Reduction of surface radiative forcing observed from remote sensing data during global COVID-19 lockdown

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ABSTRACT

The calamity of the COVID-19 pandemic during the early half of 2020 not only caused a huge physical and economic loss but altered the social behavior of the whole world. The social and economic stagnation imposed in many countries and served as a major cause of perturbation in atmospheric composition. This paper utilized the relation between atmospheric composition and surface radiation and analyzed the impact of global COVID-19 lockdown on land surface solar and thermal radiation. Top of atmosphere (TOA) and surface radiation are obtained from the Clouds and Earth’s Radiant Energy System (CERES) and European Reanalysis product (ERA5) reanalysis product. Aerosol Optical Depth (AOD) is obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) while Nitrogen dioxide (NO₂) and sulfur dioxide (SO₂) are obtained from Ozone Monitoring Instrument (OMI). Observations of all mentioned parameters are studied for the global lockdown period of 2020 (from January to July) and compared with the corresponding months of the previous four years (2016–19) observations. Regarding surface radiation, April 2020 is the most affected month during the pandemic in which 0.2% increased net solar radiation (NSR), while 3.45% and 4.8% decreased net thermal radiation (NTR) and net radiation (NR) respectively was observed. Average radiative forcing during March-May 2020 was observed as 1.09 Wm⁻², −2.19 Wm⁻² and −1.09 Wm⁻² for NSR, NTR and NR, respectively. AOD was reduced by 0.2% in May 2020 while NO₂ and SO₂ were reduced by 5.4% and 8.8%, respectively, in April 2020. It was observed that NO₂ kept on reducing since January 2020 while SO₂ kept on reducing since February 2020 which were the pre-lockdown months. These results suggest that a more sophisticated analysis is needed to explain the atmosphere-radiation relation.

1. Introduction

The land surface net solar radiation (NSR) and net thermal radiation (NTR) collectively contribute to the net radiation (NR), which is the backbone of land surface energy that leads the global climate cycle (Stephens et al., 2012). Thus, any perturbation in NSR and NTR eventually influences the global climate. Changes in the atmospheric composition result in NSR and NTR perturbation due to the changed proportion of absorption and scattering of radiation. Anthropogenic activities such as large traffic movements, power plants, oil refineries, industrial combustions, and crop burnings contribute to air pollution and alter the atmospheric composition. The term radiative forcing is used to assess the impact of external factors on the energy balance of the earth. The external factors include natural sources such as the total solar irradiance and anthropogenic sources such as AOD and greenhouse gases. It is important to analyze the impact of energy balance on climate change by computing the perturbations in the external factors (de Coninck et al., 2018; Lewis and Lewis, 2018; Shine, 2000). Modeling techniques are used to study the impact of air pollution on NSR, NTR, and NR assuming some ideal situation about the absence of one or more pollutants (Schultz et al., 2003; Unger et al., 2008).

Recently a real-time scenario developed in which many studies
claimed the reduction of air pollution across the world. In early 2020, a respiratory epidemic named COVID-19 (coronavirus disease 2019) was firstly reported in Wuhan (Zhou et al., 2020). Because of the widespread disease, on March 11, 2020, World Health Organization (WHO) declared COVID-19 as a global pandemic (WHO, 2020). As the disease spread over many countries, national governments of affected countries imposed lockdown (suspension of social, travel, and economic activities). To restrict the spread of this air-born disease, China government imposed a strict lockdown on 23 January 2020 till the last week of April (Lian et al., 2020). In Europe, these restrictions were started in mid-March and extended till May 2020, and then gradually the restrictions became more lenient (Ordóñez et al., 2020). In India, the lockdown period was from 25 March to 17 May (Mor et al., 2021), in Bangladesh, the lockdown period is from 26 March to 30 May (Qiu et al., 2021), Saudi Arabia imposed the lockdown from 23 March to 20 June 2020 (Anil and Alagha, 2021). Many other countries in Asia, Europe, North and South America, and Australia imposed a social and economic lockdown at a similar time of the year.

This unprecedented situation impacted many aspects of life including air quality. Due to the suspension of economic and social activities, a shutdown of industries along with the reduction in traffic was observed which are the major causes of air pollutants e.g., material particles, nitrogen dioxide (NO\textsubscript{2}), sulfur dioxide (SO\textsubscript{2}), and many others. Many studies revealed that regionally suspended anthropogenic and economic activities resulted in the changed atmospheric compositions in many parts of the world (Anil and Alagha, 2021; Chauhan and Singh, 2020; Dantas et al., 2020; Lian et al., 2020; Liu et al., 2021; Mor et al., 2021; Nichol et al., 2020; Ordóñez et al., 2020; Sharma et al., 2020; Siddique et al., 2021). Nichol et al. (2020) observed an increase of fine particulate PM\textsubscript{2.5} in China’s economic hub; the Beijing-Tianjin-Hebei region while a drastic decrease was observed in NO\textsubscript{2} in the same region. Lian et al. (2020) investigated air quality over Wuhan, China, and observed that the air quality index got 33.9% better during lockdown with respect to the pre-lockdown months. PM\textsubscript{2.5} and NO\textsubscript{2} decreased by 36.9% and 53.3% respectively while Ozone (O\textsubscript{3}) increased by 116.6%. Qiu et al. (2021) observed a remarkable 47% decrease in AOD and 3 to 43% decrease in NO\textsubscript{2} over multiple cities in Bangladesh while an average increase of 3 to 12% in O\textsubscript{3} was observed at the same time. Anil and Alagha (2021) reported a huge decrease of 12–86% in NO\textsubscript{2} over the eastern provinces of Saudi Arabia, along with an 8.7–30% decrease in SO\textsubscript{2} and 21–70% decrease in PM\textsubscript{10}. In one of the early studies about the impact of COVID-19 on air pollution, Chauhan and Singh (2020) observed a decrease in PM\textsubscript{2.5} in March 2020 over some major cities around the world including Rome (Italy), Zaragoza (Spain), Shanghai, Beijing (China), Mumbai, Delhi (India), Dubai (United Arab Emirates), Los Angles and New York City (United States of America). Ordóñez et al. (2020) studied the variations in NO\textsubscript{2} and O\textsubscript{3} during COVID-19 lockdown in Europe and established a link between meteorological parameters and air pollution. They reported a 5–55% consistent decrease in NO\textsubscript{2} over Europe associated with the low emission. Lolli et al. (2020) studied the impact of meteorological conditions and air pollution on the COVID-19 and found that AOD was positively related to the spread of the disease in Italy. Siti et al. (2021) reported a decrease in NO\textsubscript{2} while an increase in O\textsubscript{3} in many cities across the world. Using some machine learning techniques, they suggested that the changes were abrupt but smaller than expected.

Despite some recent studies about the impact of COVID-19 economic stagnation on air pollution, there remained a scholarly gap of resultant impact on surface radiation. This paper analyzes the variations of NSR, NTR, and NR during the global lockdown period and their relationship with the AOD, NO\textsubscript{2} and SO\textsubscript{2}. The global land surface aerial averages of NSR, NTR and NR are used for analysis. NSR, NTR, and NR data are obtained from CERES and ERA5 that is a product of the European center for medium-range weather forecasts (ECMWF). AOD is obtained from MODIS while NO\textsubscript{2} and SO\textsubscript{2} are obtained from OMI. The 2016 to 2019 period is taken as a reference period. Observations during the 2020-lockdown period are compared with this reference period to quantify the lockdown-driven changes in any obtained parameter.

2. Data and methods

Multiple remote sensing data sets were used in this study to analyze the impact of COVID-19 lockdown on surface NSR, NTR, and NR. For top of atmosphere (TOA) shortwave radiation (SR) and thermal radiation (TR), CERES synoptic TOA and surface fluxes and clouds SYN1deg level 3 product (hereafter SYN) was used. This product provides daily observations of TOA and surface fluxes at 1° spatial resolution. At surface level, daily SR, NTR, and NR were obtained from SYN. For monthly analysis, daily SYN observations were averaged over each month. By comparing 85 globally distributed ground stations, SYN observed a mean bias of 3 Wm\textsuperscript{-2} and -4 Wm\textsuperscript{-2} for downward SR and TR respectively (Atmospheric and Technology, 2015; Doelling et al., 2013, 2016; Su et al., 2005; Su et al., 2007). For monthly NSR, NTR, and NR, CERES Energy Balanced and Filled (EBAF) monthly product was obtained. CERES EBAF surface product provides monthly observations at 1° spatial resolution having accuracy up to 4 Wm\textsuperscript{-2} and 6 Wm\textsuperscript{-2} for NSR and NTR respectively (Kato et al., 2018; Loeb et al., 2018). These data were obtained from the NASA Langley research center CERES ordering tool at https://ceres.larc.nasa.gov. Along with remote sensing products, ERA5-land surface monthly data at 0.1° spatial resolution was used for NSR, NTR, and NR (Hersbach et al., 2020). A significant correlation of 0.88 was observed regionally for ERA5 NR in comparison with NR observed from FluxNet ground towers (Mazhar et al., 2021). ERA5 data were obtained from https://cds.climate.copernicus.eu. The reason for obtaining multiple data sets for the same parameter is to avoid any chance of sensor/method limitation in the unprecedented suspended anthropogenic activities.

To analyze any perturbation in atmospheric composition and to observe the effects of anthropogenic activities, AOD, NO\textsubscript{2} and SO\textsubscript{2} global data were obtained. A combined dark target and deep blue AOD at 0.55 μm for land and ocean (MYD08_M3 v6.1) product from Aqua MODIS was used. The product provides daily observations at 1° spatial resolution. Combined AOD is retrieved from the high-quality dark target and deep blue algorithms (Ali et al., 2020; Bilal et al., 2017; Hsu et al., 2013; Levy et al., 2013). For NO\textsubscript{2} data, OMI/Aura NO\textsubscript{2} cloud-screened total and tropospheric column L3 global gridded at 0.25° product (OMNO2d) from OMI was used. The product provides vertical column density (from the surface to TOA) under 30% cloud screened condition. OMI/Aura SO\textsubscript{2} total column L3 daily best pixel at 0.25° resolution (OMSO2e) product was used for SO\textsubscript{2} total column density. AOD, NO\textsubscript{2}, and SO\textsubscript{2} data were downloaded from https://giovanni.gsfc.nasa.gov/giovanni.

Global aerial averages were used for all the above-mentioned parameters. As discussed in section-1, the social effects of the pandemic started in March 2020 and diminished down in May 2020. We used the observations of the first seven months (i.e. January to July) of each year from 2016 to 2020. The period 2016 to 2019 was taken as a reference period, and observations from all parameters were compared with the corresponding months of 2020. January, February, and June, July 2020 were observed to see the pre and post-pandemic impacts respectively. For daily SR and TR at TOA and NSR, NTR, and NR at the surface, a standard deviation (SD) was computed for each month to observe any abrupt changes in the corresponding parameter. For monthly analysis absolute and percentage, the difference was computed for each parameter using the following equations.

Absolute difference \( = \sum_{i=1}^{n} P_{\text{ref}} - P_{i} \) \hspace{1cm} (1)
Percentage difference = \frac{P_{20} - \sum_{i=1}^{4} P_{\text{ref}}}{\sum_{i=1}^{4} P_{\text{ref}}} \times 100 \quad (2)

where $P_{20}$ refers to the mean monthly value of the parameter in 2020; $P_{\text{ref}}$ means the 4-year monthly average (2016–19) of the corresponding parameter. The same formula was used for the analysis of spatial anomalies.

3. Results and discussions

3.1. Relation between surface radiation and atmospheric components

Fig. 1 shows the relation between incoming and outgoing SR, TR, NSR, NTR and NR with AOD, NO$_2$, and SO$_2$. Each point represents the mean monthly observation of the corresponding location. SR, TR, NSR, NTR and NR are measured in Wm$^{-2}$, NO$_2$ is measured in 10$^{14}$ mol/cm$^2$ while SO$_2$ is measured in Dobson Unit (DU). The land surface radiation data is obtained from EBAF mean monthly spatial images. Each relation has 875 point values. SR$_{\text{in}}$ and TR$_{\text{in}}$ correspond to incoming SR and TR while SR$_{\text{out}}$ and TR$_{\text{out}}$ correspond to outgoing SR and TR.

Table 1

|       | SR$_{\text{in}}$ | SR$_{\text{out}}$ | TR$_{\text{in}}$ | TR$_{\text{out}}$ | NSR | NTR | NR |
|-------|-----------------|------------------|-----------------|------------------|-----|-----|----|
| R-value | 0.15            | 0.13             | 0.65            | 0.56             | 0.21| 0.36| 0.38|
| Standard error | 23.84            | 14.39            | 42.43           | 40.09            | 24.16| 24.34| 32.12|

All values are 99% significant at a 95% confidence level. SR$_{\text{in}}$ and TR$_{\text{in}}$ correspond to incoming SR and TR while SR$_{\text{out}}$ and TR$_{\text{out}}$ correspond to outgoing SR and TR.
and spatial information is https://hub.arcgis.com/datasets (last accessed: February 25, 2021). Mean monthly spatial images of April from 2016 to 2020 were used to obtain point observations. Radiative-atmospheric interaction is a complex phenomenon and correlation between any two parameters may be misleading. Thus, multiple linear regression was found by taking AOD, NO\textsubscript{2} and SO\textsubscript{2} as independent variables and each of SR, TR NSR, NTR and NR as the dependent variable. Incoming and outgoing SR are nominally affected by pollutants and show the R-value of 0.15 and 0.13 respectively. Outgoing SR shows the smallest standard error of 14.38 amongst all the observed relations. Fig. 1 shows that the majority of pollutant values correspond to higher incoming SR values while for outgoing SR the reverse pattern is observed. Incoming and outgoing TR shows the highest correlation with R-value of 0.65 and 0.56 but with higher standard error of 42.43 and 40.09 respectively. This leads to the fact that TR is more affected by the absorption or scattering of the observed pollutants. Pollutant values are evenly distributed over all TR observations. Like SR, NSR shows a weaker R-value of 0.21 with a standard error of 24.16. NTR and NR show a relatively stronger correlation with 0.36 and 0.38 and standard error of 24.43 and 32.11 respectively. The majority of pollutant values correspond to higher NSR and lower NTR values.

An observable fact from these relations is that neither of the R-value is convincingly strong. A major reason for the weak correlation is that these radiations are mainly affected by the biophysical parameters such as albedo, land surface temperature and land cover (Anderson et al., 2011; He et al., 2015; Nair et al., 2007; Wild et al., 2007). Despite these factors, the radiative forcing of atmospheric pollutants has a significant effect on surface radiations (Agudelo-Castaneda and Teixeira, 2014; Ali et al., 2019; Bais et al., 1993; Davis, 2017; Etminan et al., 2016). From a huge body of literature, the link between air pollutants and surface radiation is well established (Khodakarami and Ghobadi, 2016; Menon et al., 2010; Solomon et al., 1999; Wang et al., 2020). AOD affects the SR by either absorbing or scattering through the atmosphere and contributes to radiative forcing (Ali and Assiri, 2019; Ali et al., 2019; Bilal et al., 2019; Khan et al., 2020; Kumar et al., 2017). NO\textsubscript{2} involved in the absorption of visible and infrared radiation contributes to radiative forcing (Etminan et al., 2016; Schultz et al., 2003; Solomon et al., 1999; Vasilkov et al., 2009). Despite the small impact on global radiative forcing, locally NO\textsubscript{2} induced radiative forcing has an impact of 2 to 4 Wm\textsuperscript{-2} (Vasilkov et al., 2009). SO\textsubscript{2} has less radiative forcing than NO\textsubscript{2}, still, it has a consistent greenhouse effect in the climate (Bais et al., 1993; Giorgi et al., 2002; Khodakarami and Ghobadi, 2016).

### Table 2

A comparison of SD values for TOA SR and TR during 2020-lockdown with reference period. The Reference columns refer to the 4-years monthly averaged SD value of the corresponding month from 2016 to 2019.

| Month | TOA SR (Wm\textsuperscript{-2}) | TOA TR (Wm\textsuperscript{-2}) |
|-------|----------------|----------------|
|       | Reference 2020 | Reference 2020 |
| Jan   | 5.58           | 5.52           |
| Feb   | 7.98           | 7.77           |
| Mar   | 4.54           | 4.74           |
| Apr   | 1.93           | 1.97           |
| May   | 0.63           | 0.89           |
| Jun   | 1.18           | 1.21           |
| Jul   | 1.41           | 1.78           |

Fig. 2 describes the daily variation of TOA SR and TR from January to July 2016–2020. In the past five years, large variations are observed in daily TOA SR for the spring and summer months, however, concerning the COVID-19 specific conditions i.e. in March–May 2020, TOA SR shows no different pattern. Contrarily, TOA TR shows large daily variations in all seasons however, regarding 2020-lockdown, only the last few days of March 2020 are observed with significant low values. Here it is not confirmed that this decrease is due to the economic stagnation because in this case, the reduction in TOA TR shall be continued till May 2020. Both TOA SR and TR exhibit no significant different pattern during the lockdown period. Table 2 presents the SD values of TOA SR and TR for the comparison of inter-monthly variations. TOA SR shows higher SD values from January to March each year but TOA TR shows less than 3 Wm\textsuperscript{-2} SD values for all the months exhibiting low TOA TR changes around the year. Here again, SD for TOA SR shows no significant difference between the pandemic duration of 2020 and the reference period. TOA TR on the other hand shows a nominal high SD value (2.6 Wm\textsuperscript{-2}) in April 2020 with respect to the reference period.

Despite variations in atmospheric pollution which is evident in previous literature TOA SR and TR did not show any visible increase or decrease concluding that the effects of economic stagnation during the COVID-19 pandemic are not large enough to reach TOA. Thus the brightening or dimming of radiation at TOA demands a vast amount of changes in the atmospheric composition which did not happen in the 2020-lockdown. Also, the long life of pollutants (either particles or gasses), restricts the outcome of atmospheric changes at the surface to reach TOA (Haywood, 2016).
3.3. Daily variations of surface radiation and atmospheric pollutants

Fig. 3 shows daily variations in global land surface NSR, NTR and NR from 2016 to 2020. Each value is a daily global aerial average obtained from SYN.

Table 3

A comparison of SD values for NSR, NTR and NR during 2020 with reference period. The Reference columns refer to the 4-years monthly averaged SD value of the corresponding month from 2016 to 2019.

| Month | NSR | NTR | NR |
|-------|-----|-----|----|
|       | Reference 2020 | Reference 2020 | Reference 2020 |
| Jan   | 0.36 | 0.42 | 1.18 |
| Feb   | 0.72 | 0.65 | 1.08 |
| Mar   | 3.08 | 3.32 | 1.09 |
| Apr   | 5.81 | 5.52 | 1.06 |
| May   | 5.87 | 6.22 | 0.93 |
| Jun   | 1.45 | 1.52 | 1.08 |
| Jul   | 4.23 | 3.32 | 1.01 |

Fig. 4. Daily variations of AOD, NO\textsubscript{2} and SO\textsubscript{2} from 2016 to 2020 (January to July each year). Each value represents the global aerial average. AOD is obtained from MODIS while NO\textsubscript{2} and SO\textsubscript{2} are obtained from OMI.

was a pre-lockdown day. From March to May 2020, minimum and maximum values 116.5 and 170.7 Wm\textsuperscript{-2} respectively. NTR gradually decreased from the last week of March till mid-May 2020. This was the period in which the global pandemic was at its peak. Economic activities were suspended in most of the countries around the world. In the 2020-lockdown, NTR shows the least value of ~83.3 Wm\textsuperscript{-2} (a historical least in the last five years) on 12 May 2020, while the maximum value observed as ~75.43 Wm\textsuperscript{-2} on 13 March 2020. April 2020 has an SD value of 1.42 Wm\textsuperscript{-2} which is the maximum for April during the last five years.

NR is dominated by NSR and shows a similar temporal trend as NSR. However, the influence of the reduced NTR in April 2020 is evident in NR, and less than average NR values are observed during these days. In
2020-lockdown, a minimum value of NR is observed as 37.31 Wm$^{-2}$ on 2 March and the maximum value observed as 89.37 Wm$^{-2}$ on 28 May. Neither of them is historical minimum or maximum observations. With 4.3 and 6.6 Wm$^{-2}$, SD of NR shows the historical minimum and maximum value in April and May 2020 respectively.

Land surface radiation are influenced by greenhouse gasses and aerosols. For a better understanding of the variations of surface radiation, AOD, NO$_2$, and SO$_2$ were analyzed from January to July 2016 to 2020. Fig. 4 shows the daily variations of AOD, NO$_2$, and SO$_2$. In 2020, during January and February (before economic stagnation) AOD shows prominent high values than the previous years but it gradually decreased from March to the middle days of May and then started rising again. Here it is noteworthy that AOD is an event-dependent variable, and the global average gives only an overall picture of the AOD event occurrences. NO$_2$ tropospheric column average shows less values throughout 2020 as compared with the reference duration. The daily least value of $3.02 \times 10^{14}$mol/cm$^2$ is observed on 3 March 2020. After May 2020, NO$_2$ increased gradually. Increasing NO$_2$ column averages in summer months is a pattern that is also observed in the reference duration. The increased NO$_2$ during summer 2020, still remained lower than the reference observations. Total column SO$_2$ shows an early increase in January 2020, and decrease subsequently till July. The two least daily SO$_2$ total column values observed in 2020 as 0.141DU on 4 January and 0.148Du on 22 April.

Fig. 5 presents the absolute daily difference of NSR, NTR, NR, AOD, NO$_2$, and SO$_2$ computed from Eq. (1). The shaded region shows the 2020-lockdown period and the dotted line represents the zero absolute difference. For NTR and NR negative absolute difference is observed during 2020-lockdown describing the prominent reduction in NTR and NSR. NSR shows a mixed pattern during 2020-lockdown i.e. negative absolute difference in some days while the positive absolute difference for other days. From the lower panel of Fig. 5, AOD shows a decrease during the 2020-lockdown with respect to pre and post-lockdown months. NO$_2$ and SO$_2$ remained below zero difference line approximately throughout the year 2020 which shows that NO$_2$ and SO$_2$ decreased during 2020-lockdown as well as pre and post lockdowns months.

AOD reduction during 2020-lockdown in many cities across the world is evident from recent literature (Nichol et al., 2020; Qiu et al., 2021; Siddique et al., 2021). At most significant NO$_2$ reduction was found in Wuhan China, eastern provinces of Saudi Arabia, most countries in Europe and Brazil by many recent studies (Anil and Alagha, 2021; Dantas et al., 2020; Lian et al., 2020; Ordóñez et al., 2020). Globally most steep and abrupt decrease of NO$_2$ was reported by Liu et al. (2021), and Shi et al. (2021). The decline in SO2 measurements is also reported by many studies (Anil and Alagha, 2021; Liu et al., 2021; Ordóñez et al., 2020; Shi et al., 2021) while a minor increase in SO$_2$ in India was also reported (Mor et al., 2021).
respectively. These values are 3.3%, 4.8%, and 0.03% less than the reference period (2016–2019). It is noteworthy that global lockdown was not imposed simultaneously in all the countries. However, due to a prominent decrease in NTR, NR from SYN and EBAF shows 0.9 Wm\(^{-2}\) and 1.1 Wm\(^{-2}\) lesser NTR values than the previous 4-year monthly average. NTR shows a similar decrease of 3.4% and 3% in April and May respectively, from SYN and EBAF while this decrease is 3% and 1.7% respectively in ERA5 data. In continuation of this behavior, June 2020 shows a decrease of 2.1% in SYN and ERA5 while 1.7% in EBAF data. The average value of NTR and NR during 2020-lockdown is 1.36 Wm\(^{-2}\) and 0.81 Wm\(^{-2}\) respectively.

Fig. 6 shows the monthly variations in NSR, NTR, and NR using the global land surface mean monthly values obtained from SYN, EBAF, and ERA5 data sets. For monthly analysis, absolute and percentage differences are computed for surface radiation and atmospheric pollutants, using Eqs. (1) and (2) respectively. Table 4 shows the absolute difference between the monthly averages of 2020 with respect to the reference period. NSR shows a similar temporal pattern in all obtained data sets. In SYN and EBAF, NSR shows a decrease of 2.1% in March 2020 in all the obtained data sets. April 2020 observes higher values (1.7 and 2 Wm\(^{-2}\)) lesser than the previous 4-year monthly average value, observed from SYN, EBAF, and ERA5 respectively. In May 2020, SYN and EBAF show the 2.4 Wm\(^{-2}\) respectively. In May 2020, SYN and EBAF show the 2.4 Wm\(^{-2}\) and ERA5 shows 1.1 Wm\(^{-2}\) lesser NTR values than the previous 4-year monthly average. NTR shows a similar decrease of 3.4% and 3% in April and May respectively, from SYN and EBAF while this decrease is 3% and 1.7% respectively in ERA5 data. In continuation of this behavior, June 2020 shows a decrease of 2.1% in SYN and ERA5 while 1.7% in EBAF data. The average value of NTR and NR during 2020-lockdown is 1.36 Wm\(^{-2}\) and 0.81 Wm\(^{-2}\) respectively.

In line with the daily analysis, NTR shows the decreased observations in April and May 2020 in all the obtained data sets. April 2020 observations are 2.6, 2.8, and 1.7 Wm\(^{-2}\) lesser than the previous 4-year monthly average value, observed from SYN, EBAF, and ERA5 respectively. In May 2020, SYN and EBAF show the 2.4 Wm\(^{-2}\) and ERA5 shows 1.1 Wm\(^{-2}\) lesser NTR values than the previous 4-year monthly average. NR shows a similar decrease of 3.4% and 3% in April and May respectively, from SYN and EBAF while this decrease is 3% and 1.7% respectively in ERA5 data. In continuation of this behavior, June 2020 shows a decrease of 2.1% in SYN and ERA5 while 1.7% in EBAF data. The average value of NTR and NR during 2020-lockdown is 1.36 Wm\(^{-2}\) and 0.81 Wm\(^{-2}\) respectively.

Table 4
The monthly absolute difference of NSR, NTR and NR from the reference period (2016–2019) is computed from Eq. (1).

| Month | NSR | SYN | EBAF | ERA5 | NTR | SYN | EBAF | ERA5 | NR | SYN | EBAF | ERA5 |
|-------|-----|-----|------|------|-----|-----|------|------|-----|-----|------|------|
| Jan   | −0.24 | −0.35 | −0.79 | −0.90 | −0.84 | 1.41 | −1.14 | −1.19 | 0.61 |
| Feb   | −0.11 | 1.06 | −0.01 | −0.81 | −1.61 | 0.06 | −0.86 | −0.55 | 0.06 |
| Mar   | 0.78  | 1.63 | 0.21 | −1.30 | −1.25 | 0.55 | −0.52 | 0.38 | 0.76 |
| Apr   | 0.62  | 0.28 | 1.76 | −2.65 | −2.88 | −1.78 | −2.03 | −2.61 | −0.02 |
| May   | 0.97  | 1.38 | 2.02 | −2.43 | −2.44 | −1.05 | −1.46 | −1.06 | 0.98 |
| Jun   | 0.42  | 0.50 | 0.65 | −1.73 | −1.36 | −1.30 | −1.31 | −0.86 | −0.65 |
| Jul   | 0.96  | 0.83 | −1.34 | −1.32 | −1.51 | 0.66 | −0.41 | −0.68 | −0.68 |

All values are measured in Wm\(^{-2}\).

Table 5
Monthly absolute and Percentage difference of AOD, NO\(_2\) and SO\(_2\) from January to July 2016–2020 with respect to the reference period (2016–2019).

| Month | AOD | SYN | EBAF | ERA5 | NO\(_2\) | SYN | EBAF | ERA5 | SO\(_2\) | SYN | EBAF | ERA5 |
|-------|-----|-----|------|------|--------|-----|------|------|--------|-----|------|------|
| Jan   | 0.0342 | 21.9% | −0.303 | −8.0% | 0.0014 | 7.6% |
| Feb   | 0.0231 | 13.8% | −0.205 | −8.1% | −0.0013 | −7.1% |
| Mar   | 0.0111 | 6.5% | −0.175 | −4.9% | −0.0014 | −6.8% |
| Apr   | 0.0053 | 3.1% | −0.205 | −5.4% | −0.0017 | −8.8% |
| May   | −0.004 | −0.3% | −0.308 | −7.3% | −0.0025 | −11.7% |
| Jun   | 0.0096 | 5.8% | −0.178 | −4.0% | −0.0032 | −13.5% |
| Jul   | −0.0057 | −3.1% | −0.185 | −4.2% | −0.0025 | −9.1% |

Abs columns refer to absolute difference while % columns refer to percentage difference. In absolute difference, NO\(_2\) is measured in 10\(^{12}\) mol/cm and SO\(_2\) is measured in DU.

3.4. Monthly variations of surface radiation and atmospheric pollutants

Fig. 6 shows the monthly variations in NSR, NTR, and NR using the global land surface mean monthly values obtained from SYN, EBAF, and ERA5 data sets. For monthly analysis, absolute and percentage differences are computed for surface radiation and atmospheric pollutants, using Eqs. (1) and (2) respectively. Table 4 shows the absolute difference between the monthly averages of 2020 with respect to the reference period. NSR shows a similar temporal pattern in all obtained data sets. In SYN and EBAF data, NSR shows no prominent variations in those months of 2020 when the economic activities were slowed down around the globe. But in ERA5, during April and May NSR shows relatively higher values (1.7 and 2 Wm\(^{-2}\) respectively) than the reference period. The percent difference of this increment is 1.7% in both months. Apart from this, a 1.3% (1.6 Wm\(^{-2}\)) increase is observed in March 2020 in EBAF data which is not evident from SYN and ERA5 data. During the 2020-lockdown period overall 0.79 Wm\(^{-2}\), 1.09 Wm\(^{-2}\) and 1.3 Wm\(^{-2}\) NSR radiative forcing are observed from SYN, EBAF and ERA5 data, respectively. The minor variations may respond differently in different algorithms (Zhu et al., 2012).

It is noteworthy that global lockdown was not imposed simultaneously and the span of strict lockdown expands many months in the first half of 2020, but March, April, and May were the months when most...
countries opted for the closure of social and economic activities. Thus during this period, variations in atmospheric composition and surface radiation were righteously associated with the impact of the lockdown strategies.

Fig. 7 shows the monthly variations of AOD, NO$_2$, and SO$_2$. In the pre-lockdown months of 2020, prominent higher values of AOD are observed, but then the monthly average of AOD decreased gradually till May 2020, which shows 0.3% reduced (0.162) observations than the reference period. For NO$_2$ the least monthly average of $3.33 \times 10^{14}$ mol/cm$^2$ is observed in February 2020. Note that, this is the month before the pandemic prevailed in the whole globe. During April and May 2020, NO$_2$ mean monthly average values are $3.5$ and $3.9 \times 10^{14}$ mol/cm$^2$ respectively which are 5.4% and 7.3% less than the monthly averages of April and May observed in the reference duration. After May 2020, NO$_2$ increased gradually. In the monthly analysis, SO$_2$ shows an increased value in January 2020, and then gradually decreased till July. It is interesting to observe that SO$_2$ shows smaller mean monthly values from February to July 2020 than the corresponding months of reference duration. From April to June 2020 SO$_2$ column values are 0.0174, 0.0185, and 0.02 DU which are respectively 8.8%, 11.7%, and 13.5% less than the corresponding months of the reference period.

Although in recent literature, a significant decrease in regional AOD is reported over many parts of the world (Nichol et al., 2020; Qiu et al., 2021; Siddique et al., 2021), it was found that only May 2020 has a minor decrease of 0.2% than the reference period. Here the contextual discussion is needed for unbiased analysis. In January and February 2020, AOD showed an increase of 21.9% and 13% respectively over the reference period. The prominent increase gradually reduced to 6.5% and 3.1% in March and April 2020. After lockdown, in June 2020, global AOD again showed an increase of 5.8%. Thus it can be concluded that
although global AOD showed an apparent increase during the 2020-lockdown, still actually it falls gradually during the lockdown months of 2020 as compared with the pre-lockdown months. Also, the life span of suspended particles restricts a sudden reduction in AOD even when the emission of particles is slowed down (Haywood, 2016).

Many studies about air quality during the 2020-lockdown reported that NO\textsubscript{2} decreased significantly and relate this decrease with the economic stagnation (Anil and Alagha, 2021; Dantas et al., 2020; Lian et al., 2020). Here it is found that NO\textsubscript{2} did not only decreased during the lockdown but also in pre-lockdown months, i.e. January and February 2020, global NO\textsubscript{2} column concentration showed a more prominent decrease of 8% and this decrease continued in post-lockdown months i.e. June and July 2020 which showed a 4% and 4.2% decrease respectively. This result leads towards two facts; firstly the approach of comparing 2020-lockdown months with the same months of 2019, or only compare few pre-lockdown months with the lockdown months, used by many recent studies limits them for the narrow window of 2020-lockdown which might not give the required liberty to analyze the true variations. Secondly, NO\textsubscript{2} emission reduction during the COVID-19 economic stagnation is not the only reason for the temporal decrease of NO\textsubscript{2} column concentration. Future dedicated studies about NO\textsubscript{2} will potentially reveal the detailed reasons behind the decreasing pattern of

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**Fig. 10.** Monthly percentage variations in NSR, NTR, NR, AOD, NO\textsubscript{2} and SO\textsubscript{2} in April 2020 with respect to the reference period over multiple point locations across the world. The first row represents the locations from North, South America and Australia, from second to the fourth row represents the random locations in Africa, Europe and Asia respectively.
NO₂.
SO₂ showed an increase of 7.6% in January 2020, after then, it showed a consistent decrease of 7.1%, 6.8%, 8.8%, 11.7%, 13.5%, and 9.1% from February to July 2020 respectively. A prominent decrease in a globally pre-lockdown month (February) and post-lockdown months (June and July) weakens the argument that the decrease was caused only due to the emission reduction. Apart from the argument that the global decrease of two important gaseous pollutants, NO₂ and SO₂ are not only bounded with the 2020-lockdown emission reduction, yet a collective decrease of all pollutants including AOD resulted in the anomalies of NSR, NTR, and NR. Table 5 presents the summary of absolute and percentage difference between each month of 2020 with the corresponding reference month for AOD, NO₂ and SO₂.

3.5. Spatial anomalies

Fig. 8 shows the percentage spatial anomalies of NSR, NTR, NR, AOD, NO₂, and SO₂ for April 2020 with respect to the reference period. NSR, NTR, and NR obtained from EBAF are used to observe corresponding anomalies. Here positive values represent the increased while negative values represent the decreased observations of the particular parameter during April 2020. NSR is dominated by the positive anomaly, especially near the North Pole. NTR on the other hand is dominated by negative anomaly except for the few regions in the southern part of Pakistan and India, and south of Australia. Similarly, NR shows a mixed pattern with the dominating negative anomalies in North and South America while positive anomalies in most of the Asian countries. The second row of Fig. 8 shows the anomalies of air pollutants; AOD, NO₂, and SO₂ for April 2020. AOD shows a significant increase in some part of Russia and China, while shows a mixed pattern for the rest of the world during the 2020-lockdown. NO₂ shows the most prominent negative anomalies except for the few sparse regions in the Southern hemisphere. SO₂ shows the most different spatial pattern with equal distribution of negative and positive anomalies. Although the monthly average of SO₂ for April 2020 is 8.8% lesser than the reference period, yet spatially, the positive and negative anomalies are equally distributed.

For a better comparison of spatial anomalies, few random points were selected across the globe. The location of selected points is presented in Fig. 9 while Fig. 10 shows the variations in NSR, NTR, NR, AOD, NO₂ and SO₂ over these point locations. The most significant variations are observed for SO₂ which shows prominent changes (increased or decreased) in different countries of the world. NO₂ shows the only increase in Canada; all other locations show a decrease in NO₂. Locations in Russia, the USA and Algeria show a prominent increase while locations in Estonia and Nepal show a prominent decrease in AOD. As compared to atmospheric pollutants, surface radiation shows small variations. The random behavior of surface radiation and air pollutants emphasizes the fact obtained from Fig. 1 that there exists a relation between both of them and the surface radiation are a complex phenomenon that is not controlled only by atmospheric composition.

4. Conclusion

The unprecedented situation of social and economic stagnation across the world during the global COVID-19 pandemic provided an opportunity to investigate the real-time impacts of variations in atmospheric composition on surface radiation. In this study, variations in global land surface NSR, NTR, and NR were analyzed as an outcome of perturbations in AOD, NO₂ and SO₂. The impact of lockdown during the COVID19 pandemic is not strong enough to reach TOA as no brightening or dimming of SR and TR was observed at TOA. Suspension of pollutants in the atmosphere for a long time was another potential cause for the undisturbed TOA SR and TR. However variations in surface radiation were observed as NSR showed no prominent variations, but NTR was significantly decreased throughout the 2020-lockdown period consequently NR also showed a decrease during the same time. April 2020 was the most affected month and showed prominent negative anomalies in NTR and NR. All observed air pollutants i.e., AOD, NO₂ and SO₂ reduced during the COVID-19 lockdown consequently global air quality was improved. The footprints of NO₂ reduction extended back to pre-lockdown months, indicating that apart from low emission during the lockdown, there might be some other factors involved in the global NO₂ reduction. In April 2020, collective emission reduction of 5.4% and 8.8% in NO₂ and SO₂ respectively appeared as 0.2% increase (0.27 Wm⁻²) in NSR, 3.45% decrease (−2.88 Wm⁻²) in NTR and 4.8% decrease (−2.61 Wm⁻²) in NR. One limitation of this study is that for all the observed parameters, global aerial averages were used hence many fine and important details were compromised. It would be an interesting future study for some regional analysis. Pixel to pixel analysis might reveal more accurate findings.

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Data availability statement

The data presented in this study are available on request from the corresponding website.

Declaration of Competing Interest

All authors declare that there are not any personal or financial conflicts of interest.

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