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The U.S. power sector emissions of CO_2 and NO_x during 2020: Separating the impact of the COVID-19 lockdowns from the weather and decreasing coal in fuel-mix profile

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ABSTRACT

In recent years, the United States power sector emissions of CO_2 and NO_x have decreased due to declining coal and increasing natural gas and renewables in the fuel-mix. In April 2020, the COVID-19 social restrictions in the United States led to a decline in electricity demand from the commercial and industrial sectors. In this study, we estimate the changes in the emissions of CO_2 and NO_x from the U.S. power sector due to three factors: 1) weather, 2) the fuel-mix change in the past five years, and 3) the COVID-19 social restrictions. We use a multivariate adaptive regression splines (MARS) model to separate the impacts of outdoor temperature and type-of-day from the COVID-19 on power generation, and the daily operation status of 3013 power units to account for the fuel-mix change. We find that electricity demand changes due to COVID occurred mostly from March to June 2020, with electricity demand generally returning to 2015–2019 levels starting in July 2020. We find the U.S. power sector CO_2 emissions, reported by EPA, dropped by 29.8 $MTCO_2$ (−26%) in April 2020, relative to the average April emissions between 2015 and 2019. Of that reduction, we attribute declines of 18.3 ± 4.0 $MTCO_2$ (−18 ± 4%) to the COVID-19 lockdowns, declines of 13.7 ± 4.2 $MTCO_2$ (−12 ± 4%) to a fuel-mix change, and increases of 2.3 ± 1.1 $MTCO_2$ (+2 ± 1%) due to weather variability compared to the five prior years. For the same month, the power sector NO_x emissions dropped by 27.6 thousand metric tons (−42%) in April 2020, relative to the past five-year monthly average. Of that reduction, we attribute declines of 10.5 ± 2.4 thousand metric tons (−22 ± 5%) to the COVID-19 lockdowns, declines of 18.5 ± 2.5 thousand metric tons (−28 ± 4%) to a fuel-mix change, and increases of 1.4 ± 0.6 thousand metric tons (+2 ± 1%) due to weather variability. This result highlights the importance of accounting for weather and fuel-mix changes when estimating the impact of COVID-19 on the power sector emissions.

1. Introduction

Over the past decade, the U.S. power sector has seen trends of increasing use of natural gas (a fossil fuel) and renewables and decreasing use of coal. This trend in the U.S. fuel-mix profile has been driven by economic considerations (IEA, 2019; Fell and Kaffine 2018) and by actions taken in response to state and regional climate goals (Murray and Maniloff 2015; Martin and Saikawa 2017). In 2010, the U.S. total electricity generation was 4125 TWh, only 0.05% lower than in 2019. However, the fuel-mix profile in 2010 was significantly different from that in 2019. In 2010, combustion of coal was the largest source (45%) of electricity generated in the U.S., followed by natural gas (23%), nuclear (20%), renewables (10%), and petroleum/other sources (1%) (EIA, 2020c). In 2019, the U.S. power sector generated 4127 TWh of electricity (EIA, 2020c). As a result of the fuel-mix change, in 2019, natural gas was the largest source (38%) of the U.S. electricity generation, followed by

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coal (23%), nuclear (20%), renewables (18%), and petroleum/other sources (1%). Natural gas and coal, the two largest energy sources in 2019, are fossil fuels. Per unit of energy produced, natural gas power plants in the U.S. emitted on average 43% of CO_2 and 25% of NO_x compared with coal power plants during 2019 (EPA, 2020a, EIA, 2021).

As a benefit of the fuel-mix change over the past decade, there has been significant improvement in the emission intensities of CO_2 and NO_x in the U.S. power sector (Schivley et al., 2018; de Gouw et al., 2014; Lu et al., 2012). In 2019, the emissions of CO_2 from the U.S. electricity generation sector were 1617 million metric tons ($MTCO_2$), 29% decreased from the same sectoral emissions of CO_2 in 2010 (2270 $MTCO_2$) (EIA, 2020e). The emissions of NO_x from the electricity generation sector were 860 thousand metric tons in 2019, 61% decreased from the power sector emissions of NO_x in 2010 (2230 thousand metric tons). In 2019, emissions of CO_2 from the electricity generation account for 31% of the U.S. total energy-related emissions of CO_2, and emissions of NO_x from power sector account for 11% of the national total reported emissions (EPA, 2020b).

During the Severe Acute Respiratory Syndrome Corona Virus 2 (SARS-CoV-2 or COVID-19) global pandemic period in 2020, human activities were significantly reduced worldwide (WHO, 2020). As a result, reduction in emissions of CO_2 (Le Quéré et al., 2020, Liu et al., 2020; Turner et al., 2020; Parida et al., 2020; Zheng et al., 2020) and NO_x (Zhang et al., 2020; Goldberg et al., 2020; Keller et al., 2020; Laughner et al., 2021) were reported for many countries. In the United States (U.S.), federal, state, and local government offices issued various social activity regulations and stay-at-home orders starting in March 2020 (NGA, 2020). The U.S. Energy Information Administration (EIA) published reports that show significant disruptions in electricity consumption patterns over the Midcontinent Independent System Operator (MISO) and the New York Independent System Operator (NYISO) after accounting for temperature changes (EIA, 2020a, 2020b). According to these EIA reports, weekday electricity demand over MISO decreased by 9%–13%, and weekday demand over NYISO decreased by 11%–14% from the expected levels during late March to April 2020.

In this study, we quantify the impact of COVID-19 on U.S electricity generation and electricity-sector CO_2 and NO_x emissions in 2020. We separate the impacts from the following three factors: 1) the outdoor temperature (i.e., energy demand for heating and cooling), 2) type of day (i.e., decreased electricity demands during weekends/holidays compared to weekdays), 3) long-term trends of fuel-mix change (i.e., from coal to natural gas and renewables). In section 2, a multivariate adaptive regression splines (MARS) model is presented and used to estimate daily electricity generation for major interconnection regions as a function of various indicators such as outdoor weather, day of the week, and holidays. In section 3.1, our estimates of reductions in electricity generation due to COVID-19 are presented. In section 3.2, the impacts of COVID-19 on power sector emissions of CO_2 and NO_x are presented, and such impact is compared to the impact of the recent fuel-mix change in the U.S. power sector.

2. Methods

2.1. Electricity generation, weather, weekends and holidays

In this study, data for electricity generation as well as emissions of CO_2 and NO_x are obtained from the U.S. Environmental Protection Agency Air Markets Program Data (EPA AMPD) and the U.S. Energy Information Administration (EIA) (EIA, 2020d, EPA, 2020a). To account for variability in weather, heating degree days (HDD) and cooling degree days (CDD) data are obtained from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (NOAA CPC, 2020). For each of 344 state climate divisions, NOAA CPC calculates daily HDD (or CDD) as the negative (positive) difference between the mean daily temperature (average of the daily maximum and minimum) and the 65 °F (=18.3 °C) base. Then, NOAA CPC estimates state-level daily HDD (or CDD) by population-weighting HDD (or CDD) for climate divisions in each state.

The U.S. power system comprises three major grids: Western, Eastern, and Texas Interconnections. Within each interconnection, regional balancing authorities manage electricity supply to match demand, while the three interconnections operate independently with limited exchange of electricity (de Chalendar et al., 2019). To represent the Western Interconnection, the power sector and HDD/CDD data are aggregated for the following states: Washington, Oregon, Idaho, California, Nevada, Utah, Arizona, Colorado, New Mexico, Montana, Wyoming (hereafter 'West', the brown area in Fig. 1g). Similar data for all other states in the contiguous U.S. (CONUS) are aggregated to represent the Eastern and Texas Interconnections (hereafter 'East & Texas', the purple area in Fig. 1g), given similar fuel-mix profiles in two regions. For the aggregation of state-level HDD/CDD data, CDD values are weighted by state populations, and HDD values are weighted by the number of state-wide electricity heating households obtained from EIA (EIA, 2020f). Text S1 describes the aggregation processes of the power sector and HDD/CDD data.

In this study, multivariate adaptive regression splines (MARS) is adopted to estimate daily electricity generation as a function of HDD, CDD, and an indicator for weekends and holidays. MARS is a numerical method used to investigate nonlinear relationships in multi-dimensional data (Friedman 1991; Friedman and Roosen 1995). Several studies have shown that energy demand exhibits nonlinear relations with HDD and CDD: a response of energy demand (i.e., air conditioning) per degree increase in CDD is relatively higher at the temperature of 85 °F (29 °C) compared to a response at the temperature of 65 °F (18 °C) (Almuhtady et al., 2019; Giannakopoulos and Psiloglou 2006; Harvey 2020). For MARS, a set of piecewise linear basis functions is used to model nonlinear relationships between a response variable and predictors. We include an indicator for weekdays and holidays as a predictor variable to account for the typical decrease in electricity demand during weekends and holidays (Pruckner et al., 2014). Regression coefficients are determined from the training data from January 2015 to December 2019 (1826 days). The first two months of 2020 (i.e., before the COVID-19 outbreak) are excluded from the training data, as this period can be used for model evaluation (Fig. S3). Further description of the model is given in Text S2. One MARS model is developed for the East & Texas (MARS-ELEC$^{E\&T}$, Equation (1)) and a second for the West (MARS-ELEC^{WEST}, Equation (2)). MARS-ELEC consists of a set of linear basis functions ($[\pm(x-c)]_+$), a type of day variable (Di), and the intercept as following:

$$\widehat{E}_i^{E\&T} = 0.02\cdot\left[HDD_i^{E\&T}-2.44\right]_+ + 0.10\cdot\left[HDD_i^{E\&T}-9.37\right]_+ + 0.26\cdot\left[CDD_i^{E\&T}-3.28\right]_+ - 0.25\cdot\left[3.28-CDD_i^{E\&T}\right]_+ - 0.61\cdot D_i + 8.01 + \varepsilon_i \tag{1}$$

$$\widehat{E}_i^{West} = 0.02\cdot\left[HDD_i^{West}-1.42\right]_+ + 0.03\cdot\left[1.42-HDD_i^{West}\right]_+ + 0.02\cdot\left[11.56-HDD_i^{West}\right]_+ + 0.04\cdot\left[CDD_i^{West}-0.04\right]_+ + 0.61\cdot\left[0.04-CDD_i^{West}\right]_+ - 0.11\cdot D_i + 1.59 + \varepsilon_i \tag{2}$$

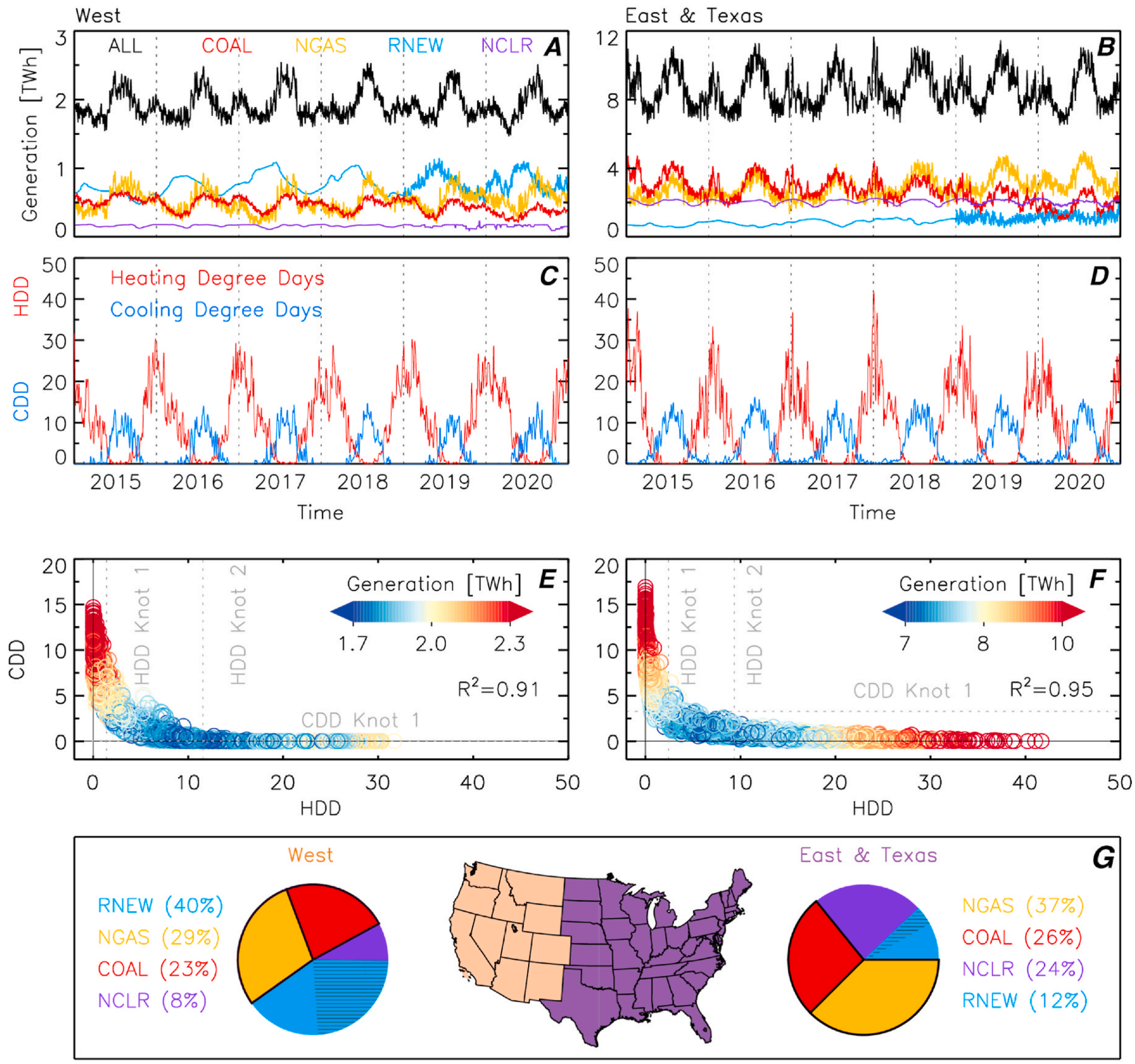

Fig. 1. Electricity generation and temperature conditions for the West (a, c, e) and the East & Texas (b, d, f). (a, b) Time series of daily electricity generation from four energy sources: Coal, natural gas (NG), nuclear (NCLR), and renewables (RNEW) (Source: EPA, EIA). The total generation is shown as a black line (ALL). (c, d) Heating degree days (HDD) and cooling degree days (CDD) averaged for 3-days (Source: NOAA CPC). (e, f) Scatter plots of electricity generation as a function of 3-day running mean of HDD and CDD for 2015 to 2019. Vertical and horizontal gray lines indicate knot (cut point) values determined for a multivariate adaptive regression spline model (MARS-ELEC), presented in section 2. (g) Geographic region of the West (brown) and the East & Texas (purple). Pie charts show the electricity fuel-mix composition of each region for 2019. The black outline for Natural Gas (NGAS) and Coal portions highlights fossil-fuel energy sources. The dashed blue area indicates Hydroelectric energy, and the solid blue portion area is other renewable energies (i.e., Solar, Wind, and Geothermal). See Fig. S1 for the time series of electricity generation from each renewable energy source. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

$$where\ [X]_+ = \begin{cases} X, & if\ X > 0 \\ 0, & if\ X \leq 0 \end{cases}$$

where i represents date and $E\&T$ indicates the East & Texas. Variable $\widehat{E}$ is a model estimate of total electricity generation for each region (unit: TWh), *HDD* and *CDD* are heating degree days and cooling degree days averaged in three-day running windows. Three-day running averages are applied to the HDD and CDD values to account for the temporal lead and/or lag in the electricity demand in response to varying outdoor temperatures. Training MARS-ELEC models with three-day running means of HDD and CDD showed improved model performance compared to the models trained with either two-day running means or single-day values (Table S1). The values of c are knots (cut point) of the basis function ($[\pm(x-c)]_+$), which partition the data into disjoint regions (Equation (2)). Variable D_i is 0 for regular weekdays and 1 for weekends, federal holidays, and four additional days (the last day of year, the day after Thanksgiving, and the day before and after Christmas). Variable ε_i is the error component. The two standard deviations (2σ) of residuals for the period of January 2015 to December 2019, shown in Fig. S3, are determined as the uncertainty range of the model estimate during 2020.

The MARS-ELEC^{WEST} has three HDD terms (two terms with a cut-point value of 1.42 and a term with a cut-point value of 11.56, Equation (2)). In comparison, the MARS-ELEC$^{E\&T}$ has only two HDD terms (Equation (1)). Such difference in a number of HDD terms between two MARS-ELEC models indicates that electricity generation in the West region has a higher degree of nonlinearity in response to mild temperatures (63.58 °F or 17.54 °C) than in the East & Texas region (i.e., difference in comfort temperature preference between the two regions).

2.2. The U.S. Power sector emissions of CO_2 and NO_x

In this study, we attribute the changes in the power sector emissions of CO_2 and NO_x between 2020 and 2015-19 average to the weather, fuel-mix change in the U.S. power sector, and COVID-19 social restrictions as followings:

$$\Delta NOx_{m,\ 2020}^{EPA} = NOx_{m,\ 2020}^{EPA} - \left(\sum_{y=2015}^{2019} NOx_{m,y}^{EPA} \Big/ 5 \right) = \Delta NOx_{m,\ 2020}^{Weather} + \Delta NOx_{m,\ 2020}^{Fuel\ mix} + \Delta NOx_{m,\ 2020}^{COVID} \quad (3)$$

$$\Delta NOx_{m,\ 2020}^{Weather} = NOx_{m,\ 2020}^{Scenario\ A} - \left(\sum_{y=2015}^{2019} NOx_{m,y}^{EPA} \Big/ 5 \right), \quad where\ Scenario\ A\ is \begin{cases} Fuel\ mix: 2015-19 \\ Weather: 2020 \end{cases} \quad (4)$$

$$\Delta NOx_{m,\ 2020}^{Fuel\ mix} = NOx_{m,\ 2020}^{Scenario\ B} - NOx_{m,\ 2020}^{Scenario\ A}, \quad where\ Scenario\ B\ is \begin{cases} Fuel\ mix: 2020 \\ Weather: 2020 \end{cases} \quad (5)$$

$$\Delta NOx_{m,\ 2020}^{COVID} = NOx_{m,\ 2020}^{EPA} - NOx_{m,\ 2020}^{Scenario\ B} \quad (6)$$

where variable $NOx_{m,\ y}^{EPA}$ indicates the power sector emissions of NO_x reported by EPA Air Markets Program Data (AMPD) on month m of year y. Equations (3)–(6) are applied to each of the East & Texas region and the West region, respectively. Analogs of Equations (3)–(6) are also used to estimate changes in the power sector emissions of CO_2.

Scenario A assumes the situation where the fuel-mix is the mean of the past five years (2015–2019) and the weather condition is 2020. Emissions of NO_x for scenario A are estimated as followings:

$$NOx_{m,\ 2020}^{Scenario\ A} = \widehat{E}_{m,2020} * \left(\sum_{y=2015}^{2019} NOx_{m,y}^{EPA} \Big/ E_{m,y}^{EPA} \right) \Big/ 5 \quad (7)$$

where variable $\widehat{E}_{m,2020}$ indicates a MARS-ELEC model estimate of total electricity generation estimated using HDD and CDD values for month m in 2020 (see Equations (1) and (2)). Variable $E_{m,y}^{EPA}$ is monthly total electricity generation reported by EPA AMPD and EIA for month m of year y.

Scenario B assumes the situation where both the fuel-mix and weather conditions are set to those of 2020. The reductions in the power sector emission of CO_2 and NO_x due to COVID-19 social restrictions vary with the fuel-mix composition of power units affected by COVID-19. For the competitive U.S. electricity markets, lower marginal cost units (solar, wind, hydro, geothermal, nuclear) receive priority in dispatch compared to higher marginal cost units (coal and natural gas) until demand is met (Borenstein and Bushnell 2015). Following the scheme of

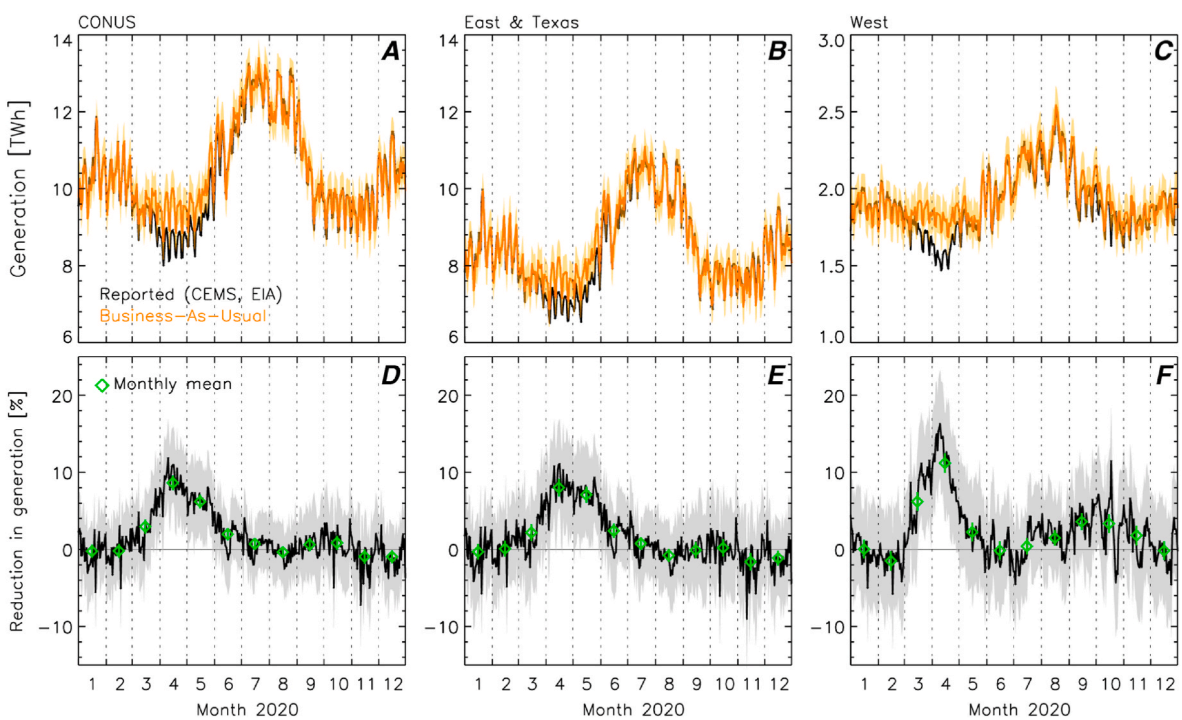

Fig. 2. Impacts of COVID-19 on electricity generation over the CONUS (a, d), East & Texas (b, e), and West (c, f). Upper panels show daily electricity generation from January to December 2020 (a, b, c). The black lines indicate actual generation reported by EPA (combustion-based units) and EIA (nuclear and renewables units). The orange lines indicate our BAU estimate of electricity generation, found as a function of outdoor temperature and type of day indicator (MARS-ELEC, Equations (1) and (2)). Orange shaded area is the uncertainty range of BAU generation, determined as the 2σ of model residuals for the five-year training dataset (see Section 2). For the lower panels, the black lines show the percentage reduction of actual generation relative to the BAU (d, e, f), and gray areas are 2σ uncertainty range. Green diamonds and error bars show a monthly mean reduction in electricity generation and the 2σ uncertainty, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

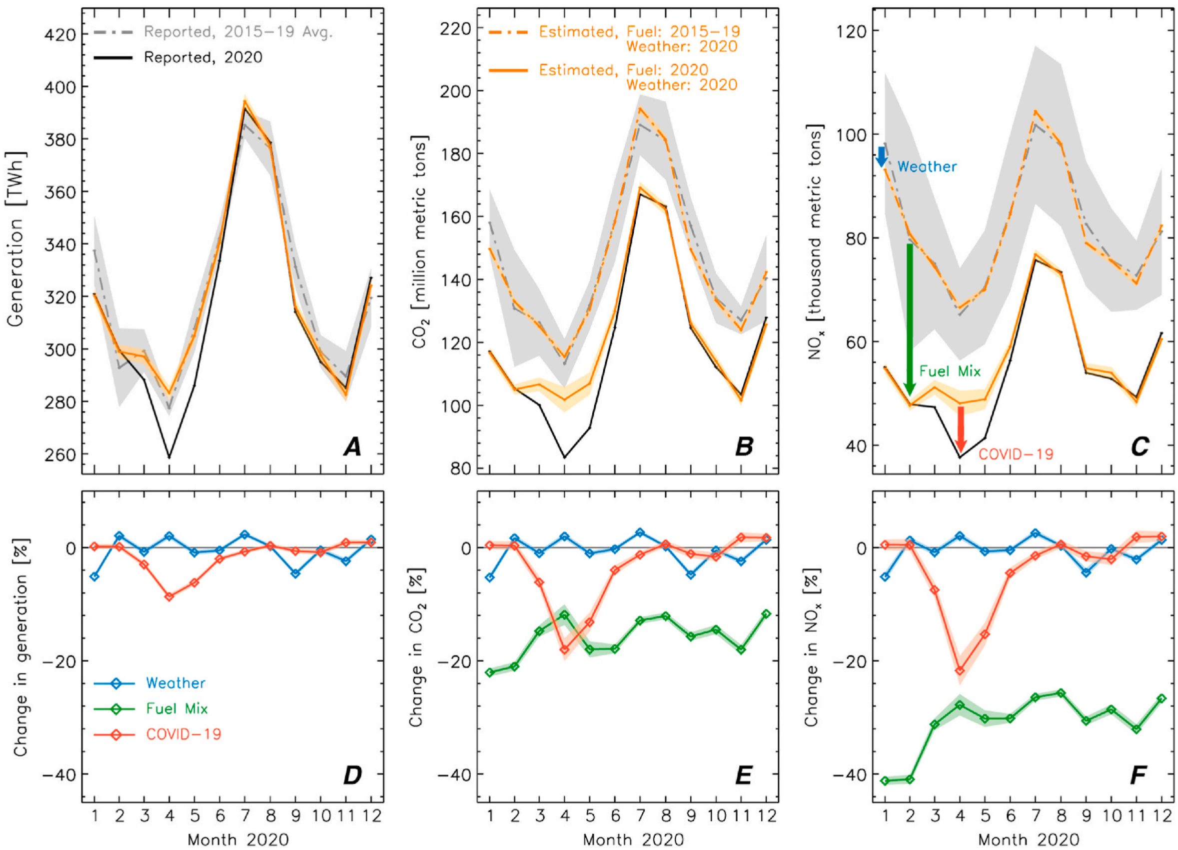

Fig. 3. The monthly electricity generation (a, d), CO_2 emission (b, e), and NO_x emission (c, f) from power units in the CONUS. Upper panels show the monthly generation and emissions of CO_2 and NO_x from January to December 2020 (a, b, c). Black solid lines indicate generation/emissions reported by EIA/EPA for 2020. Gray dotted lines and areas indicate the mean and the standard deviation of each reported variable from 2015 to 2019. Orange dotted lines are our estimate of the emissions for the scenario in which the fuel-mix profile is 2015–19 average and the weather conditions are 2020. Orange solid lines are our estimates of the generation/emissions for the scenario in which the fuel-mix profile and the weather conditions are 2020 (the business-as-usual scenario with no COVID-19 outbreak). The Orange shaded area shows a 2σ uncertainty range. Blue, Green, and Red arrows highlight the impact of weather, fuel-mix change, and COVID-19 social restrictions, respectively. Lower panels show the percentage change of each variable due to weather, fuel-mix change, and COVID-19 (d, e, f). Same formatted Figures for the East & Texas and the West regions are shown in Figs. S5 and S6. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

unit dispatch in competitive markets, we relate the decline in electricity generation due to COVID-19 (Fig. 2) to changes in the operation of coal-fired and natural gas-fired units, which have relatively high marginal costs (Equation (8)). Emissions of NO_x for scenario B are estimated as followings:

$$NOx_{m,\ 2020}^{Scenario\ B} = NOx_{m,\ 2020}^{EPA} + \left(\Delta E_{m,2020}^{Coal} * NOx_{m,2020}^{Coal} \middle/ E_{m,2020}^{Coal}\right) + \left(\Delta E_{m,2020}^{Gas} * NOx_{m,2020}^{Gas} \middle/ E_{m,2020}^{Gas}\right) \quad (8)$$

Variables $NOx_{m,2020}^{Coal}$ and $NOx_{m,2020}^{Gas}$ are the emissions of NO_x reported by EPA AMPD for coal-fired units and gas-fired unites, respectively. Variables $E_{m,2020}^{Coal}$ and $E_{m,2020}^{Gas}$ are the monthly electricity generation reported for coal-fired units and gas-fired units. Variables $\Delta E_{m,2020}^{Coal}$ and $\Delta E_{m,2020}^{Gas}$ are the reduction in the electricity generation due to COVID-19 for coal-fired units and gas-fired units, estimated by analyzing the daily operation status of 3013 power units from 1 January to August 12, 2020. See Text S3 for the detailed descriptions on the unit operation status analysis. Based on the unit operation status analysis, changes in the electricity generation due to COVID-19 are estimated as followings $\Delta E_{m,2020}^{Coal} = \left(\widehat{E}_{m,2020} - E_{m,2020}^{EPA}\right)*0.58$ and $\Delta E_{m,2020}^{Gas} = \left(\widehat{E}_{m,2020} - E_{m,2020}^{EPA}\right)*0.42$. The 2σ uncertainty range of scenario B emissions of CO_2 and NO_x (orange areas in Fig. 3) are determined by propagating uncertainties associated with each term in Equations (3)–(8), as detailed in Text S3.

3. Results and discussion

3.1. Electricity generation and outdoor temperature

Fig. 1a–b shows daily electricity generation for the West and East & Texas regions, from January 2015 to December 2020. Electricity generation in both regions shows a bimodal seasonal cycle, peaking in summer and winter. The heating degree days (HDD) and cooling degree days (CDD), proxies of energy demand for spatial heating and cooling, are used to account for variations in electricity generation due to weather (Chang et al., 2016; Beheshti et al., 2019). Fig. 1c–d shows the three-day running means of HDD and CDD, exhibiting seasonal cycles. Fig. 1e–f shows the variation of electricity generation as a function of HDD and CDD for the West and East & Texas regions, respectively, from January 2015 to December 2019. Scatter plots of electricity generation versus each HDD and CDD, individually, are shown in Fig. S2.

Pétron et al. (2008) published one of the earlier studies that connected the U.S. power sector emissions of CO_2 and the weather from 1998 to 2006. Pétron et al. (2008) reported that monthly total power sector emissions of CO_2 during the summer (i.e., average temperature >20 °C) show strong correlations with monthly regional CDD, having R^2 values ranging from 0.45 to ~0.82 for the eight U.S. subregions. Our study adopts a more sophisticated approach. We use the MARS algorithm to model nonlinearity between the power generation and the weather, incorporating HDD, CDD, and weekdays/holidays variables.

Our MARS-ELEC models have shown R^2 values of 0.89 (East & Texas) and 0.82 (West) for the daily training dataset (January 2015–December 2019) (Fig. S2).

3.2. Electricity generation and COVID-19

We use MARS-ELEC$^{E\&T}$ and MARS-ELEC^{WEST} (Equations (1) and (2)) to estimate the business-as-usual (BAU, i.e., no COVID-19 outbreak) electricity generation for the East & Texas and the West. In Fig. 2b and c, the orange lines show our estimate of the BAU electricity generation from January to December 2020. For the first two months of 2020, prior to the major outbreak of COVID-19 in the CONUS, the BAU estimate of electricity generation shows excellent agreement with the actual generation reported by EPA (combustion-based units) and the EIA (nuclear and renewable units), with the mean percentage error (MPE) of 0.1% for the East & Texas and 0.7% for the West. The MARS-ELEC performs well at reproducing patterns of higher generation for colder days (higher HDD) and lower generation on weekends and holidays. The generalized R^2 of the model estimates of electricity generation versus reported values is 0.95 for MARS-ELEC$^{E\&T}$ and 0.91 for MARS-ELEC^{WEST} for the training set data (January 2015–December 2019, Figs. S3b and S3c).

The impact of COVID-19 on electricity generation becomes apparent around mid-March, as daily generation reported by EPA and EIA show decreased values compared to the BAU values. On March 19, 2020, the state of California issued its first state-wide stay-at-home order, and a total of 44 states in CONUS and the District of Columbia were under partial or full lockdown by April 7, 2020 (NGA, 2020). For the East & Texas, the weekly reduction in generation peaked at 9 $\pm$ 2% (5.0 $\pm$ 1.2 TWh) during the third calendar week of April (04/13–04/19). For the West, the weekly reduction peaked at 15 $\pm$ 3% (1.9 $\pm$ 0.3 TWh) during the second calendar week of April (04/06–04/12) (Fig. 2e and f). For the entire CONUS, the total electricity generation during April 2020 was 258.7 $\pm$ 0.1 TWh, which is 9 $\pm$ 1% lower than our BAU estimate (Fig. 2d). This value is also the lowest April level in the 20 years for which EIA records are available (1991–2020). In mid-April, the reduction in electricity generation due to COVID-19 begin to mitigate for both regions. The West showed a faster return to the BAU level than the East & Texas. In August 2020, a modest resurgence of reduced generation was seen in the West (Fig. 2f), while electricity generation remained at the BAU level in the East & Texas (Fig. 2e).

3.3. Power sector emissions of CO_2 and NO_x: Weather, fuel-mix change, and COVID-19

According to the EPA and EIA reports, the monthly emissions of CO_2 and NO_x in 2020 (black solid lines in Fig. 3b and c) are always lower than the monthly mean emissions for the previous five years (2015–2019, gray dotted lines Fig. 3b and c), even before the COVID-19 outbreak. Meanwhile, electricity generation had shown notable decreases relative to the five-year means only from March to May 2020, when the COVID-19 social restrictions were most strict (Fig. 3a). We estimate the impacts of weather, fuel-mix change, and COVID-19 on the reported changes in electricity generation and emissions of CO_2 and NO_x by considering the two scenarios: 1) the fuel-mix profile of the U.S. power sector is set to 2015–19 average while the weather being 2020 conditions (orange dotted lines in Fig. 3b and c), 2) both the fuel-mix profile and the weather are set to 2020 conditions (the business-as-usual scenario with no COVID-19 outbreak, orange solid lines in Fig. 3a–c).

The weather in April 2020, when the COVID-19 social restriction was most strict, was slightly colder than the average April weather from 2015 to 2019, which led to 2% increases in emissions of CO_2 and NO_x. The weather in March and May 2020 was slightly milder than the past five years mean, resulting in 1% decreases in emissions of CO_2 and NO_x. For 2020, our estimates of the weather impact on the emissions range from 5% decline to 2% increase, with an annual mean of 1% decrease (A gap between the gray dotted line and orange dotted line in Fig. 3b and c or Blue line in Fig. 3e and f).

In recent years, the U.S. power sector has seen increasing natural gas and renewables and decreasing coal in fuel-mix profiles (see section 1, Fig. 1, and Fig. S7). We estimate that such fuel-mix change led to the declines of monthly emissions of CO_2 by 12–22% (13.7–33.0 $MTCO_2$), with the mean monthly decrease of (16%) 22.8 $MTCO_2$ (A gap between the orange solid line and orange dotted line in Fig. 3b or Green line in Fig. 3e). For April 2020, we estimate the emissions of CO_2 declined by 12% (13.7 $MTCO_2$) due to the fuel-mix change. The fuel-mix change had more significant impacts on the emissions of NO_x. We estimate the emissions of NOx declined by 28–41% (18.5–38.4 thousand metric tons) due to the fuel-mix change, with the mean monthly decline of 31% (25.3 thousand metric tons). For April 2020, we estimate the emission of NO_x declined by 28% (18.5 thousand metric tons) due to the fuel transition.

The impacts of COVID-19 on the power sector emissions of CO_2 and NO_x are most notable from March to June 2020, with the reductions peaking in April 2020 (A gap between black solid line and orange solid line in Fig. 3b and c or the red lines in Fig. 3e and f). For the CONUS in April 2020, our estimate of the decline in the emission of CO_2 due to COVID-19 is 18 $\pm$ 4% (18.3 $\pm$ 4.0 $MTCO_2$), whereas the decrease in the emission of NO_x due to COVID-19 is 22 $\pm$ 5% (10.5 $\pm$ 2.4 thousand metric tons). Table S2 summarizes the impacts of COVID-19 on electricity generation and concomitant emissions of CO_2 and NO_x for CONUS, East & Texas, and West from March to December 2020.

The impacts of the fuel-mix change (i.e., improvements on the emission intensities) on the monthly emissions of NO_x (green line in Fig. 3f) are always greater than the impact of COVID-19 (red line in Fig. 3f) throughout 2020. For the CONUS, emission of NO_x during April 2020 decreased by 42% (27.6 thousand metric tons) from the average emission of April 2015–2019 (a gap between the black solid line and gray dotted line in Fig. 3c). Such reduction is ~2.6 times greater than the reduction induced by COVID-19 (10.5 $\pm$ 2.4 thousand metric tons, red line in Fig. 3f). Also, the emission of CO_2 in April 2020 declined by 26% (29.8 $MTCO_2$) from the average emission of April 2015–2019; a reduction 1.6 times greater than the impact of COVID-19 on the same month. These results suggest that using uncorrected prior-year emissions as a baseline will result in an overestimation of the impact of COVID-19, given the recent downward trends in the emissions of CO_2 and NO_x from the U.S. power sector.

Liu et al. (2020) and Le Quéré et al., 2020 assessed the impact of COVID-19 on sector-specific CO_2 emissions (power, transport, industry, residential, etc.) across the globe in near-real-time. Our study focuses on a single sector (power) in a single country (the U.S.). According to Liu et al. (2020), U.S. power sector emissions of CO_2 declined by 66.3 $MTCO_2$ during the first half of 2020. Our study suggests the decline is 43.2 $\pm$ 6.1 $MTCO_2$ for the first six months of 2020. Two factors might contribute to the greater decline reported in Liu et al. (2020). First, Liu et al. (2020) used CO_2 emission intensity for 2019 to calculate emissions for 2020. Our analysis shows significant improvements in the CO_2 emission intensity for the U.S. power sector, even from 2019 to 2020 (Fig. S7). Second, Liu et al. (2020) corrected power generation for temperature differences between 2019 and 2020. The temperature corrections are only applied to the countries that show a good correlation between daily power generation and temperature ($R^2 > 0.5$). Such temperature correction may not have been applied to the U.S. power sector data, as Supplementary Fig. 1 of Liu et al. (2020) shows a significant decline in electricity generation during January and February 2020, prior to a major outbreak of COVID-19. Le Quéré et al., 2020 reported that U.S. emission of CO_2 declined by 207 (112–314) $MTCO_2$ from January to April 2020 for the following six sectors: power, industry, surface transport, public buildings and commerce, residential, and aviation. They calculated the U.S. power sector CO_2 emissions for 2020 by multiplying the emissions for 2019 to fractional changes in weather-corrected electricity demand for the same weeks between 2019 and 2020. This approach also does not account for the decline in emission intensity in the U.S. power sector.

4. Conclusions

In this study, we estimate the impact of COVID-19 on electricity generation and concomitant emissions of CO_2 and NO_x for the CONUS, East & Texas (geographical proxy of the Eastern and the Texas Interconnections, the purple area in Fig. 1g), West (geographical proxy of the Western Interconnections, brown area in Fig. 1g). As a whole for the CONUS, we estimate that electricity generation in April 2020 decreased by 9 ± 1% (24.6 ± 2.6 TWh) as a direct result of COVID-19 restrictions, reaching the lowest April level in the past 20 years. Due to the reduced generation of electricity in April 2020, monthly emissions of CO_2 from the power sector are estimated to have fallen by 18 ± 4% (18.3 ± 4.0 $MTCO_2$). The size of reduction in CO_2 emission in April 2020 is comparable to the total amount of fossil-fuel CO_2 ($FFCO_2$) emitted from the State of Pennsylvania during April 2019 (16.9 $MTCO_2$), according to the Open-Source Data Inventory for Anthropogenic CO_2 (ODIAC2020, ;Oda and Maksyutov (2020)). Emissions of NO_x from the power sector in April 2020 are estimated to have fallen by 22 ± 5% (10.5 ± 2.4 thousand metric tons) due to COVID-19.

We show that the fuel-mix change in the U.S. power sector from 2015 to 2020 has had a significant impact on the emissions of CO_2 and NO_x. We estimate that, in April 2020, the BAU (i.e., no COVID-19) emissions of NO_x from the U.S. power sector declined by 18.5 ± 2.5 thousand metric tons from the average emissions of April 2015–2019 (Fig. 3c), as a result of the improved emission intensity during this period. For the same month, our estimate of the decrease in the emissions of NO_x due to the COVID-19 social restrictions is 10.5 ± 2.4 thousand metric tons (Fig. 3c). This result highlights the importance of the structural change in the power sector (i.e., a transition from coal to natural gas/renewables) that brings co-benefits of reducing greenhouse gas emissions and improving air quality.

There are several limitations to our study. First, we analyzed the daily operation status of 3013 coal-fired and gas-fired electricity generating units to attribute the observed reductions in electricity generation to specific fuel sources. More detailed source attribution would require the use of dispatch and economic models, which could address complicated questions such as what would be the price of coal and natural gas if there had not been a global outbreak of COVID-19? Second, our study did not consider the impacts of COVID-19 on finer scales (i.e., hourly load, sector-specific demand). Third, our study analyzed the direct impact of COVID-19 (i.e., reduced electricity demand due to change in human activities), while indirect impacts of COVID-19, such as delay in construction, maintenance, retirement of power plants, are not considered. Future studies should be conducted at finer spatial, temporal, and sectoral scales. Also, another potential application of the MARS-ELEC model would be to study sulfate aerosol pollution in the U. S. Such a study could be conducted by incorporating the power sector emissions of SO_2 and PM2.5 composition and sulfur deposition measurements into the MARS-ELEC modeling framework (van Donkelaar et al., 2019; Snider et al., 2016; Fedkin et al., 2019). Despite these limitations, our study provides a reliable assessment of the direct impact of COVID-19 on electricity generation and concomitant emissions of CO_2 and NO_x by accounting for both meteorology and the recent trend of fuel-mix change.

CRediT authorship contribution statement

D.Y. Ahn: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. **R.J. Salawitch:** Conceptualization, Methodology, Writing – review & editing, Supervision. **T.P. Canty:** Conceptualization, Writing – review & editing. **H. He:** Conceptualization, Writing – review & editing. **X.R. Ren:** Conceptualization, Writing – review & editing. **D.L. Goldberg:** Methodology, Writing – review & editing. **R.R. Dickerson:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

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

Acknowledgments and Data Availability

Support from the National Institute of Standards and Technology (NIST) for the Fluxes of Greenhouse Gases in Maryland (FLAGG-MD) project and the Maryland Department of the Environment (MDE) is gratefully acknowledged. The authors appreciate the helpful comments provided by Joel Dreessen at MDE as well as Anna Karion and Kim Mueller at NIST. The power sector electricity generation and emissions data set used in this study are publicly available from U.S. Environmental Protection Agency Air Market Program Data (EPA AMPD) website (https://ampd.epa.gov/ampd/) and U.S. Energy Information Administration (EIA) website (https://www.eia.gov). The raw state-level daily heating degree days and cooling degree days data are publicly available from the NOAA CPC website (https://www.cpc.ncep.noaa.gov/products/analysis_monitoring/cdus/degree_days/). Annual state-level population data are publicly available from the U.S. Census Bureau website (https://www.census.gov/data/tables/time-series/demo/popest/2010s-state-total.html). The version of the ODIAC xemission data product (ODIAC2020) is available from the Global Environmental Database website hosted by the Center for Global Environmental Research (CGER), National Institute for Environmental Studies (NIES), Japan (http://db.cger.nies.go.jp/dataset/ODIAC/).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.aeaoa.2022.100168.

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