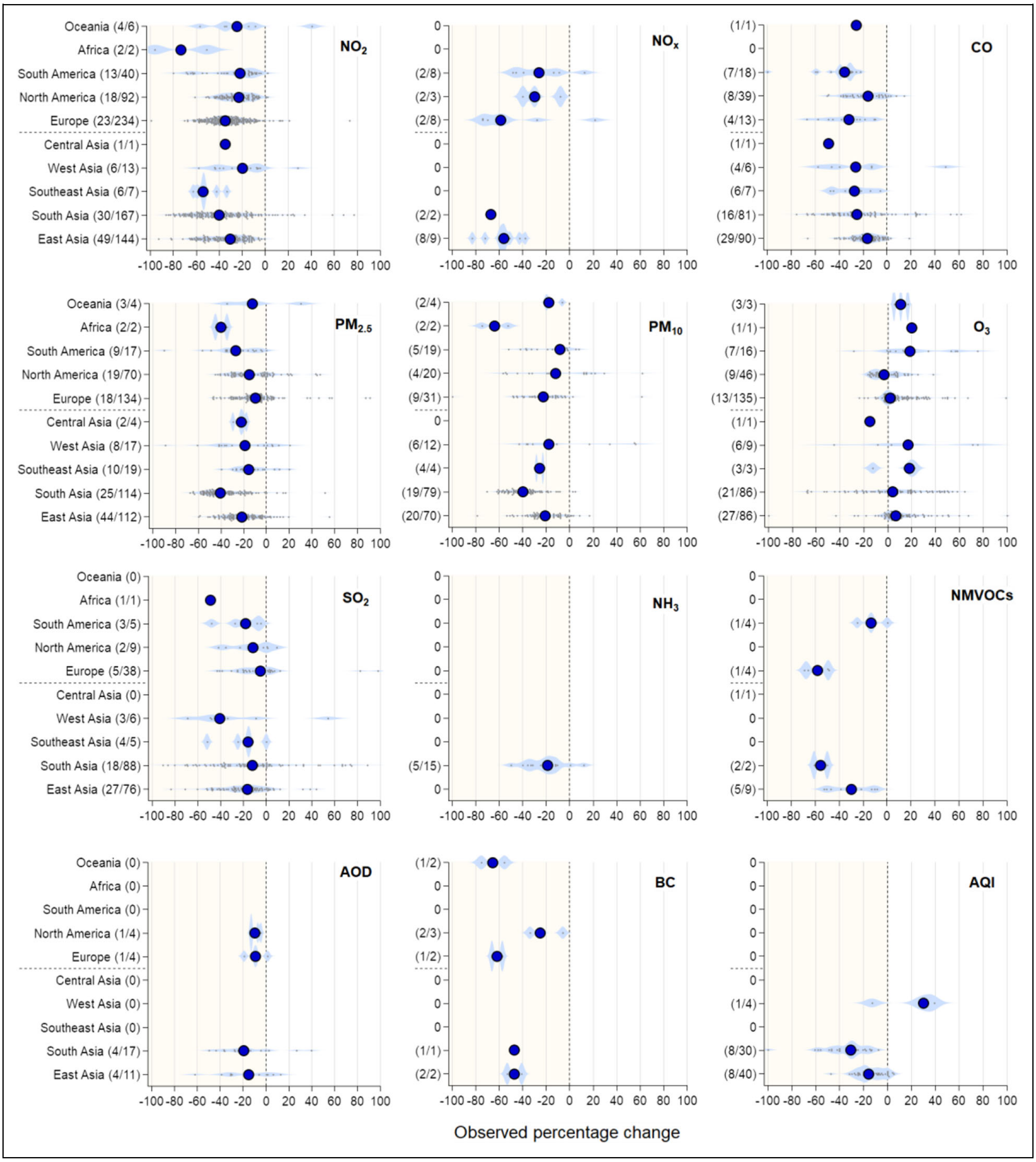


**Figure 5.** Distribution of the observed changes of pollutants as percentage difference during the lockdown for different regions of the world. Circle markers indicate the median values, and gray dots individual data sets averaged for periods ranging from days to several weeks. Numbers in parenthesis correspond to the number of publications and the number of measurements performed at each region/continent. DOI: https://doi.org/10.1525/elementa.2021.00176.f5



for both methods, with 19 or more data points per SI bin. Measurements were sparse for the 20–40 SI bin and statistically significant only for $NO_2$ (14). The same analysis was done for compounds less studied in the literature: CO, $SO_2$, and $PM_{10}$ (Figure S2). The change of these three pollutants did not correlate with the SI when at least three bins were populated, although dependencies on SI may become apparent for CO, $SO_2$, and $PM_{10}$ as more studies are published. Although there were only 44, 33, and 33 data sets in total that accounted for meteorology when reporting a change in concentration for CO, $SO_2$ and $PM_{10}$, respectively, stronger reductions were evident for all pollutants with increasing SI.

With the emissions of primary pollutants expected to decrease as the lockdown measures become stricter, these results highlight the importance of accounting and

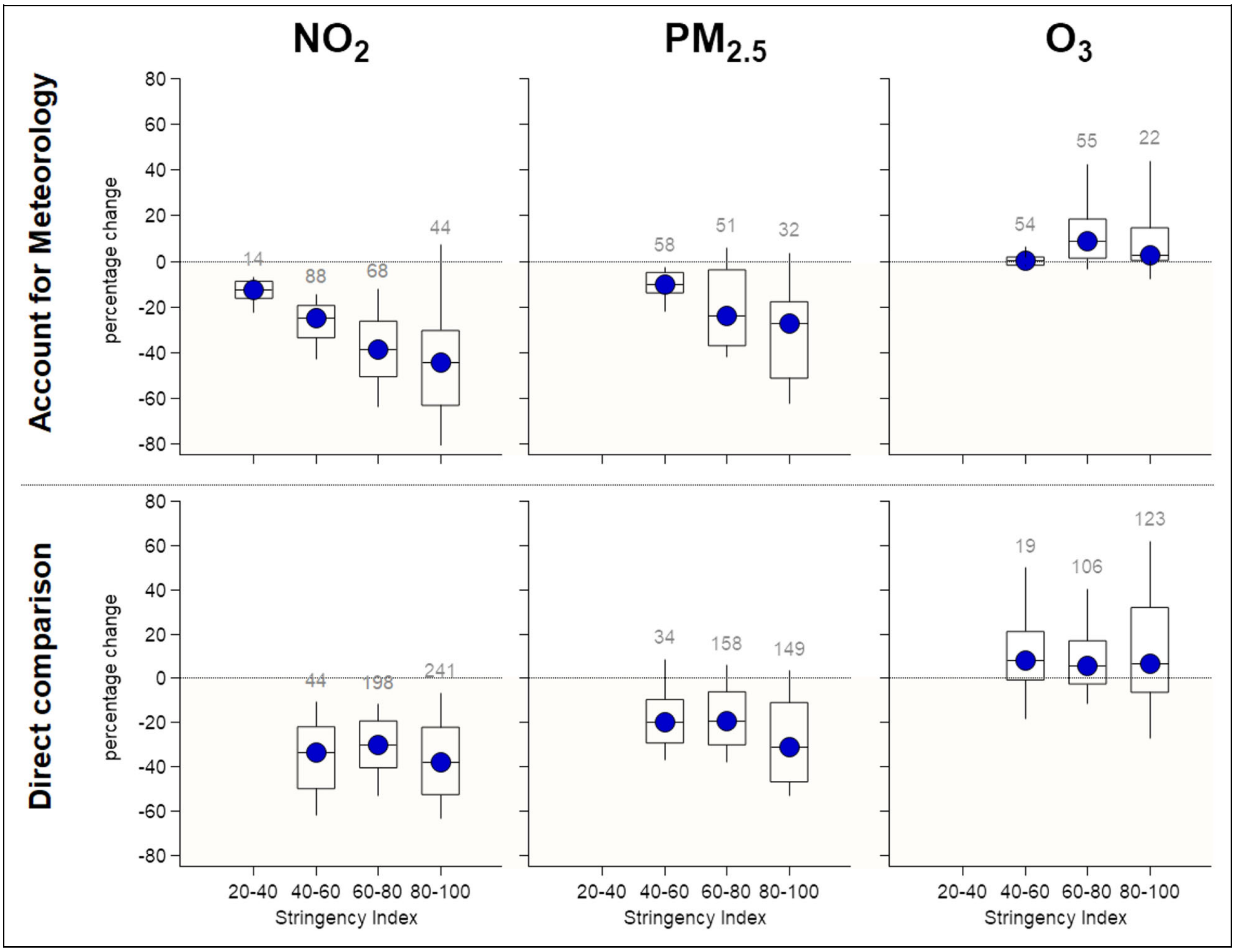


**Figure 6.** Pollutant changes during lockdowns are binned into intervals of the stringency index. Box and whiskers (10th, 25th, 50th, 75th, and 90th percentiles) are separated into studies that compared pollutant concentrations without accounting for meteorology in the bottom row and studies that accounted for the effects of meteorology in the top row. The number of studies per bin is provided above the whisker. DOI: https://doi.org/10.1525/elementa.2021.00176.f6

quantifying the effects of meteorology in order to quantitatively link changes in atmospheric abundance with changes in emissions. Although a direct comparison of reference to lockdown periods is valuable for identifying air-quality exceedances, its representativeness depends on the similarity of the meteorology during the reference period to the lockdown period. Furthermore, pollutants such as CO and $NO_x$ arise from direct emissions, while $PM_{2.5}$ is often largely from secondary processes and $O_3$ has both local secondary production and destruction superimposed on a large background. Meteorology influences both the dilution and deposition of primary emissions, as well as the production and destruction of secondary species through the availability of oxidants and the rates of atmospheric chemical processes (see **Figure 1**). It should be stressed that data sets included in this work were from northern hemisphere springtime (Figure S1). Although an $O_3$ increase with other pollutant reductions was evident for this period, such increases can have different $NO_x$-VOC sensitivities than do summertime $O_3$ changes. Although an $O_3$ increase is evident in the existing literature, more analysis is required as more papers are published throughout the year to assess the effects of emission reductions on summer $O_3$ formation.

In the following, each pollutant will be further investigated on a per country basis using all available data sets including studies that do and do not correct for the effects of meteorology. Although this introduces higher uncertainties, it improves the global data coverage and provides better statistics for comparisons to emission inventories. The distribution of studies that makes direct comparisons and those that correct for meteorological effects will be discussed for each pollutant, and a comparison to emission inventories will be performed when available.

### 3.3.2. Observed changes in $NO_2$ compared with estimates based on the EDGAR emission inventory

**Figure 7** shows the median decrease in $NO_2$ concentration (circles) during lockdowns for each country colored by the SI. Included in this calculation are studies using both the direct comparison approach (67%) and studies that correct for meteorological effects (33%). An overview of the measurements grouped by observation type as ground-based only (48%), satellite only (12%), or both

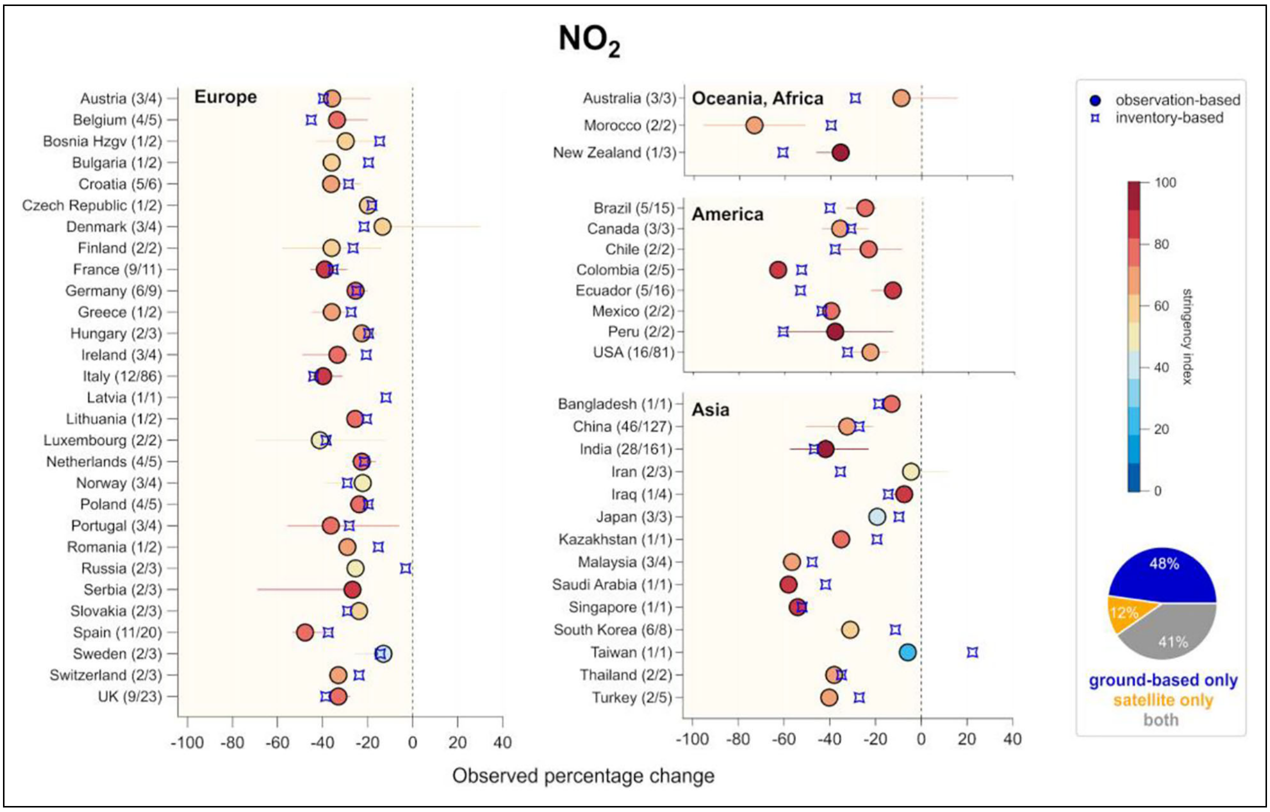


**Figure 7.** Observed median percentage decrease of $NO_2$ (circle markers) for each country. Error bars indicate the 25th and 75th percentiles of the distribution. The markers are colored by the median stringency index based on all measurements associated with each country. Numbers in parenthesis correspond to the number of publications and the number of data sets collected at each region/continent. Also shown as star squares is the Emissions Database for Global Atmospheric Research inventory $NO_x$ emissions decrease calculated by Forster et al. (2020). The pie chart indicates the platforms used for the measurements. DOI: https://doi.org/10.1525/elementa.2021.00176.f7

(41%), is also provided. Also plotted is the adapted EDGAR inventory median decrease in emissions during lockdowns based on Forster et al. (2020; star squares). It should be noted here that Forster et al. (2020) implement the reductions in the emission inventory by scaling individual emission sectors. Studies mostly report data from lockdowns when stringency indices are greater than 50. Both observations and inventory-based reductions are reported as percentage difference.

**Figure 8** plots the observed median decrease of $NO_2$ for each studied country against that country's inventory decrease (Forster et al., 2020). The observed decrease for each country is further binned by percentage decrease (<20%, 20%–30%, 30%–40%, 40%–50%, and >50%), and the median inventory decreases for each observation-based bin are calculated. The bin ranges were chosen arbitrarily to ensure more than five data points per bin. These binned data are then colored by the median SI. For most countries, the observations and emission inventory agree within a factor of 2 (shaded area in **Figure 8**). The $NO_2$ decrease is driven for both atmospheric observations and the emission inventory by the stringency of the lockdown measures, with larger $NO_2$ decreases observed for higher stringency indices. Overall, despite the $NO_2$ observation-based uncertainties associated with instrument limitations (Section 2.2.1), satellite measurement uncertainties (Section 2.2.2), meteorological dependencies in determining the effects of shutdown (Section 2.3), and the uncertainties associated with inventory estimation reductions (Forster et al., 2020), the two approaches result in consistent emissions decreases, in line with the SI. This suggests that the stringency of lockdown measures has a strong influence on emissions from transportation, as exhibited by mobility data sets used to adjust global emission inventories (Forster et al., 2020). The similarity between changes in the emissions inventory and changes in atmospheric observations due to lockdown measures further confirms the importance of traffic as a source of $NO_x$ in cities around the world. A more detailed analysis of the differences between the two approaches is beyond the scope of this review.

### 3.3.3. Observed changes in $SO_2$ compared with estimates based on the EDGAR emission inventory

**Figure 9** shows the median decrease in $SO_2$ concentration during the lockdown for each country colored by the SI (circles). Studies examining changes in $SO_2$ mostly used the direct comparison approach (80%), but 20% of studies corrected for meteorological effects. Also shown is the adapted EDGAR inventory median percentage drop in

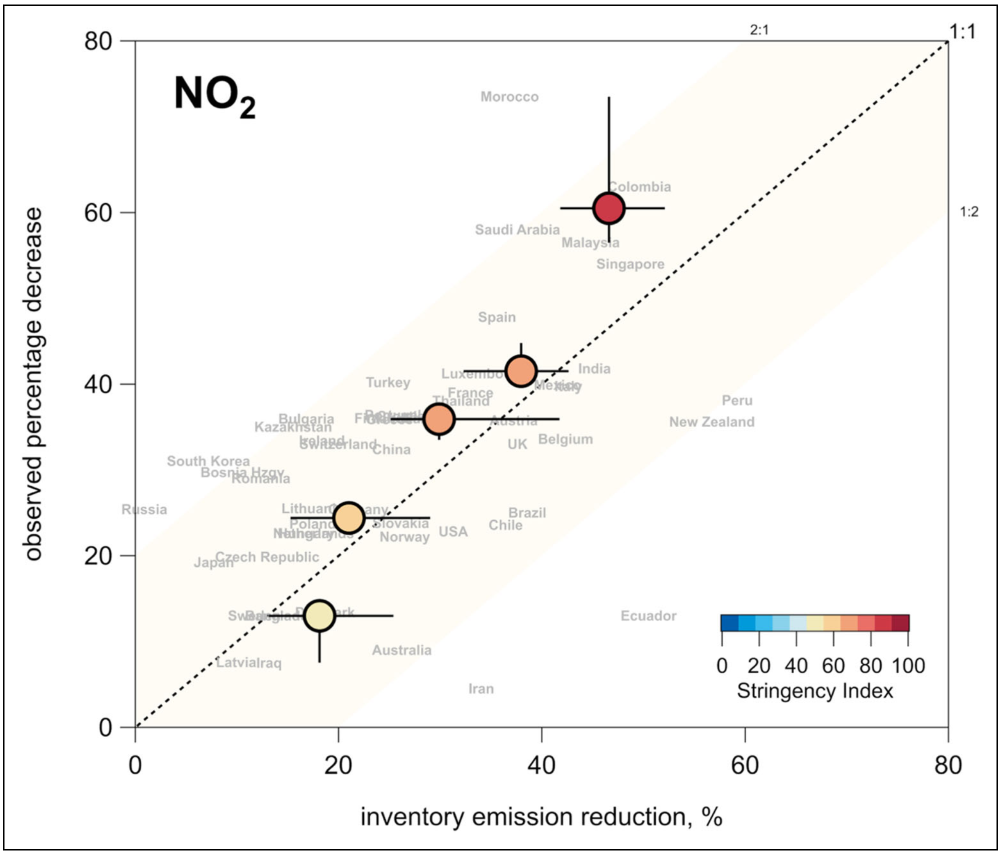


**Figure 8.** Observed percentage change of $NO_2$ during the lockdown based on literature (*y*-axis) compared to the Emissions Database for Global Atmospheric Research inventory reductions based on Forster et al. (2020). The median decrease for each country is shown in gray. Markers indicate the observed median decrease binned for all countries by <20%, 20%–30%, 30%–40%, 40%–50%, and >50%, with the inventory-based medians, colored by the median stringency index. Horizontal and vertical lines indicate the 25th and 75th percentiles of the distribution within each bin. DOI: https://doi.org/10.1525/elementa.2021.00176.f8

$SO_2$ emissions during the lockdown based on Forster et al. (2020; star squares). The pie charts show the breakdown by study measurement type, that is, ground-based, satellite, or both, for China (91%, 5%, and 5%, respectively), India (80%, 0%, and 20%, respectively), and for all other countries (76%, 8%, and 16%, respectively). All studies reported measurements from lockdown periods with an SI greater than 50. The majority of the studies were performed in China (25) and India (17), while three or fewer studies were performed for the remaining 18 countries.

Qualitatively, the inventory $SO_2$ emissions decreased with increasing SI, but the observed $SO_2$ changes were poorly correlated with either (**Figure 10**). Countries expected to account for the majority of $SO_2$ emissions globally based on the 2015 EDGAR inventory were China, India, and the United States, plus international shipping emissions (Figure S3). Observed $SO_2$ decreases and the Forster inventory reduction estimates showed discrepancies for China (16% vs. 26%), India (14% vs. 41%), and the United States (7% vs. 21%), suggesting that discrepancies on global scale emission estimates may also be expected. All but two studies were done in urban environments, and the average time period per study was greater than 50 days, resulting in urban-dominated $SO_2$ statistics for a long time period. The inventory $SO_2$ emission reductions are greater for the energy and manufacturing sources than from transportation. A lack of consistency in predicted versus observed $SO_2$ reductions (**Figure 10**) may therefore point toward uncertainties in the $SO_2$ inventory. $NO_2$, by contrast, arises primarily from transportation and shows better agreement between observation and inventory reduction estimates (**Figure 8**). However, there are fewer $SO_2$ observations and substantially fewer with meteorological normalization. There are also larger uncertainties associated with its measurement from ground-based and satellite-borne instruments. Further assessment of $SO_2$, a major precursor for $PM_{2.5}$, is an important topic for further study as more high-quality results from the COVID-19 period become available.

#### 3.3.4. Observed changes in PM compared with estimates based on the EDGAR emission inventory

**Figure 11** shows the median decrease in $PM_{2.5}$ concentration during lockdowns for each country colored by the SI (circles). Included in this calculation are studies using the direct comparison approach (i.e., no meteorological correction, 70%) and studies that correct for meteorological effects (30%). Effectively all analysis available to date considers $PM_{2.5}$ mass, and there is only limited information available on the changes in aerosol composition in

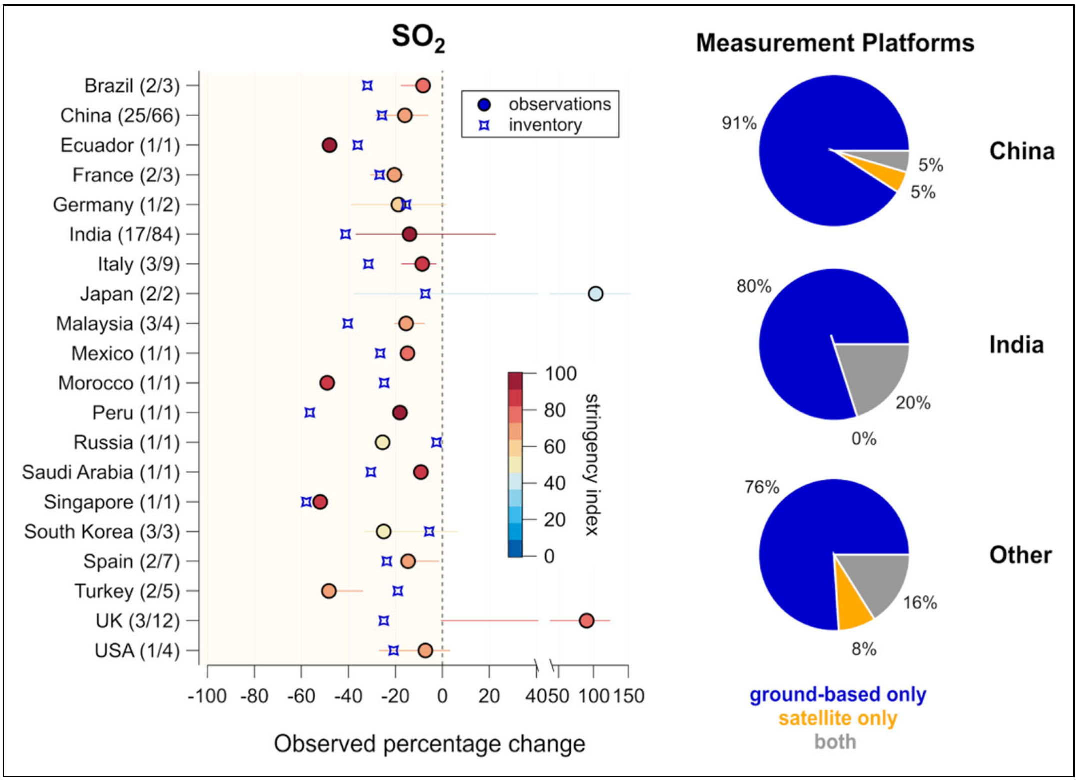


**Figure 9.** Observed median percentage decrease of $SO_2$ (circle markers) for each country. Error bars indicate the 25th and 75th percentiles of the distribution. The color of the markers indicates the median stringency index based on all studies associated with each country. Numbers in parentheses correspond to the number of publications and the number of measurements performed at each region/continent. Also, shown as star squares is the Emissions Database for Global Atmospheric Research inventory $SO_2$ emissions decrease calculated by Forster et al. (2020). The pie charts indicate the measurement platforms used by the studies for China, India, and all other countries. DOI: https://doi.org/10.1525/elementa.2021.00176.f9

response to lockdown measures. Also shown is the inventory median decrease in $PM_{2.5}$ emissions during the lockdowns approximated by both the organic and BC emission reductions based on the adjusted EDGAR inventory (Forster et al., 2020; star squares). We note that global inventories typically do not include speciated fractions of $PM_{2.5}$, which can be significant and reported by national-scale inventories (e.g., road dust, brake wear, tire wear). An inventory prediction of $PM_{2.5}$, which has both primary and secondary sources, is complicated by secondary PM formation, as discussed further below. $PM_{2.5}$ studies mostly report data from lockdowns when stringency indices are greater than 50.

**Figure 12** further highlights the challenges associated with the comparison of $PM_{2.5}$ observations to the adapted EDGAR inventory based on Forster et al. (2020). The observed decreases for each country are further binned into percentage decrease ranges as in **Figure 8**. As the SI increased, the observed $PM_{2.5}$ median decreased; however, the inventory $PM_{2.5}$ emission reductions were poorly correlated. $PM_{2.5}$ can either be directly emitted or formed via secondary chemistry from a wide variety of other primary emissions ($NO_x$, $SO_2$, $NH_3$, NMVOCs, etc.). Therefore, a direct comparison of emission inventories and observations is challenging if the primary and secondary sources are not disentangled.

By the literature cutoff time of this review (September 30, 2020), only a few studies had been published that investigated the effects of secondary chemistry and local primary emissions on PM levels and composition in China (Chang et al., 2020; Chen et al., 2020a; Cui et al., 2020; Dai et al., 2020; Li et al., 2020b; Sun et al., 2020; Zheng et al., 2020), Bangladesh (Masum and Pal, 2020), and South Africa (Williams et al., 2020). More studies will be essential to understand the complexity of $PM_{2.5}$ pollution. For example, studies that address the possible effects of long-range transport that affect background PM levels are needed. Furthermore, changing atmospheric chemistry regimes can change secondary PM production rates. Characteristic examples that highlight this complexity are (1) the effects of $NO_x$ reductions on organic peroxy radical ($RO_2$) chemistry affecting dimer formation and highly oxygenated molecules (e.g., McFiggans et al., 2019), (2) changes in organic and inorganic equilibrium partitioning, due to changes in particle acidity and the associated shifts between nitrate and sulfate formation in the particle-phase (e.g., Guo et al., 2016; Wang et al., 2016; Wang et al., 2020d), (3) changes in production rates of organic and inorganic pollutants due to increased availability of oxidants when emissions are reduced (e.g., Nault et al., 2018; Shah et al., 2018; Laughner and Cohen, 2019; Womack et al., 2019), and (4) changes in the rate of nighttime

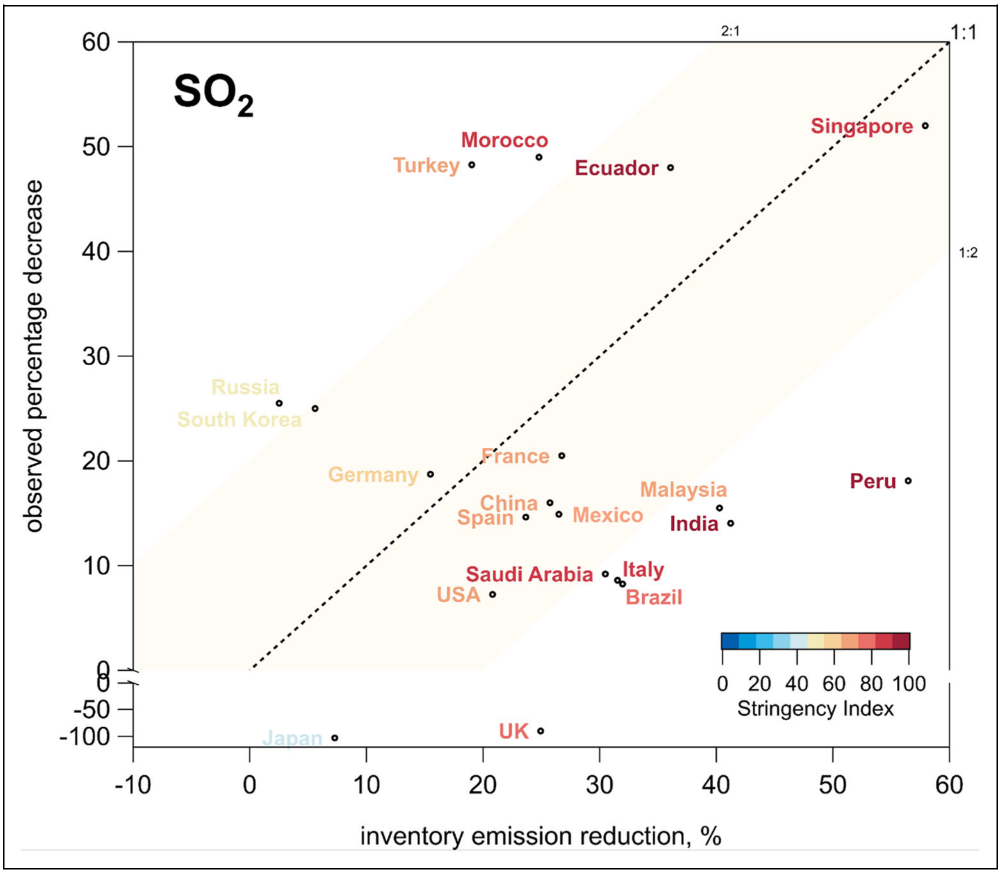


**Figure 10.** Observed percentage decrease in $SO_2$ during the lockdown based on literature (*y*-axis) compared to the Emissions Database for Global Atmospheric Research inventory emission reductions (Forster et al., 2020). The color of the country indicates the stringency index and the circle markers the percentage changes. Measurements were predominantly from studies that did not account for the effects of meteorology (80%). Due to the limited number of measurements, no additional binning of the data is performed as in **Figure 9.** DOI: https://doi.org/10.1525/elementa.2021.00176.f10

chemical processes (e.g., Kiendler-Scharr et al., 2016). PM composition measurements in addition to PM mass will be essential to assess these and other effects in order to elucidate changes in PM pollution arising from the COVID-19 emission reductions.

### 3.3.5. Changes in $O_3$

**Figure 13** shows the observed median change in $O_3$ concentration from ground-based measurements during the lockdown for each country colored by the SI (circles). Included in this calculation are studies using the direct comparison approach without meteorological normalization (69%) and studies that correct for meteorological effects (31%). A violin plot shows the overall distribution of $O_3$ changes. Studies for most countries had SI values above 50 and either showed minor median $O_3$ decreases or increases in the 5%–20% range. $O_3$ increases greater than 50% were observed for Milan, Italy (reflected by the high 75th percentile values; Collivignarelli et al., 2020), as well as studies in Peru (Venter et al., 2020), Ecuador (Parra and Espinoza, 2020; Zambrano-Monserrate and Ruano, 2020), and Iraq (Hashim et al., 2020). To assess whether the changes in $O_3$ were driven by changes in emissions, the change in observed $O_3$ was plotted against the SI for each country together with the medians binned as done for **Figures 8** and **12** (**Figure 13**, right panel). As the lockdown measures became more stringent, the percentage change in $O_3$ increased, suggesting that significant changes in $O_3$ formation were driven by emission reductions.

$O_3$ is a secondary pollutant whose formation results from the interplay of $NO_x$, VOC emissions, and meteorology (Sillman, 1999). Most regions have a significant background $O_3$ concentration, and local emissions may either deplete $O_3$ from this background or produce it photochemically. Although $NO_x$ emission reductions were evident during the lockdown, changes in VOC concentrations and composition have not been well investigated (see **Figure 5**). Furthermore, the literature covered in this review was predominantly focused on February, March, and April (Figure S1). Studies were also weighted toward the northern hemisphere, representing late winter and early spring. During these months, $O_3$ concentrations are expected to be low due to reduced wintertime photochemistry (Khoder, 2009). For the studied periods, it is therefore expected that an increase in $O_3$ could be more sensitive to NO emission reductions that would reduce $O_3$ titration. However, summertime measurements of $O_3$,

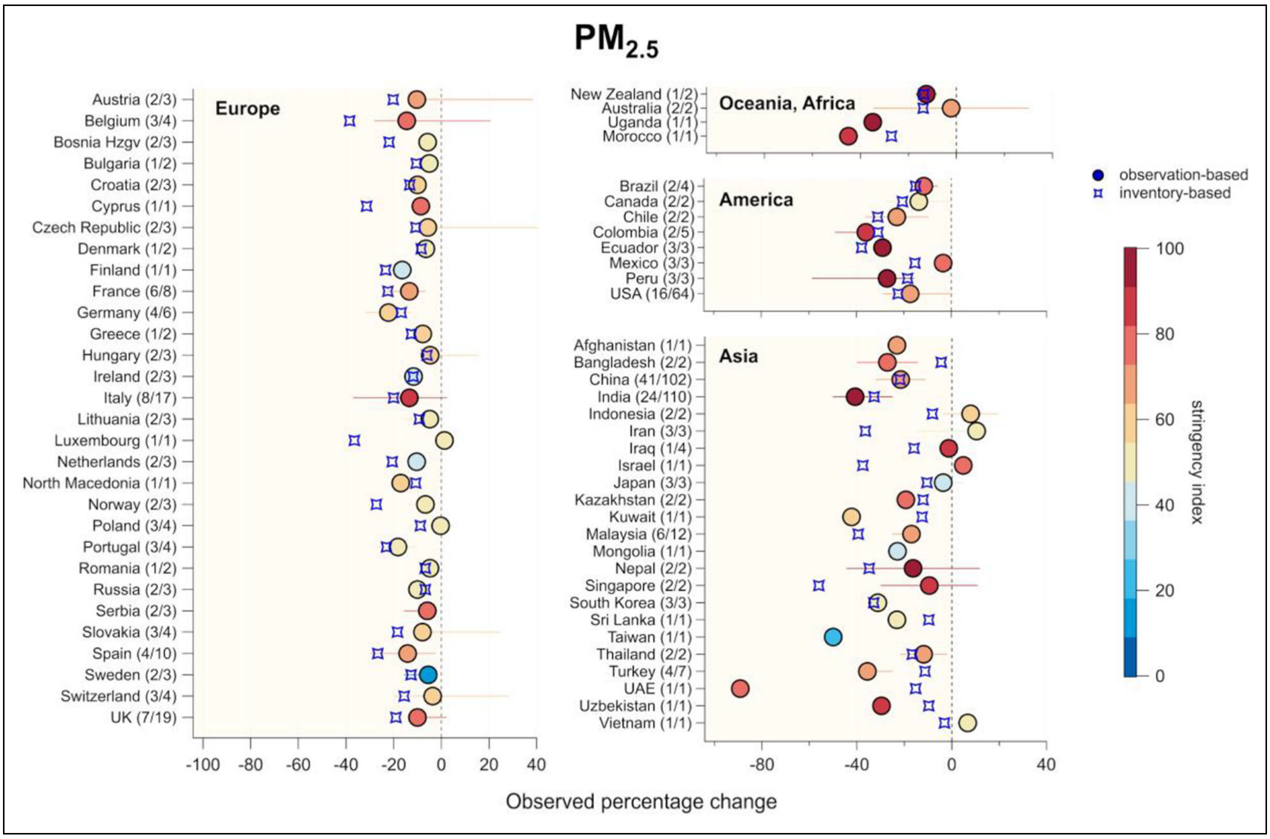


**Figure 11.** Observed median percentage decrease in $PM_{2.5}$ (circle markers) for each country. Error bars indicate the 25th and 75th percentiles of the distribution. The color of the markers indicates the median stringency index based on all measurements associated with each country. Numbers in parentheses correspond to the number of publications and the number of data sets collected at each region/continent. Also, shown are the Emissions Database for Global Atmospheric Research inventory emission reductions calculated by Forster et al. (2020; star squares). DOI: https://doi.org/10.1525/elementa.2021.00176.f11

$NO_x$, and VOCs are essential to investigate how changes in emissions affect $O_3$ formation when photochemistry is at its peak. Greater biogenic VOC and wildfire biomass burning emissions during the summer significantly alter VOC speciation and abundance. It is therefore evident that although reduced emissions increased $O_3$ concentrations in late winter and early spring, more studies will be necessary to address COVID-19-related shifts in summertime $O_3$, which is sensitive both to the local chemical environment and broad-scale changes in the ozone background.

### 3.3.6. Changes in other pollutants

**Figure 14** shows the median change in pollutant concentrations for $PM_{10}$, $NH_3$, $NO_x$, AOD, BC, AQI, NMVOCs, and CO during the lockdown for each country colored by the SI. Note that for AQI, no unique definition exists, and it is used to assess the simultaneous presence of multiple pollutants. For example, in the United States, AQI is calculated based on the concentration of PM, $O_3$, $SO_2$, and CO (Bishoi et al., 2009), whereas in China, AQI is determined by the concentrations of the above four pollutants plus $NO_2$ (Fareed et al., 2020). Studies using the direct comparison approach accounted for 80%, 100%, 56%, 57%, 86%, 82%, 50%, and 72% of the data sets for $PM_{10}$, $NH_3$, $NO_x$, AOD, BC, AQI, NMVOCs, and CO, respectively. For the majority of countries, a decrease in pollutant concentrations was evident during the lockdowns compared to reference periods (see also **Table 8**). On average, decreases of 22% (±19%), 9% (±13%), 43% (±25%), 9% (±20%), 51% (±13%), 11% (±28%), 59% (±64%), and 27% (±18%) were observed for $PM_{10}$, $NH_3$, $NO_x$, AOD, BC, AQI, NMVOCs, and CO, respectively. More studies are needed to better understand the effects of the lockdowns on the above pollutant concentrations. With most of the current literature failing to account for the possible effects of meteorology, these results suggest a need for future studies in this area. Furthermore, NMVOCs and $NH_3$ can contribute to PM pollution through atmospheric chemical processes, and BC has direct impacts on climate forcing, which highlights the need to better monitor their concentrations.

### *3.4. Progress toward compliance with air quality standards during COVID-19*

An interesting question is to what degree emissions reductions during the COVID-19 pandemic brought regions into compliance with air quality standards. **Table 1** lists the WHO exposure guidelines for a series of common air pollutants. Assessment of compliance with these standards requires comparison to absolute pollutant

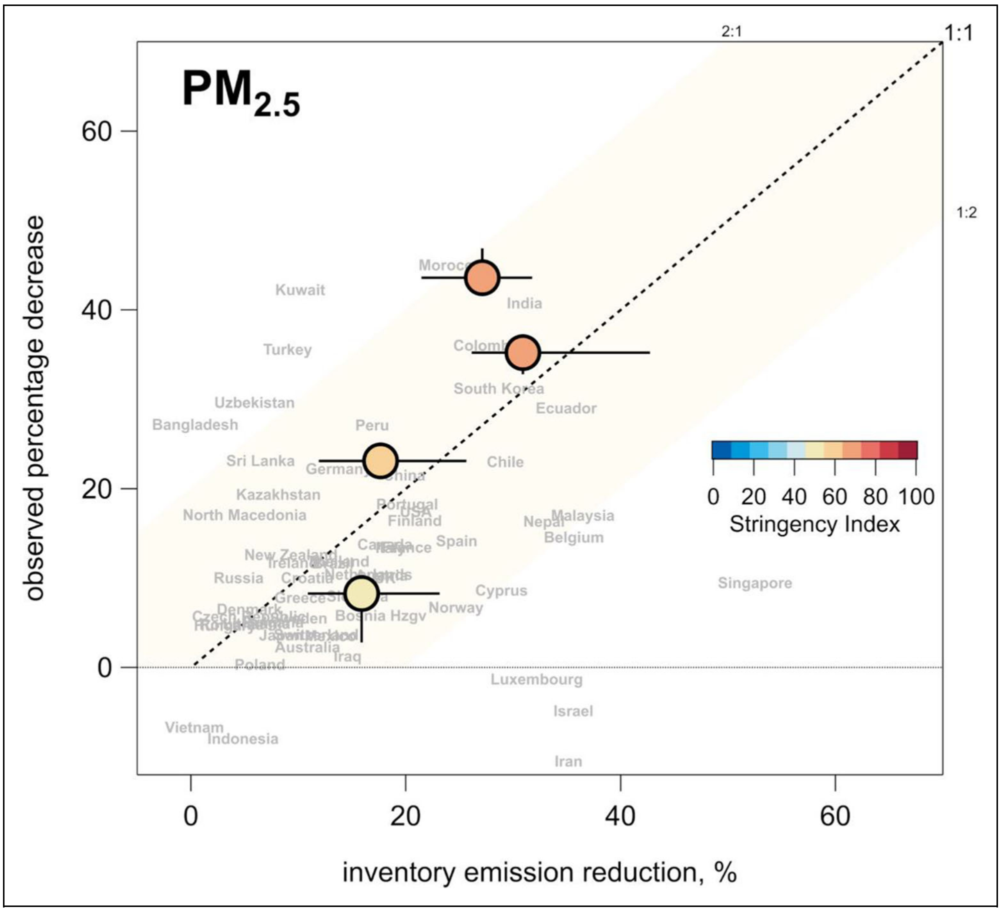


**Figure 12.** Observed percentage decrease in $PM_{2.5}$ during lockdowns based on literature (*y*-axis) compared to the Emissions Database for Global Atmospheric Research inventory percentage decrease in emissions (Forster et al., 2020). The median decrease for each country is shown in gray. Markers indicate the observed median decrease binned for all countries by <20%, 20%–30%, 30%–40%, 40%–50%, and >50%, with the inventory-based medians, colored by the median stringency index. Horizontal and vertical lines indicate the 25th and 75th percentiles of the distribution within each bin. DOI: https://doi.org/10.1525/elementa.2021.00176.f12

concentrations. Only a subset of the literature reviewed here reports data in absolute units, with the majority reporting relative changes without providing the underlying concentration values. This section therefore summarizes literature that reported the concentration of $NO_2$, $PM_{2.5}$, $O_3$, and CO using the direct comparison approach.

**Figure 15** shows the mean concentrations of these four pollutants during lockdowns (circle markers) and reference periods (star markers) reported by 96 publications across different continents. Asia, the largest and most populous continent, is further separated into different geographical regions. Violin plots show the distribution of concentrations reported within each region. Circle markers are colored by the percentage change of the mean lockdown concentration with respect to mean reference period concentrations per region/continent. Also shown are the WHO guideline values for $NO_2$, $PM_{2.5}$ and $O_3$ for different exposure times, including 1 year, 24 h, and 8 h. Finally, the number of publications and the number of collected measurements (from different sites and/or times) are provided in parentheses per region/pollutant. Although the WHO guideline values are limited to multiple-hour or annually averaged exposure times for the different pollutants, observation-based concentration averages range from 1 week to 5 months. A direct comparison of observations to the WHO guideline values is therefore challenging. However, the WHO guideline values for hourly and annual means provide a range of concentrations that put the observed means into perspective. For example, if monthly measurements of a pollutant are greater than the hourly WHO guideline values, then exceedances by definition occurred during the studied period; if observations are greater than the annual guideline values, then exceedances could also occur if high concentrations were to persist beyond the observation period. In the following, each pollutant is examined separately, and the literature corresponding to each pollutant is provided in **Tables 5–8.** Concentration changes on a national level are further discussed in Section S4 and downloadable from the database (See Section 2.1).

The mean $NO_2$ concentration reported by all studies for lockdown conditions was 22 ± 18 μg $m^{-3}$ (1 standard deviation) and lower than the reported mean, 31 ± 15 μg $m^{-3}$, for the respective reference periods. The lockdown and reference concentrations from 100% ground-based measurements were below the WHO annual guideline

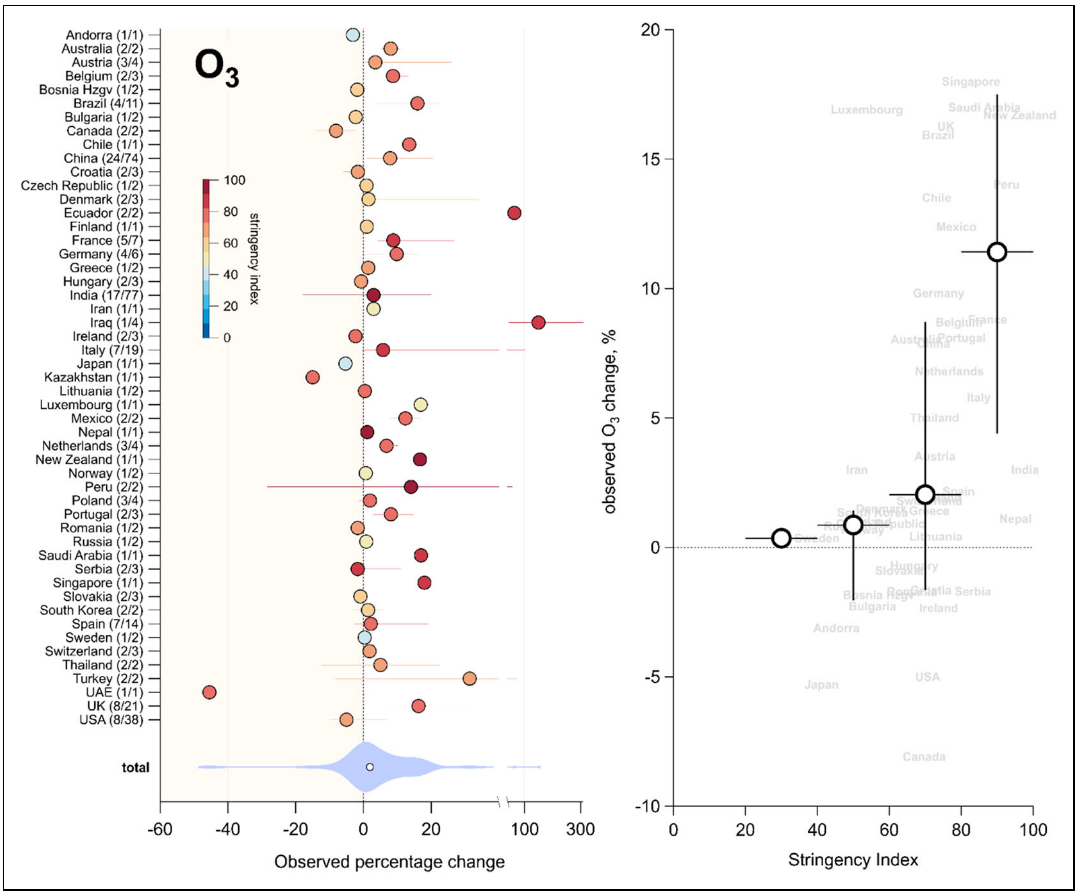


**Figure 13.** Observed median percentage change of $O_3$ (circle markers) for each country. Error bars indicate the 25th and 75th percentiles of the distribution. The color of the markers indicates the median stringency index based on all studies for each country. Numbers in parenthesis correspond to the number of publications and the number of measurements performed at each region/continent. The violin plot at the bottom left shows the distribution of all observed $O_3$ changes. In the right panel, the change in observed $O_3$ is plotted against the stringency index for each country together with the medians binned as done for **Figures 9** and **13.** DOI: https://doi.org/10.1525/elementa.2021.00176.f13

values, and $NO_2$ concentrations decreased during the lockdown compared to the reference period for all regions except West Asia. Literature corresponding to these measurements is provided in **Table 5.**

The mean $PM_{2.5}$ concentration reported for lockdown conditions was 24 $\pm$ 14 µg m$^{-3}$ and lower than the reported mean, 32 $\pm$ 22 µg m$^{-3}$, for the respective reference periods. The lockdown and reference concentrations (80% ground-based, 2% satellite, 18% both) were above the WHO mean annual guideline value of 10 µg m$^{-3}$ for nearly all regions, and mean values in Asia often exceeded the 24-h guideline value of 25 µg m$^{-3}$. $PM_{2.5}$ decreased during the lockdown compared to the reference periods for all regions except West Asia. However, this decrease was not sufficient to reduce concentrations below the WHO guideline values during the lockdown, especially for regions in Asia. This variability in $PM_{2.5}$ concentrations may reflect the much wider variety of $PM_{2.5}$ sources with secondary $PM_{2.5}$ responding to the changes in $NO_x$, VOCs, $SO_2$, and $NH_3$ as well as many other sources. Literature corresponding to these measurements is provided in **Table 6.**

The mean $O_3$ concentration reported by all studies for lockdown conditions was 43 $\pm$ 21 µg m$^{-3}$ and higher than the reported mean, 36 $\pm$ 19 µg m$^{-3}$, for the respective reference periods. The lockdown and reference concentrations from 100% ground-based measurements were below the 8-h mean WHO guideline value (100 µg m$^{-3}$, approximately 50 ppb) for all regions. However, the ground-based mean values were calculated as averages for multiple weeks/months, including nighttime measurements, allowing for the possibility that midday $O_3$ might still have exceeded the 8-h guideline value. $O_3$ increased during the lockdowns compared to the reference periods for all regions except South Asia. An overview of the literature corresponding to these measurements is provided in **Table 7** and is dominated by urban measurements (>98%).

The mean CO concentration reported by all studies for lockdown conditions was 580 $\pm$ 310 µg m$^{-3}$ and lower than the reported mean, 630 $\pm$ 440 µg m$^{-3}$, for the respective reference periods. There are currently no WHO guideline values for CO to compare to; however, the U.S., European, and Chinese guidelines shown in **Table 1** are

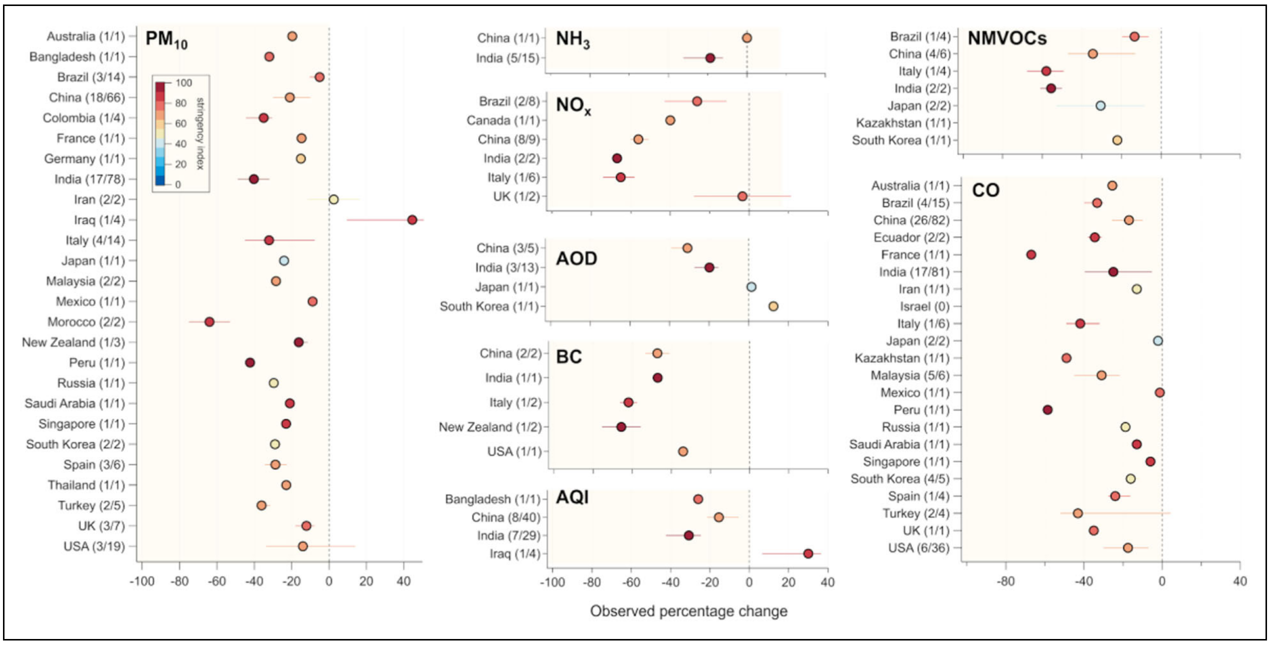

**Figure 14.** Observed median percentage change of all other pollutants (circle markers) for each country. Error bars indicate the 25th and 75th percentiles of the distribution. The color of the markers indicates the median stringency index based on all studies for each country. Numbers in parentheses indicate the number of publications and the number of data sets collected at each region/continent. DOI: https://doi.org/10.1525/elementa.2021.00176.f14

significantly greater than the observed CO concentrations. CO decreased during the lockdowns compared to the reference periods for all regions. An overview of the literature corresponding to these measurements is provided in **Table 8.**

## 4. Conclusions and outlook

Analysis of emissions changes and their resulting influence on air quality worldwide during the COVID-19 pandemic is a rapidly evolving topic of intense public and scientific interest. This review provides a summary of the current literature that has examined mainly the stringent, early lockdown periods in February–May 2020. Despite the short duration of the observational time period and the limited time since that period to this writing, the number of papers and the depth of the analysis is substantial. Already, there are several initial conclusions, recommendations for careful consideration and best use of the observations, and a list of suggestions for further analysis. This review synthesizes these reported changes in air pollutants during the COVID-19 lockdowns and further provides context for these changes using the SI, a unified, globally consistent measure of the policy response to confining the pandemic. All data digitized for analysis in this review are available on the website in https://covid-aqs.fz-juelich.de. This website is designed as a living version of this review, that is, as new literature emerges, authors of published papers are encouraged to upload their data to the database, thus complementing the data coverage in space, time, and compound dimensions.

Much of the COVID-19 air quality literature surveyed for this review does not explicitly account for the effect that the year-to-year variability, largely driven by meteorology, has on observed atmospheric concentration changes. The dependence of concentration changes on the SI are readily apparent in the meteorologically corrected data but not in the uncorrected data. We recommend that all future analyses take explicit account of meteorology and specify the method for doing so, for example, as outlined in Section 2.3.2, or perform chemical transport modeling (Section 2.3.3) since disregarding this consideration largely increases the associated uncertainties.

Two of the main species arising from primary emissions analyzed to date are $NO_2$ and $SO_2$, both of which have readily available ground-based monitoring networks and satellite remote sensing data sets. They also arise from different emission sectors, with $NO_x$ (for which $NO_2$ is a proxy) having its largest contribution from transportation and $SO_2$ from power generation and certain industrial sources. For $NO_2$, the observed changes correspond within uncertainties with the estimated emission inventory reductions when accounting for COVID-19 lockdowns. The analysis of $NO_2$ also encompasses the largest number of publications and the largest number that explicitly account for meteorological effects. Analysis of $SO_2$, by contrast, shows distinct evidence for reductions during the lockdown periods, but those emissions reductions are not as clearly associated with predictions from inventories. This difference may be due to incomplete information of the impacts of COVID-19 on industrial activity and the more limited publication database of $SO_2$ changes during COVID-19, especially for papers that account for meteorology, or uncertainties in the measurement database for $SO_2$. We recommend further investigation of the $SO_2$ reductions, especially since this has the potential to inform inventories for this critical $PM_{2.5}$ precursor.

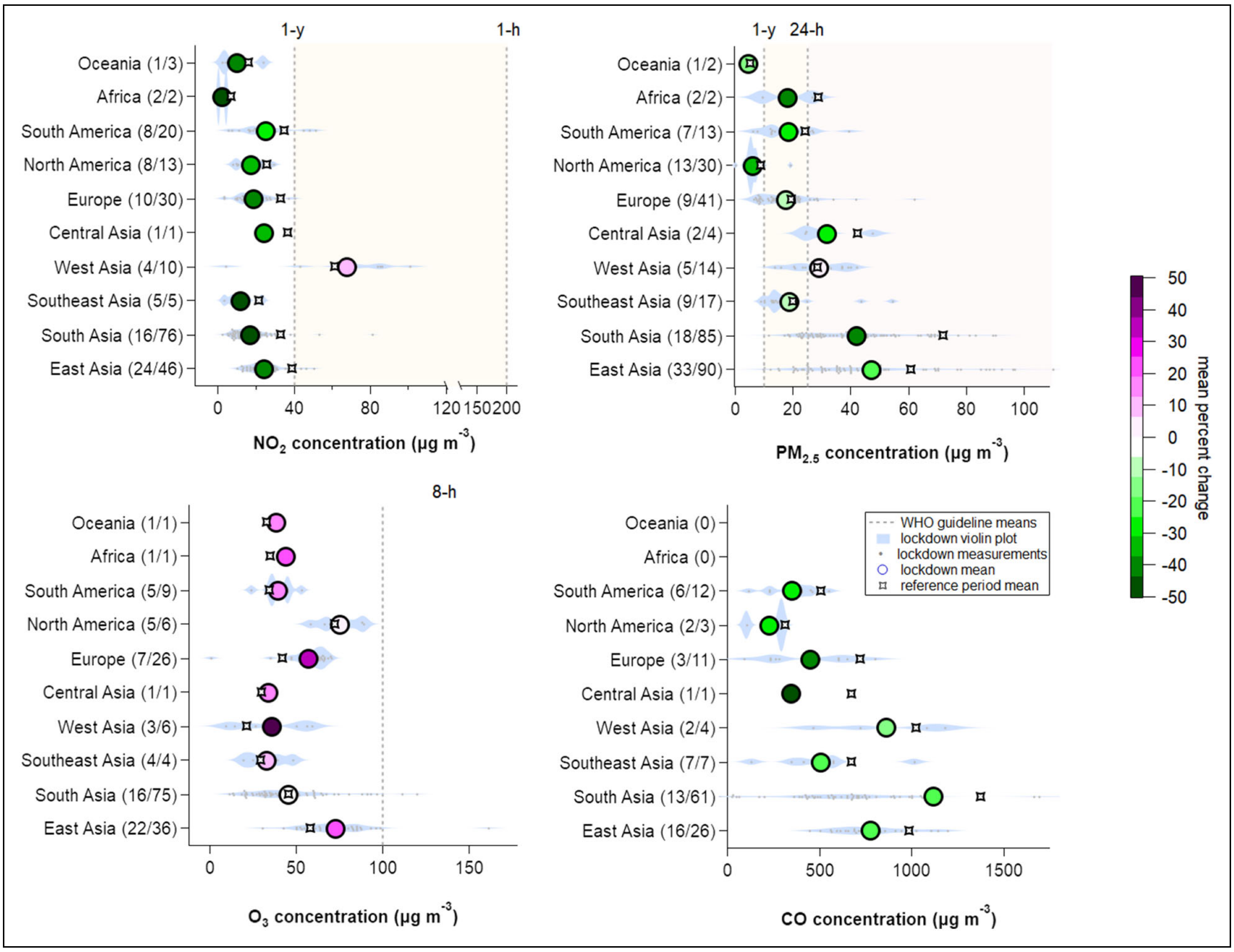


**Figure 15.** Distributions of the absolute concentration of pollutants, shown as violin plots, around the world during the lockdown period and the reference period (star square markers indicate the mean) for each study. Blue shaded area shows the density of samples at each concentration, and gray dots show the individual data sets averaged for periods ranging from days to several weeks. The hour/year mean World Health Organization guideline values are shown as vertical dashed lines. Numbers in parentheses indicate the number of publications and the number of data sets collected at each region/continent. DOI: https://doi.org/10.1525/elementa.2021.00176.f15

Analysis of changes on primary emissions of other species, such as CO, NMVOCs, BC, and $NH_3$, is more limited. CO is covered in the literature by 67 publications, albeit predominantly without explicitly accounting for meteorological impacts on pollutant abundance. BC, $NH_3$, and NMVOCs are covered by seven, five, and 10 publications, respectively, far from providing a global overview at this stage. This reflects the frequency with which these compounds are typically measured by air quality monitoring networks. However, considering the important role of $SO_2$ and VOCs in secondary aerosol formation and of CO and VOCs in ozone chemistry, further analysis of available COVID-19 changes is needed for these species.

Both $PM_{2.5}$ and $O_3$ have large secondary sources arising from complex atmospheric chemical cycles, and together they are responsible for the majority of adverse health outcomes associated with air pollution. Total $PM_{2.5}$ mass and $O_3$ are covered comparatively widely in the literature, although there is little information on speciated $PM_{2.5}$ composition. The COVID-19 literature shows that $PM_{2.5}$ decreases with increasing SI, whereas $O_3$ increases with SI. Key uncertainties in the understanding of these changes should be addressed through the combined use of observational and atmospheric chemistry modeling approaches. With the chemistry leading to ozone and secondary aerosol (both organic and inorganic) formation being nonlinearly dependent on $NO_x$ levels, the lockdown periods and seasonality of its effect on pollutants offers unique possibilities to assess model abilities in capturing changes on local to global scales. Further analysis of photochemically active periods with reduced emissions in the northern hemisphere in forthcoming literature may be particularly informative.

More use can be made of the high-resolution capabilities of the TROPOMI sensor, in particular for $NO_2$. Analyses of the data at high resolution may provide COVID-19 emission impact estimates of different sources and source sectors such as individual power plants, highways, shipping, urban areas, industrial complexes, and airports. The influence of the day-to-day changes in weather is, however, substantial on such local scales, and we recommend that such high-resolution satellite-based studies make use of high-quality weather analyses and chemical modeling. When using satellite $NO_2$ measurements, we advise that the averaging kernels remove the dependency on the retrieval a priori profile shape, which can always be done when three-dimensional CTMs are involved in the analysis. Satellite instruments like TROPOMI and OMI measure at one given overpass time (e.g., 13:30), but it should be considered that the diurnal profile of the emissions may have changed during the lockdowns. Satellite retrievals often suffer from systematic uncertainties. In the case of TROPOMI $NO_2$, we mention a negative bias compared to surface remote sensing observations, with an apparent linear scaling with the tropospheric column amount over polluted regions. This scaling suggests that relative changes, for example, the percentage reduction compared to a reference time period, are not so sensitive to the negative bias, and we recommend reporting such relative differences, which is done in most of the papers studied in this review.

As the atmospheric chemistry community makes continued efforts toward observational coverage of the pandemic influences on atmospheric composition, we anticipate that additional data sets will become available for further analysis. We recommend attention to the following issues, although this list is certainly far from comprehensive.

First, changes in $O_3$ associated with COVID-19 emissions reductions, particularly during photochemically active seasons, may be informative for assessing the sensitivity of this photochemistry to $NO_x$ and VOCs in different regions. The northern hemisphere late winter and early spring period that dominates this review reflects $O_3$ data that are not particularly sensitive to photochemistry. However, careful comparisons of meteorologically normalized $O_3$ to detailed photochemical models may elucidate $NO_x$ and VOC sensitivities that can inform regional $O_3$ mitigation strategies across the world.

Second, changes in $PM_{2.5}$ may enable similar sensitivity analyses to primary emissions. As $PM_{2.5}$ composition depends on a number of emission sources and chemical cycles, a broader analysis of chemically speciated $PM_{2.5}$ data, where available, will be especially informative.

Third, but related to both of the above, the seasonality of $O_3$ and $PM_{2.5}$ may be addressed if there are sufficient observations of emissions reductions across different hemispheres or times of year. Given the trajectory of the COVID-19 pandemic at the time of this writing, such an analysis may be feasible even within the northern hemisphere. Particularly for $PM_{2.5}$, there is a well-known seasonality, with severe effects arising from distinct cycles and emissions that occur in midlatitude summer and winter.

Fourth, expansion of the available analyses to include a larger number of species would help to constrain and inform emissions inventories. This review has provided an initial analysis of the difference between $NO_2$ and $SO_2$. Further analysis, to include detailed analysis of CO, BC, $NH_3$, and especially speciated NMVOCs, where available, would provide unprecedented tests of the current understanding of emissions inventories across an array of sectors.

Fifth, analysis of the radiative forcing associated with short-lived climate forcers is a priority. For example, regional emissions changes should lead to both local and hemispheric effects on $O_3$. The influence on this broader scale, or background $O_3$, needs to be evaluated through both modeling and observational efforts. Remote sensing $O_3$ products and vertical profiles from, for example, $O_3$ LIDAR networks will be particularly informative. Similarly, changes in $PM_{2.5}$ affect both regional air quality and global climate. Widespread global reductions in primary emissions and $PM_{2.5}$ precursors must similarly be evaluated in terms of their short-term climate forcing in 2020.

Finally, changes in the oxidative capacity of the global atmosphere arising from COVID-19 may also have occurred with changes in $NO_x$ and other species, but those changes have yet to be evaluated. Such changes have the potential to influence the lifetime of methane, an important greenhouse gas. Model evaluations will be informative in this regard since we anticipate few, if any, observations of the influence lockdowns have on oxidants such as $HO_x$ radicals.

We note that this review has been limited in scope to air pollutants that are of importance as short-lived climate forcers. However, to our knowledge, no information is currently available on short-lived climate forcers such as methane and halogenated compounds. $N_2O$ and $CO_2$ are beyond the scope of this review with the latter evaluated elsewhere (Le Quéré et al., 2020). The developing analysis of the COVID-19 emission reductions will certainly address these topics.

## Data accessibility statement

The review compiles data published in the peer-reviewed literature. All data are accessible through https://covid-aqs.fz-juelich.de designed as a living version of this review. The data sets from the website are provided with free and unrestricted access for scientific (noncommercial) use including the option to generate targeted reference lists. Users of the database are requested to acknowledge the data source and reference this review in publications utilizing the data set. As new literature emerges, authors of published papers can upload their data to the database, thus complementing the data coverage in space, time, and compound dimensions.

## Supplemental files

The supplemental files for this article can be found as follows:

Text S1–S4. Figure S1–S4. Table S1–S2. Docx.

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## Competing interests
The authors declare no competing interests.

## Author contributions
Performed the literature review and categorized the papers: GIG, JBG, SB, BCM, AKS.

Extracted data from the reviewed literature and performed analyses: GIG, JBG.

Provided Figure 1: CT.

Provided Figure 4: HE, ACL.

Designed the database and web page: ARG, AP.

All authors contributed to the interpretation of data, drafted and/or revised this article, and approved the final version for submission.

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