**Vegetation activity enhanced in India during the COVID-19 lockdowns: evidence from satellite data**

**Avinash Kumar Ranjan1, Jadunandan Dash2, Jingfeng Xiao3, Amit Kumar Gorai1\***

*1Department of Mining Engineering, National Institute of Technology Rourkela, Odisha-769008, India*

*2Geography and Environmental Science, University of Southampton, Highfield, Southampton, SO17 1BJ, United Kingdom*

*3Earth Systems Research Center, Institute for the Study of Earth, Oceans, and Space, University of New Hampshire, Durham, NH 03824, United States*

\*Corresponding author: (AKG) [amit\_gorai@yahoo.co.uk](mailto:amit_gorai@yahoo.co.uk), Contact: +91-7749006070

AKR ([avinash.ranjan07@yahoo.com](mailto:avinash.ranjan07@yahoo.com)), JD ([J.DASH@soton.ac.uk](mailto:J.DASH@soton.ac.uk)), JX ([j.xiao@unh.edu](mailto:j.xiao@unh.edu))

**Abstract**

The Severe Acute Respiratory Syndrome-COronaVIrus Diseases 2019 (SARS-COVID-19) has sternly affected the entire world in terms of human health, loss of lives, and huge economic losses. However, pandemic-triggered lockdown (LD) events (as a preventive measure) have compelled to stop or reduce major economic activities, exerting positive impacts on the terrestrial environment. We deployed a variety of satellite products (i.e., normalized difference vegetation index (NDVI), solar-induced chlorophyll fluorescence (SIF), and aerosol optical depth (AOD)) along with gridded climatic data (temperature (TEMP), precipitation (PREC), and net radiation (NR)) data to quantify the changes in vegetation activity during the LD period over the Indian biogeographic provinces (BGPs) as compared to the average conditions over the previous three years (2017-2019). The analysis of the NDVI and SIF data revealed that vegetation greenness and productivity significantly enhanced during LD periods (by up to 37 to 55%, respectively). The influence of climatic drivers (PREC, TEMP, and NR) on vegetation activity was also investigated. We found that the enhancement in the vegetation activity (over BGPs) during the LD period was not entirely driven by the climatic parameters, and was therefore inferred to be also influenced by the LD events. Moreover, vegetation greenness and productivity around the mining clusters were largely improved during the LD period (by up to 78%) over the coal mining, followed by iron ore mining (up to 63%), and stone mining (up to 41%) clusters). In a nutshell, it can be deliberated that COVID-triggered preventive measures (i.e., country-level LD, travel bans, industry ban, curtail in mining capacity, among others) likely enhanced vegetation health and productivity. Thereby, regulatory measures can be seen as a viable option for improving the terrestrial environmental conditions in the context of climate change in the near future.

**Keywords**: *Pandemic; NDVI; Solar-induced chlorophyll fluorescence; Aerosol optical depth; Mining*

1. **Introduction**

The SARS-COVID-19 has harshly traumatized the world through human-to-human transmission, and caused a large number of human deaths and substantial economic losses across the globe (Bukhari and Jameel 2020; Mofijur et al. 2021). Globally, 237,383,711 confirmed cases of COVID-19, including 4,842,716 deaths, had been reported to the World Health Organization (WHO) as on 5:52 pm CEST (Central European Summer Time), 11 October 2021 (<https://covid19.who.int/>). According to the Ministry of Health and Family Welfare, Government of India, 2,14,900 active cases and 4,50,963 deaths were recorded in India (as on 12 October 2021) (<https://www.mohfw.gov.in/>).

In order to avoid or stop the COVID-19 pandemic risks of transmission, various preventive measures (such as social distancing, nationwide multi-period lockdowns (LDs), extensive travel bans, and mass quarantines) have been implemented in most parts of the world. The complete LD or shutdown in various regions of the globe has substantially impacted the local to global level socio-political relations and economic growth (Long and Feng 2020). On the other hand, the complete shutdown, travel bans, and industrial shutdown, have significantly helped to improve the environmental condition, including air quality, urban heat island (UHI), and water quality across the globe, owing to the curbing of the release of anthropogenic greenhouse gases and air pollutants (Yunus et al. 2020; Tobías et al. 2020; Parida et al. 2021). The deterioration of environmental conditions (e.g., poor air quality, increasing UHI, deforestation, degradation of grasslands) across the globe due to several anthropogenic interventions (e.g., population pressure, industries, motor vehicles, power plants, mining activities, deforestation) has emerged as a rising alarm in the world in the last few decades (Mehdipour and Memarianfard 2017; Motesaddi et al. 2017). However, COVID-19 pandemic-imposed LD events and complete shutdown in most parts of the globe have compelled to put a natural brake on such activities. As a result, significant improvement in the earth’s environmental condition (e.g., air quality, UHI, water quality) has been observed across the globe (Yunus et al. 2020; Alqasemi et al. 2021: Parida et al. 2021).

Over the last year (after the emergence of COVID-19), several studies have been conducted at various spatial scales (regional to global scale) to assess the changes in environmental conditions during LD or complete shutdown periods. The majority of these studies are concentrated on evaluating the air quality parameters (i.e., aerosol optical depth (AOD), particulate matter (PM2.5, PM10,) nitrogen dioxide (NO2), carbon monoxide (CO), sulphur dioxide (SO2)) (Mishra and Kulshrestha 2021; Singh et al. 2021). For example, Ranjan et al. (2020) analyzed the spatio-temporal variations in AOD concentration for India at the country level, and reported a significant reduction in the AOD level (~ 45%) as compared to the mean AOD during the past twenty years (2000-2019). Lal et al. (2020) reported a noteworthy reduction in NO2, CO, and AOD levels across the globe during the COVID-19 pandemic (January–April, 2020). Likewise, several studies focused on air quality monitoring over different regions of the globe during the LD periods (Muhammad et al. 2020; Mahato et al. 2020; Bar et al. 2021; Nigam et al. 2021).

Furthermore, some studies have investigated the water quality status (i.e., physical, chemical, and biological) during LD periods, and observed a substantial enhancement in the water quality at various parts of the globe (Dutta et al. 2020; Khan et al. 2020; Yunus et al 2020). Few researchers also investigated the LD impacts on land surface temperature (LST) and UHI. They found a noteworthy reduction in the urban LST during shutdown periods compared to historical data (Maithani et al. 2020; Teufel et al. 2021; Guha and Govil et al. 2021). Further investigations focused on the dynamics of the agricultural regions during LD periods (Pokhariyal et al. 2021; Lele et al. 2021). For example, Saxena et al. (2021) assessed the agricultural condition of India, and reported a significant increase in the normalized difference vegetation index (NDVI) during the LD period in 2020 relative to the previous year. Besides, some researchers used multiple biophysical variables (i.e., NDVI, Normalized Difference Water Index (NDWI), LST) to evaluate the impacts of lockdown events on environmental conditions at the regional scale (Ghosh et al. 2020; Sahani et al. 2020; Firozjaei et al. 2021).

Despite these efforts, no study has investigated the impacts of the LD on the activity of various ecosystem types (e.g., forest, grassland) at large spatial scales. The wide-ranging impact of the LD events on the environmental condition over various parts of the world brings an impetus to measure the condition of vegetation under different biogeographic zones. We hypothesized that a complete LD impacted vegetation greenness and productivity as major anthropogenic-based anti-environmental deeds (i.e., major aerosol sources, greenhouse gas emissions, mining dust pollution) were partially or completely stopped. Moreover, the reduced air pollution concentration (especially aerosols concentration) in the lower tropospheric region might increase the availability of direct radiant energy, which in turn could enhance vegetation productivity (Pokhariyal et al. 2021). Pollutants (e.g., particulate matter, SO2, NOx, etc.), predominantly caused by anthropogenic activities (e.g., industrial and power plant emissions, vehicular emissions, transportation, mining industries, among others) physically damage the vegetation leaves and reduce the size of stomata. Subsequently, it causes a deficiency in foliage chlorophyll content (chlorosis), changes in vegetation phenology, decreased photosynthesis and vegetation growth, etc. (Conesa et al. 2006; Florentina and Lo 2011; Nowak et al. 2014; Kayet et al. 2019a). Some previous studies also demonstrated that especially mine-induced dust pollution accumulated on the foliage significantly disrupted the rate of photosynthesis activity and thereby affected vegetation health and productivity (Sekhar and Mohan 2014; Kayet et al. 2019b; Jha et al. 2019). Therefore, it is a unique opportunity to explore the changes in vegetation activity during the COVID-19 LD periods. It could provide insight into the functions of vegetation (e.g., health, productivity) with minimal anthropogenic influence and highlight any potential impact on vegetation growth and productivity under the anthropogenic impacts (e.g., mining activities, industrial emissions, transportation emissions).

The current study aims to assess the impacts of COVID-19 imposed LD events on vegetation activity (greenness and productivity) across the different biogeographic provinces of India. The study also examines that whether the changes in vegetation activity were influenced by LD events or by the key climatic variables (i.e., precipitation, temperature, and net radiation). To our knowledge, this is the first study to assess the status of vegetation activity during LD events at the country scale. The objectives of the present investigation are (1) to quantify the variations in vegetation activity over different biogeographic provinces of India during the lockdown (LD[[1]](#footnote-1)) (25 March to 31 May, 2020) and unlock (UL[[2]](#footnote-2)) (1 June to 30 November, 2020) periods (**Table** 1) as compared to the mean conditions over the last three years (2017-2019); (2) to investigate the activity of vegetation patches around the mining clusters (opencast) during both LD and UL period as compared to last three years mean conditions; (3) to scrutinize whether the changes in vegetation activity were driven by the LD events or by the key climatic variables (i.e., precipitation, temperature, and net radiation).

**Table 1:** Details of phase-wise lockdown and unlock events implemented in India.

|  |  |  |
| --- | --- | --- |
| **Lockdown phases** | **Date and duration** | **Present study** |
| Phase 1 | 25 March 2020 – 14 April 2020 (21 days) | Lockdown period (LD) |
| Phase 2 | 15 April 2020 – 3 May 2020 (19 days) |
| Phase 3 | 4 May 2020 – 17 May 2020 (14 days) |
| Phase 4 | 18 May 2020 – 31 May 2020 (14 days) |
| Unlock 1.0 | 1 June 2020 – 30 June 2020 (30 days) | Unlock period  (UL) |
| Unlock 2.0 | 1 July 2020 – 31 July 2020 (31 days) |
| Unlock 3.0 | 1 August 2020 – 31 August 2020 (31 days) |
| Unlock 4.0 | 1 September 2020 - 30 September 2020 (30 days) |
| Unlock 5.0 | 1 October 2020 - 31 October 2020 (31 days) |
| Unlock 6.0 | 1 November 2020 - 30 November 2020 (30 days) |

1. **Study area**

The status of vegetation activity during the COVID-19 LD periods was studied over the different biogeographic provinces of India. The study identified the different biogeographic provinces in India (**Figure 1**) as defined by Rodgers and Panwar (1988). According to Rodgers and Panwar (1988), India can be categorized into 10 biogeographical zones and 26 biogeographical provinces (**Table S1**) based on the regional climate, geography, and biomes. The study examined the changes in vegetation activity for all the biogeographical provinces. Moreover, specific attention was paid to the changes in vegetation activity over different mining clusters of Jharkhand (JH) and Odisha (OD) state, India. These two states (JH and OD) are India’s mineral-rich and leading mining states. JH has ~40% and 29% of India’s mineral and coal reserves, respectively, wherein, OD carries > 35% of the country’s natural resources and provides significant reserves of iron ore, bauxite, coal, nickel, chromite, among others. So, it is presumed that curtailing the working capacity of mines during the LD periods would have led to a reduction in dust emissions. As a result, there are chances of enhancement in the vegetation activity around the mining clusters.

In total, 25 vegetation patches around different mining clusters (i.e., coal, stone, bauxite, and chromite mines) were demarcated over the JH and OD states, India. The polygons were digitized around these mining clusters based on the visual interpretation of high spatial resolution imageries on Google Earth. The nearby vegetation patches with a 1 to 2 km radius (roughly) from the edge of the mining clusters were included in the digitized polygons. Due to the uneven expansion and multiple mining patches, it was difficult to consider different mining patches within a mining cluster. Thus, the different mining patches in the same region were considered as a single mining cluster. The details of the 25 mining clusters are provided in Table **S2 (Supplementary file**).



**Figure 1**. Distributions of vegetation types, different biogeographic provinces, and mining clusters in India. The vegetation type distribution map is reclassified from the MODIS land cover product (MCD12Q1) for the year 2019 based on the International Geosphere-Biosphere Programme (IGBP) classification scheme.

1. **Data and methods**
   1. **Data**

We used multiple satellite/gridded products, including the normalized difference vegetation index (NDVI), solar-induced chlorophyll fluorescence (SIF), and aerosol optical depth (AOD) along with ancillary datasets including land cover, precipitation, and temperature, and analyzed the spatio-temporal dynamics of vegetation activity and drivers during lockdowns (LD) period (25 March to 31 May, 2020) and unlock (UL) period (1 June to 30 November, 2020) as compared to the mean condition during the reference period (average of the same period over the preceding three years (2017-2019)). The three-year period (reference period) was considered to be able to average out any localized impact on vegetation due to extreme events (e.g., rainfall, storm, heat stress, among others) and seasonal biases. As the mining clusters were a very dynamic landscape, a time period longer than three years would capture the impact of the changes in the land-use pattern, rising atmospheric carbon dioxide concentrations, extreme climate events (e.g., drought), and disturbances (e.g., fire, hurricanes, logging), which could have directly influenced the environmental condition at a large scale.

The NDVI and SIF variables were used as measures of changes in vegetation activity. NDVI and SIF have been widely used as measures of vegetation greenness and productivity, respectively (Xiao et al. 2019a). AOD was considered as an indicator of air quality status and a key proxy of the air pollution concentration (especially particulate matter) in the lower tropospheric region. In addition, three key climatic parameters, namely, precipitation, temperature, and net radiation, were used to evaluate the influence of climatic drivers on vegetation activity during LD periods. The details of datasets used in this study are provided in **Table 2**.

The combined (Terra and Aqua) MODIS land cover (MCD12Q1, v06) data for the year 2019 was used to delineate vegetation cover in India. The product is derived from MODIS reflectance data with a supervised classification, which yields overall classification accuracy of >75% (Friedl et al. 2002; 2010). The International Geosphere-Biosphere Programme (IGBP) classification scheme of MCD12Q1 provides 17 land cover classes. The forests (i.e., evergreen, deciduous, and mixed forests), shrublands, savannas, and grasslands, were included in the analyses, while water bodies, built-up, snow/ice, and barren land were masked out (refer to **Table S3**). The land cover product was deployed to delineate the vegetation and non-vegetation features over the different BGPs in India. Later, the vegetation map was used to extract the different satellite variables (e.g., NDVI, SIF) for the vegetation patches only.

The study used the NDVI dataset with 16-day composites derived from the Terra MODIS (MOD13Q1, v6) at 250 m spatial resolution (Huete et a. 2002) to quantify the vegetation activity over the Indian biogeographic provinces. The best quality pixels were identified during the data processing. The study considered only grid cells with NDVI > 0.1 in the analyses. The NDVI is perhaps the most popular vegetation greenness index and has been widely used as a proxy for vegetation activity (Xiao et al. 2019a). The assessment of NDVI during LD periods shall help to understand the direct or indirect impact of LD on the vegetation activity over the Indian biogeographic provinces and mining associated vegetation patches.

The study also used the global gridded solar-induced chlorophyll fluorescence (SIF) dataset – the global, OCO-2 based SIF product (GOSIF, v2) with high temporal (8-day) and spatial (0.05°) resolutions (Li and Xiao 2019) for assessing the vegetation condition during LD periods. SIF has brought significant advancements in measuring terrestrial photosynthesis in the last two decades. SIF is directly associated with plant physiological processes, and can better detect the substantial variations in vegetation activity than the conventional reflectance-based vegetation indices (e.g., NDVI, enhanced vegetation index or EVI) (Li et al. 2018; Xiao et al. 2019b). The GOSIF dataset was developed by Li and Xiao (2019) by using Orbiting Carbon Observatory-2 (OCO-2) SIF soundings, MODIS data (EVI), and meteorological reanalysis datasets (air temperature, photosynthetically active radiation, vapor pressure deficit). The methodology, validation, and spatio-temporal patterns of this product have been described in Li and Xiao (2019). The GOSIF dataset for the study period was downloaded from <http://data.globalecology.unh.edu/>.

The MODIS-based MCD19A2 (v6) product is used in the present study for retrieving the daily AOD concentration. MCD19A2 is a MODIS Terra and Aqua combined Multi-angle Implementation of Atmospheric Correction (MAIAC) Land Aerosol Optical Depth (AOD) Level-2 gridded product having a spatial resolution of 1 km. AOD at the green band (550 nm) was used in this study due to its better consistency (Lyapustin and Wang 2018). The daily AOD datasets were acquired and processed (only best quality pixels) for the study periods in GEE.

Precipitation (referred to as PREC hereafter), temperature (hereafter TEMP), and net radiation (from now NR) data were also used to understand the effects of climate on vegetation conditions during the LD periods. The PREC, TEMP, and NR data were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), the European Centre for Medium‐Range Weather Forecasts Re‐Analysis version 5 (ERA‐5 reanalysis), and National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR), respectively. CHIRPS precipitation data were developed by a modified inverse distance weighting algorithm using gauge-based precipitation datasets. The model has good correlations with the observed data (R>0.75) in many areas across the world (especially over South America, Africa, and India) (Funk et al. 2015). The ERA-5 reanalysis TEMP data was produced at a 1-hourly time step using a more advanced 4-dimensional variational assimilation scheme, and it offers more consistent data than ERA-Interim (Tarek et al. 2019). The Global Forecast System (GFS) atmospheric model was used to develop the gridded NR dataset, and the grid point statistical interpolation (GSI) technique was used for atmospheric analysis at 6-hour intervals. The CFSR reanalysis data strongly correlates with the in-situ observations (R2 > 0.9). These climatic datasets (PREC, TEMP, and NR) were pooled and processed in the web-based climate engine cloud platform (<http://climateengine.org/>).

**Table 2**. Details of satellite/gridded datasets used in the present study.

|  |  |  |  |
| --- | --- | --- | --- |
| **Data** | **Satellite/ Sensor/ Spatial resolution/ Temporal resolution** | **Data acquisition (Date/Year)** | **Citation of data source** |
| **Land cover** | MODIS Terra and Aqua  MCD12Q1 (500 m)  Yearly composite | 2019 | Friedl and Sulla-Menashe 2019 |
| **NDVI** | MODIS Terra  MOD13Q1 (250 m)  16-days composite | 25 March – 30 November,  For 4 years (2017-2020) | Didan 2015 |
| **SIF** | GOSIF (0.05˚ ×0.05˚)  8-days composite | 25 March – 30 November,  For 4 years (2017-2020) | Li and Xiao 2019 |
| **AOD** | MAIAC MCD19A2  (1 km) Daily | 25 March – 30 November,  For 4 years (2017-2020) | Lypustin and Wang 2019 |
| **Precipitation** | CHIRPS (0.05˚ ×0.05˚)  Daily | 25 March – 30 November,  For 4 years (2017-2020) | Funk et al. 2015 |
| **Temperature** | ERA5 reanalysis  (0.25˚ ×0.25˚)  Daily | 25 March – 30 November,  For 4 years (2017-2020) | European Centre for Medium-Range Weather Forecasts, 2019 |
| **Net Radiation** | NCEP-CFSR reanalysis  (0.2˚ ×0.2˚)  Daily (6 hourly) | 25 March – 30 November,  For 4 years (2017-2020) | Saha et al. 2010 |

* 1. **Methods**

The present investigation consists of data acquisition, satellite data preprocessing, data extraction, data management, spatial data analysis, map preparation, and geo-statistical analysis.

For estimating the effect of LD on vegetation activity metrics (i.e., NDVI, SIF), it was mandatory to examine the hypothesis that the means of other controlling factors like PREC, TEMP, NR remained the same during the LD and UL periods as compared to the reference period. To examine the hypothesis, a paired student’s t-test (paired two samples for means) was conducted (at α = 0.05; n = 26). The mean values of the different satellite variables over the 26 BGPs were considered for the assessment. The test results indicated that PREC and NR were not significantly different during the LD period from those of the reference period (**Table S4**), although the means of TEMP were significantly different during the LD and UL periods as compared to that of the reference period. On the other hand, the means of NDVI and SIF for both LD and UL periods were found to be different from those of the reference period. Therefore, it was expected that variations in vegetation activity were not totally influenced by climatic factors, especially during the LD period.

The anomaly percentage was calculated for the selected satellite-derived variables to quantify the deviations in the vegetation activity metrics (i.e., NDVI, SIF) during the LD and UL period compared to the reference period using **Eqn.** **(1)**. The anomalies of PREC, TEMP, NR, and AOD were also calculated (**Figs. S4**, **S5**, **S6,** and **S7;** Supplementary file) for the LD period so that the influences of climatic variables and air pollutants on vegetation activity could be assessed.

**(1)**

where is the average condition of satellite variables (i.e., NDVI, SIF) during the LD periods in 2020; is the three years (2017-2019) average condition of satellite variables during the same time period of the year.

Furthermore, the coefficient of determination (R2) was calculated between anomalies of climatic variables (PREC, TEMP, and NR), air pollutant (i.e., AOD), and vegetation activity metrics (i.e., NDVI, SIF). The correlation analysis could help to determine the degree of control of each climatic factor on the vegetation activity during the LD and UL periods. Additionally, the multiple regression analysis was performed for each vegetation activity metric by considering the three climatic variables (PREC, TEMP, and NR) as explanatory variables to understand the combined effect of climatic variables on vegetation activity. The statistical significance level (p-value) of the correlation between activity metrics and climatic variables was also estimated using the t-test. These analyses were performed by extracting data (mean value) for 26 BGPs and 25 mining clusters in India.

1. **Results** 
   1. ***Vegetation activity over biogeographic provinces of India during the LD and UL periods***

The phase-wise NDVI and NDVI anomaly of vegetation over the different biogeographic provinces (BGP’s) of India during the LD and UL periods are presented in **Figure 2.** Vegetation activity as measured by NDVI over the different BGPs was substantially improved during the LD and UL periods (2020) as compared to the mean condition over the last three years (2017-2019; referred to as the reference period hereafter). A remarkable improvement in the vegetation activity over the Desert (3B), Semi-arid (4A, 4B), Deccan Peninsula (6A, 6B, 6C, 6D, 6E), and West-coast (8A) region (**Figure 2c** and **3f)** was observed during the LD periods. Vegetation activity over the Trans-Himalaya (1A, 1B), Himalaya (2A, 2B, 2D), Desert(3A), Western Ghat (5A, 5B), East-Coast (8B), and Island (10A) regions exhibited relatively less improvement during the LD and UL periods. Moreover, some provinces such as the Coast (8C), North-East (9A, 9B), and Island (10B) did not show much enhancement in vegetation activity during the LD periods.

The BGP’s distribution frequency of NDVI anomaly pixels (during LD and UL phase) is presented in **Figure S1** (Supplementary file)**.** Most of the BGPs are observed with the highest pixel frequency of positive NDVI anomaly (up to 33%). While a remarkable pixel frequency of negative NDVI anomaly (up to – 33%) was also observed over the BGPS. Besides, the distribution frequency of NDVI anomaly pixels greater than 33% (and less than 33% in case of negative anomaly) was comparatively very less. The histogram showing the distribution frequency of NDVI anomaly pixels over entire India during the LD and UL phase is also presented in **Figure S2** (Supplementary file)**.** Besides, **~**7, 98, 714 and 7, 38, 999 sqkm area was observed with positive NDVI anomaly during LD and UL phase, respectively. Wherein, ~ 2, 97, 688 and 3, 73, 683 sqkm area was observed under negative NDVI anomaly during LD and UL phase, respectively. The details of area coverage of NDVI anomaly pixels corresponding to different ranges at the equal interval (like, 0-33%, 33-66%, and 66-99%) are summarized in **Table S5** (Supplementary file)**.**



**(d)**

**(f)**

**(e)**

**(c)**

**(b)**

**(a)**

**Figure 2.** Spatial distribution of NDVI and NDVI anomaly over the biogeographic provinces of India. a and d: long-term (2017-2019) mean NDVI during lockdown (LD) and unlock (UL) periods, respectively; b and e: mean NDVI for the LD and UL periods (2020), respectively; c and f: the NDVI anomaly during the LD and UL periods, respectively.

**Figure 3** shows the average (zonal) NDVI anomaly of different BGPs. Positive NDVI anomalies were found for most of the BGPs, indicating enhanced vegetation greenness and productivity during the LD events. By contrast, few BGPs (i.e., 1B, 2C, 8C, 9A, 9B, and 10B) exhibited negative NDVI anomalies during the LD and UL periods. The negative NDVI anomaly over these regions was mostly within a small range between 0.1 – 10%. The negative anomaly of vegetation activity metrics over these provinces may be attributed to the topographic pattern and vegetation types. These regions (especially the Himalayas and Northeast regions) are mostly hilly and are predominantly covered with evergreen forest types (refer to location map; **Figure 1**).

The largest increases in the vegetation activity during the LD and UL periods (24% and 37%, respectively) were observed over the Central Highlands (6A) and Chota Nagpur provinces (6B) of Deccan Peninsula and Kutchchh province (3B) of Desert region (**Figure 3**). Other provinces of the Deccan Peninsula and the Western Ghats also showed a positive NDVI anomaly (~10 – 20%). Few provinces (i.e., 1A, 2A, 2B, 2D, 3A, 5B, 7B, 8B, and 10A) also showed positive NDVI anomaly but with a lower percentage (~0.2 – 5%). These lower anomaly percentages may be attributed to the topographic pattern (hilly region) and the vegetation types (predominantly evergreen forest). Moreover, it can be deliberated that these regions might have had less impact of anti-environmental deeds during the normal days (i.e., before the pandemic), and hence vegetation status over these regions would have been better earlier (see **Figures 2a** and **2b**). Consequently, less deviation in the NDVI anomaly was detected during the LD and UL periods (2020) as compared to the reference period. However, it should be noted that these percentages were calculated by taking the average of all the pixels that correspond to the vegetation in particular provinces. Therefore, the disparity in the total number of pixels in particular provinces may slightly influence the mean anomaly percentage (zonal) of satellite variables.

**Figure 3**. Mean NDVI anomaly over the different biogeographic provinces of India during the LD and UL periods (2020) as compared to long-term (2017-2019) mean NDVI for the same periods of the year.

In line with the NDVI data, the SIF data also showed more or less similar changes in vegetation activity during the LD and UL periods over the BGPs of India (**Figure 4**). The major portion of India exhibited positive SIF anomalies during the LD and UL periods (2020) compared to the last three-year mean condition (**Figure 4**). The histogram showing the distribution frequency of SIF anomaly pixels over entire India is presented in **Fig S3** (Supplementary file). Comparatively, the Deccan Peninsula (especially Central Highlands (6A), Chhota Nagpur (6B), and Eastern Highlands (6C)) had utmost improvement in the vegetation activity during the LD period than other BGPs. The Western Ghat regions also exhibited significant activity improvement, wherein the Desert province (3A) had the least and negative anomaly patches. The Himalayan provinces (2A, 2B, 2C) and North-east provinces (9A, 9B) also had mixed SIF anomaly patches, which indicates the minor enhancement in vegetation activity over these regions. During the UL period, more or less similar spatial pattern was observed over the BGPs with enhancement in vegetation activity, but the percentage increase was lower than that in the LD period.

The total area coverage of positive SIF anomaly was observed over ~ 7, 23, 158 and 7, 65, 872 sqkm area of India during LD and UL phase, respectively. Wherein, ~ 2, 89, 248 and 3, 08, 195 sqkm area was detected with negative SIF anomaly over India during LD and UL phase, respectively. Furthermore, the details of area coverage of SIF anomaly pixels corresponding to different ranges are summarized in **Table S5** (Supplementary file)**.**



**(c)**

**(a)**

**(d)**

**(f)**

**(e)**

**(b)**

**Figure 4.** Spatial distribution of SIF and SIF anomaly over the biogeographic provinces of India. a and d: long-term (2017-2019) mean SIF during LD and UL periods, respectively; b and e: mean SIF for the same time periods (2020); c and f: the SIF anomaly during LD and UL phases, respectively.

The bar diagram of the SIF anomaly for different BGPs of India also indicates the overall (zonal mean) improvement in the vegetation activity during LD and UL periods over particular BGPs (**Figure 5**). During the LD and UL periods, the maximum SIF anomaly percentage was ~55% and 47% over the Central Highlands province (6A) of Deccan Peninsula and Kutchchh province (3B) of Deseret, respectively. Remarkably, the maximum NDVI anomaly during the LD and UL periods was also noted over the same BGPs. SIF over the rest of the provinces also showed similar anomalies as NDVI. Besides, some minor inconsistency was noted between NDVI and SIF-based anomaly (zonal mean) over a few BGPs (e.g., Desert, Himalayan) (**Figure 3** and **Figure 5)**. For instance, the NDVI-based anomaly bar diagram showed an increment in vegetation activity over the Desert region (3A) during the LD and UL periods (up to 4 – 7%), wherein, the SIF-based anomaly bar diagram showed negative anomaly during the LD period (~ 23%) and positive anomaly during the UL period (~ 20%). Likewise, some inconsistency was also observed over the Tran’s-Himalaya (1A, 1B), Himalaya (2C, 2D), and Island (10A) provinces. However, the difference in the inconsistency between NDVI and SIF anomaly was not enormous. This inconsistency may be partly attributed to the differences in the native spatial resolution of both datasets (i.e., 0.05° for GOSIF; 500 m for NDVI).

**Figure 5**. Mean SIF anomaly over the different biogeographic provinces of India during the LD and UL periods (2020) as compared to the mean over the past three years (2017-2019).

Furthermore, the correlation analysis was performed between the anomaly (mean) of the climatic variables (PREC, TEMP, and NR) and the vegetation activity metrics (NDVI and SIF) (**Table 3)**. Climatic factors were found to be weakly correlated with vegetation activity metrics (i.e., NDVI, SIF), indicating that the anomalies observed in the activity metrics during the LD period were only partly influenced by the climatic factors (PREC and TEMP). The correlation between PREC and NDVI was insignificant during the LD period (R2 = 0.03); PREC was also insignificantly correlated with SIF during the LD period (p>0.05). The correlation between TEMP and vegetation activity metrics (especially NDVI) during the LD period was statistically significant (p < 0.05) but negative. Notably, a statistically significant (p < 0.05) but a weak correlation was found between NR and NDVI anomalies (R2 = 0.16) during the LD period, while an insignificant correlation was found with SIF. This indicates that NR could have some minor influence on the NDVI.

On the other hand, a significant correlation was observed between PREC and vegetation activity metrics during the UL period (R2 = 0.25 – 0.42). The good correlation between activity metrics and PREC during the UL period can be attributed to the seasonal impacts. The UL period was from 1 June to 30 November, which corresponded to the monsoon and post-monsoon season, and thereby a substantial correlation during the UL period was expected. The maximum vegetation growth typically occurs during the monsoon and post-monsoon season across the Indian territory (Parida et al. 2021). Furthermore, a weak correlation was found between TEMP and vegetation activity metrics during the UL period, while a significant (p < 0.05) correlation was found between NR and vegetation activity metrics (R2 = 0.16 – 0.35). Thus, the improvement in the vegetation activity during the UL period was pretty influenced by the individual climatic variables (especially PREC and NR). By contrast, the vegetation activity during the LD period was only scarcely driven by individual climatic variables, and the COVID-triggered LD events might have played a role in enhancing vegetation activity.

**Table 3.** Correlation analysis between mean anomaly (%) of the climatic factors and the vegetation activity metrics across BGPs of India (n=26) during the LD and UL periods.

|  |  |  |  |
| --- | --- | --- | --- |
| **Variables** | ***Period*** | **NDVI** | **SIF** |
| **PREC** | *LD* | 0.03 | 0.13 |
| *UL* | 0.24\*\* | 0.42\* |
| **TEMP** | *LD* | -0.18\*\* | -0.05 |
| *UL* | -0.008 | -0.01 |
| **NR** | *LD* | 0.16\*\* | 0.06 |
| *UL* | 0.35\* | 0.29\* |

(**Note**: \* represents that correlation is significant at p < 0.01; \*\* represents that correlation is significant at p < 0.05; non-star represents that correlation is not significant)

* 1. ***Vegetation activity around mining clusters during the LD and UL periods***

As we got a rare window during COVID-induced LD events, the study paid special attention to the vegetation growth status around the mining clusters over the Jharkhand (JH) and Odisha (OD) states of India. The mean anomalies of vegetation activity metrics (i.e., NDVI, SIF) and air pollution parameter (i.e., AOD) over the vegetation patches of different mining clusters during the LD and UL periods (2020) are illustrated in **(Figure 6**). The bar diagram reveals that vegetation activity around the mining clusters was significantly enhanced (~ 40 to 80%) during the LD periods. On the other hand, the AOD level (anomaly) over the mining clusters remarkably decreased (~40%) during the LD and UL periods, which might have been possible owing to the curbing of the working capacity of these mining regions. The majority of coal mining clusters exhibited the utmost positive NDVI and SIF anomaly (during the LD period) for the vegetation patches (up to 43 – 78%; NDVI – SIF), followed by the iron ore (up to 33 – 63%) and stone mining (up to 17 – 41%) clusters. Vegetation activity over the bauxite and chromite mining clusters was also fairly improved during the LD periods (21 – 48%, 18 – 31%; NDVI – SIF, respectively). However, the maximum decrease in the AOD anomaly was noted over the stone mining regions (up to ~ 42%) followed by coal mines (up to ~ 31%) and iron ore mines (up to ~ 9%). It indicates that vegetation health around the stone mining clusters is more vulnerable to dust pollution than the coal and iron ore mines. Though the AOD level was hugely decreased over the stone mining clusters (during the LD period), the vegetation activity was relatively less improved over these regions than the vegetation activity around the coal and iron ore mining clusters. It may be interesting in future studies to focus on the characteristics of the different mine-induced (stone, coal, metal, among others) dust particles and their effect on vegetation health and productivity.

Few mining clusters (i.e., all stone mines, Lalmatia and Jagganath coal mines, Kurmitar iron ore mines, Panchpatmali and Kodingamali bauxite mines) exhibited negative NDVI anomaly during the UL period. However, the negative anomaly of activity metrics over these regions was relatively small (~ 2 – 7 %) during the UL period, while the negative anomaly over stone mining regions was much higher (up to 20%). It can perceive that these mining clusters were possibly functional during the UL phase with remarkable working capacity, which might have influenced the vegetation greenness and productivity.

Stone mining clusters

Coal mining clusters

Iron ore mining clusters

Others

**Mining clusters**

**Figure 6.** Mean NDVI, SIF, and AOD anomaly over the different mining clusters across the JH and OD state of India during the LD and UL periods (2020) as compared to the means over the previous three years (2017-2019).

The study examined the correlation (individually) between anomalies (zonal mean) of PREC, TEMP, and NR and those of NDVI and SIF (**Table 4**) to examine whether the climatic variables influenced NDVI and SIF during the LD events or not (over particular mining clusters). Correlation analysis between anomaly of AOD and vegetation activity metrics was also performed to understand the degree of influence of mine-induced dust particles on vegetation activity during the LD periods (**Table 4**). Interestingly, PREC and NR had a significant positive influence on vegetation activity (R2 = 0.19 – 0.54; p < 0.01 – 0.05) around the mining clusters during the LD period. However, in the case of biogeographic provinces, no significant correlation was found between PREC and the activity metrics (**Table 3**). NR had a moderately strong relationship with NDVI (R2 = 0.55) and a weak relationship with SIF (R2 = 0.16, p < 0.05) anomalies during the UL period. TEMP had a weak relationship with NDVI (R2 = 0.16, p < 0.05) during the UL period. Notably, the correlation between AOD and NDVI anomaly was also significant during the LD period (R2 = 0.26; p < 0.01), which indicates that the enhancement in NDVI was possibly influenced by the decrease in AOD concentration. The correlation between SIF and AOD anomalies was not statistically significant (p = 0.08). Eventually, these R2 statistics indicate that climatic parameters (especially PREC and NR) enhanced vegetation activity during the LD period, and partly during the UL period. Nonetheless, a decrease in the AOD concentration also enhanced the vegetation activity around the mining clusters.

**Table 4:** Correlation analysis between mean anomaly (%) of climatic factors, air pollutant, and vegetation activity metrics across mining clusters (n=25) during the LD and UL periods.

|  |  |  |  |
| --- | --- | --- | --- |
| **Variables** | ***Period*** | ***NDVI*** | ***SIF*** |
| ***PREC*** | *LD* | 0.29\* | 19\*\* |
| *UL* | -0.12 | 0.006 |
| ***TEMP*** | *LD* | -0.54\* | -0.46\* |
| *UL* | 0.21\*\* | 0.08 |
| ***NR*** | *LD* | 0.19\*\* | 0.54\* |
| *UL* | 0.55\* | 0.16\*\* |
| ***AOD*** | *LD* | 0.26\* | 0.13 |
| *UL* | -0.06 | -0.35\* |

(**Note**: \* represents that correlation is significant at p < 0.01; \*\* represents that correlation is significant at p < 0.05; non-star represents that correlation is not significant)

1. **Discussion**

This is the first study that evidenced a noteworthy improvement in vegetation activity (by up to 55%) over the Indian territory during LD and UL periods (2020) as compared to the past three years (2017-2019) mean condition. Particularly, a remarkable improvement in the vegetation activity was noted over the coal mining regions (up to ~ 78%) followed by iron ore mines (up to ~ 63%) and stone mining (up to 41%) regions. It indicates that COVID-triggered LD events compelled to reduce or stop the major anti-environmental deeds that could have helped improve vegetation activity. Apart from this, the utmost patches of enhanced vegetation activity (higher anomaly percentage) were observed over the grasslands patches (refer to **Figure 1** for vegetation types). Grasslands are highly responsive to changes in temporary climatic events and anthropogenic interventions. Wherein, relatively fewer patches of improved vegetation activity were observed over the savannas (woody), mixed forest, or over the evergreen forest patches. Compared to grasslands, these vegetation types are not simply swayed by the temporary climatic events and anthropogenic interventions due to their physiographic conditions. Subsequently, the regions predominantly covered with grasslands were found with a relatively higher percentage of enhanced vegetation activity than the regions mostly covered with savannas (woody), mixed forest, mangroves, and evergreen forest, among others.

The present investigation also witnessed that individual climatic parameters had less control on vegetation activity during the LD over the BGPs (R2 = 0.03 – 0.12), wherein vegetation activity was fairly influenced by climatic variables (especially PREC and NR) during the UL periods (R2 = 0.16 – 0.42). The climatic conditions (especially PREC and NR) during the LD period were somewhat identical with those during the reference period (**Table S4**), and the same variables (PREC and NR) during the UL period were different from the reference values. Therefore, other factors (possibly LD events) might have helped to improve the vegetation activity during the LD period.

On the other hand, PREC and NR along with AOD were found as influencing factors for enhancing the vegetation activity during the LD periods around the mining clusters (R2 = 0.19 – 0.50, PREC; 0.19 – 0.54, NR). Possibly, curbing the working capacity of the mines during the LD periods had offered an opportunity for the re-growth of the vegetation around mining clusters. The reduced aerosol concentration and other air pollutants in the lower tropospheric region during the LD periods could have led to higher net radiant energy, which improved vegetation activity. In this context, a noteworthy correlation between NR and vegetation activity around 25 mining clusters (R2 = 0.16 – 0.55; p < 0.01 – 0.05) was observed during the LD and UL periods.

Besides, some more insightful investigation could be done to explore the effect of mine-induced air pollution on the changes in the diffuse fraction of solar radiation. The diffuse light coming from different angles (due to higher air pollution) can increase the fraction of diffuse radiation and thereby increases the efficiency of CO2 uptake by leaves of different orientations (Alton et al. 2007; Cheng et al. 2015). However, this mechanism is ecosystem-dependent and probably depends on canopy height, leaf area index (LAI), and aerosol loading; diffuse radiation can increase or decrease the vegetation productivity (Niyogi et al. 2004; Lu et al. 2017). The relative effects of the changes in diffuse and direct radiation on vegetation activity during the LD periods should be examined in future studies.

The combined influence of climatic factors on the vegetation activity during the LD and UL period were also analyzed as summarized in **Table 5**.The results indicated that only 22% to 25% of the variation in the vegetation activity (over BGPs) was explained by the climatic factors together during the LD period. As expected, the relatively higher influence of climatic factors on activity was observed during the UL period (~ 62 – 64%). Notably, 57 – 60% variation in the vegetation activity over the mining clusters was explained by the climatic factors, wherein, it explains relatively lower variance (25 – 57%) during the UL period. It can be assumed that the part of the variance that was certainly not explained by climatic variables could likely be explained by the LD events.

**Table 5:** Coefficient of determination (R2) estimated from multiple regression analysis between the vegetation activity metrics individually (NDVI, SIF) and the climatic variables (PREC, TEMP, and NR). *(Note: n = 26 for biogeographic provinces; n = 25 for mining clusters).*

|  |  |  |  |
| --- | --- | --- | --- |
| **For** | Coefficient of determination (R2) | | |
| **NDVI** | **SIF** | **Period** |
| Biogeographic Provinces | 0.25\* | 0.22\*\* | LD |
| 0.64\* | 0.62\* | UL |
| Mining Clusters | 0.57\* | 0.60\* | LD |
| 0.57\* | 0.25\*\* | UL |

(**Note**: \* represents that correlation is significant at p < 0.01; \*\* represents that correlation is significant at p < 0.05; non-star represents that correlation is not significant)

In line with the present study, some previous studies also investigated the status of ecological conditions during the LD periods and reported substantial improvement. For instance, Ghosh et al. (2020) observed a significant increment in NDVI over four megacities of India (i.e., Delhi, Mumbai, Kolkata, and Chennai) during LD periods. Firozjaei et al. (2021) also found improvement in the ecological status during LD periods over the urban environment of Milan and Wuhan cities, China. Furthermore, Lele et al. (2021), Pokhariyal et al. (2021), Saxena et al. (2021), among others, have also reported substantial improvement in the NDVI deviation and other satellite variables over the agriculture regions during the LD periods (2020) as compared to the past years. Henceforth, it can be inferred that the pandemic-triggered LD events have helped to improve not only air quality, surface temperature, and water quality, but also vegetation health and activity.

In a nutshell, the present study revealed that vegetation activity significantly improved during COVID-triggered LD events in India. However, the present study only quantitatively discusses the enhancement in the vegetation activity during LD events based on a variety of satellite products. Some other possible angles (i.e., anthropogenic factors, climatic factors (diffuse and direct radiant energy), air pollutants, among others) behind the improved activity during LD periods need to be quantified prudently, which is a great deal for future research. Besides, the spatial resolution of gridded products (SIF, PREC, TEMP, and NR) was resampled to the MODIS product’s pixel size, which might have slightly influenced the results.

1. **Conclusions**

In the era of fast-tracked global environmental changes, persistent efforts need to be made to monitor the vegetation dynamics so that the influence of anthropogenic and nature-induced actions on vegetation health and productivity can be well understood. Understanding vegetation dynamics over time is a key input for ecosystem conservation, restoration, and adaptation to global climatic changes. Furthermore, the findings of the present investigation shall be useful to policy-makers, government bodies, non-government organizations, environmentalists, and ecologists, for formulating and implementing sustainable development programs to ensure vegetation conservation and restoration and to enhance vegetation productivity. In addition, the present study provides a pseudo measure on the impact of anthropogenic activity (e.g. mining) on vegetation greenness and productivity. Based on this comprehensive study, the following conclusions are drawn.

* Noteworthy increase in vegetation greenness and productivity during lockdown (LD) and unlock (UL) periods were observed over the Central Highlands (6A) & Chota Nagpur provinces (6B) of Deccan Peninsula, and Kutchchh province (3B) of Desert region with up to 37% increase in NDVI and up to 55% increase in SIF. The less enhanced vegetation activity was witnessed over the Trans-Himalaya, Himalaya, North-east regions, among others.
* Vegetation greenness and productivity around the mining clusters were also significantly enhanced during LD periods. The utmost enhancement in the vegetation activity during the LD period was found around the coal mining clusters (up to 78%) followed by the iron ore (up to 63%) and stone mining (up to 41%) clusters.
* Although having an utmost decrease in AOD concentration around the stone mining clusters, the vegetation activity was less improved in these regions. Wherein, the enhanced vegetation activity was relatively higher around the coal mining clusters while a smaller reduction in the AOD concentration was observed over the coal mining clusters.
* The climatic parameters (PREC, TEMP, and NR) explained only 20 – 30% variance of the vegetation activity during the LD period, which indicates that the enhancement in the vegetation greenness and productivity (over BGPs) during the LD period was not entirely driven by the climatic conditions but likely was also influenced by the LD events.
* Interestingly, PREC and NR also improved the vegetation activity (R2 = 0.19 – 0.54; p < 0.01 – 0.05) around the mining clusters during the LD period. Notably, the correlation between AOD and NDVI anomaly was also noteworthy during the LD period (R2 = 0.26; p < 0.01) signifying the influence of AOD on improved NDVI around the mining clusters.
* Inspired by the LD events, some ground-breaking approaches can be formulated by governments, policy-makers, and environmentalists in the near future for giving a window to nature for healing by itself.

**CRediT authorship contribution statement**

**AKR**: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing - original draft, Visualization. **JD**: Conceptualization, Formal analysis, Writing - review & editing, Visualization, Supervision. **JX**: Conceptualization, Formal analysis, Writing - review & editing, Visualization. **AKG**: Conceptualization, Methodology, Formal analysis, Writing - review & editing, Visualization, 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.

**Acknowledgment**

This research was conducted at the National Institute of Technology (NIT) Rourkela, Odisha, India as a part of PhD work of AKR. JX’s contribution is supported by the University of New Hampshire. The authors sincerely thanks and acknowledge the Google Earth Engine (GEE) and Climate Engine cloud platform. The mission scientists and principal investigators of different satellite datasets (MODIS NDVI, and land cover; GOSIF; CHIRPS precipitation; and ERA-based Temperature) who provided the data used in this research effort are sincerely acknowledged. The authors are also thankful to the anonymous reviewer (s) for providing constructive comments which have certainly enhanced the overall quality of the manuscript.

**Funding**

Not applicable

**Ethical approval**

All ethical practices have been followed during this research.

**Data availability statement**

The data that support the findings of this study are openly available in the Google Earth Engine cloud platform at <https://earthengine.google.com/> (NDVI); Global Ecology Group’s data repository at data.globalecology.unh.edu (SIF); Climate Engine cloud platform at <http://climateengine.org/data> (PREC, TEMP, NR).

**ORCID ID**

Avinash Kumar Ranjan: <https://orcid.org/0000-0002-6406-8544>.

Jadunandan Dash: <https://orcid.org/0000-0002-5444-2109>.

Jingfeng Xiao: <https://orcid.org/0000-0002-0622-6903>.

Amit Kumar Gorai: <https://orcid.org/0000-0002-2276-6870>.

**References**

Alqasemi, A.S., Hereher, M.E., Kaplan, G., Al-Quraishi, A.M.F., Saibi, H., 2021. Impact of COVID-19 lockdown upon the air quality and surface urban heat island intensity over the United Arab Emirates. Science of The Total Environment 767, 144330. <https://doi.org/10.1016/j.scitotenv.2020.144330>

Alton, P., Mercado, L., North, P., 2006. A sensitivity analysis of the land-surface scheme JULES conducted for three forest biomes: Biophysical parameters, model processes, and meteorological driving data: Sensitivity Analysis of Land-Model Jules. Global Biogeochem. Cycles 20, n/a-n/a. <https://doi.org/10.1029/2005GB002653>

Bar, S., Parida, B.R., Mandal, S.P., Pandey, A.C., Kumar, N., Mishra, B., 2021. Impacts of partial to complete COVID-19 lockdown on NO2 and PM2.5 levels in major urban cities of Europe and USA. Cities 117, 103308. <https://doi.org/10.1016/j.cities.2021.103308>

Bukhari, Q., Jameel, Y., 2020. Will Coronavirus Pandemic Diminish by Summer? SSRN Journal. <https://doi.org/10.2139/ssrn.3556998>.

Cheng, S.J., Bohrer, G., Steiner, A.L., Hollinger, D.Y., Suyker, A., Phillips, R.P., Nadelhoffer, K.J., 2015. Variations in the influence of diffuse light on gross primary productivity in temperate ecosystems. Agricultural and Forest Meteorology 201, 98–110. <https://doi.org/10.1016/j.agrformet.2014.11.002>

Conesa, H.M., Faz, Á., Arnaldos, R., 2006. Heavy metal accumulation and tolerance in plants from mine tailings of the semiarid Cartagena–La Unión mining district (SE Spain). Science of The Total Environment 366, 1–11. <https://doi.org/10.1016/j.scitotenv.2005.12.008>

Department of Mines and Geology, Government of Jharkhand [WWW Document], n.d. URL http://jharkhandminerals.gov.in/content/1/1 (accessed 7.21.21).

Department of Steel and Mines, Government of Odisha [WWW Document], n.d. URL https://www.odishaminerals.gov.in/StatisticsReport/BindYearWiseRevCollectionRpt (accessed 7.21.21).

Didan, K. 2015. MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V006 [Data set]. NASA EOSDIS Land Processes DAAC. Accessed 2021-05-20 from <https://doi.org/10.5067/MODIS/MOD13Q1.006>.

Dutta, V., Dubey, D., Kumar, S., 2020. Cleaning the River Ganga: Impact of lockdown on water quality and future implications on river rejuvenation strategies. Science of The Total Environment 743, 140756. <https://doi.org/10.1016/j.scitotenv.2020.140756>.

Firozjaei, M.K., Fathololomi, S., Kiavarz, M., Arsanjani, J.J., Homaee, M., Alavipanah, S.K., 2021. Modeling the impact of the COVID-19 lockdowns on urban surface ecological status: A case study of Milan and Wuhan cities. Journal of Environmental Management 286, 112236. <https://doi.org/10.1016/j.jenvman.2021.112236>.

Florentina, I., Io, B., 2011. The Effects of Air Pollutants on Vegetation and the Role of Vegetation in Reducing Atmospheric Pollution, in: Khallaf, M. (Ed.), The Impact of Air Pollution on Health, Economy, Environment and Agricultural Sources. InTech. <https://doi.org/10.5772/17660>

Friedl, M., Sulla-Menashe, D. 2019. MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V006 [Data set]. NASA EOSDIS Land Processes DAAC. Accessed 2020-09-01 from <https://doi.org/10.5067/MODIS/MCD12Q1.006>’

Friedl, M.A, D.K McIver, J.C.F Hodges, X.Y Zhang, D Muchoney, A.H Strahler, C.E Woodcock, et al. 2002. “Global Land Cover Mapping from MODIS: Algorithms and Early Results.” Remote Sensing of Environment 83 (1–2): 287–302. <https://doi.org/10.1016/S0034-4257(02)00078-0>.

Friedl, Mark A., Damien Sulla-Menashe, Bin Tan, Annemarie Schneider, Navin Ramankutty, Adam Sibley, and Xiaoman Huang. 2010. “MODIS Collection 5 Global Land Cover: Algorithm Refinements and Characterization of New Datasets.” Remote Sensing of Environment 114 (1): 168–82. <https://doi.org/10.1016/j.rse.2009.08.016>.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., Michaelsen, J. 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Scientific Data 2, 150066. doi:10.1038/sdata.2015.66 2015.

Ghosh, S., Das, A., Hembram, T.K., Saha, S., Pradhan, B., Alamri, A.M., 2020. Impact of COVID-19 Induced Lockdown on Environmental Quality in Four Indian Megacities Using Landsat 8 OLI and TIRS-Derived Data and Mamdani Fuzzy Logic Modelling Approach. Sustainability 12, 5464. <https://doi.org/10.3390/su12135464>.

Guha, S., Govil, H., 2021. COVID-19 lockdown effect on land surface temperature and normalized difference vegetation index. Geomatics, Natural Hazards and Risk 12, 1082–1100. <https://doi.org/10.1080/19475705.2021.1914197>.

Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment 83, 195–213. <https://doi.org/10.1016/S0034-4257(02)00096-2>

Jha, C. S., Rakesh, Singhal, J., Reddy, C. S., Rajashekar, G., Maity, S., Patnaik, C., Das, A., Misra, A., Singh, C. P., Mohapatra, J., Krishnayya, N. S. R., Kiran, S., Townsend, P., & Martinez, M. H. 2019. Characterization of Species Diversity and Forest Health using AVIRIS-NG Hyperspectral Remote Sensing Data. Current Science, 116(7), 1124. <https://doi.org/10.18520/cs/v116/i7/1124-1135>.

Kayet, N., Pathak, K., Chakrabarty, A., Kumar, S., Chowdary, V.M., Singh, C.P., Sahoo, S., Basumatary, S., 2019a. Assessment of foliar dust using Hyperion and Landsat satellite imagery for mine environmental monitoring in an open cast iron ore mining area, Journal of Cleaner Production. Elsevier Ltd. <https://doi.org/10.1016/j.jclepro.2019.01.305>.

Kayet, N., Pathak, K., Chakrabarty, A., Singh, C. P., Chowdary, V. M., Kumar, S., & Sahoo, S. 2019b. Forest health assessment for geo-environmental planning and management in hilltop mining areas using Hyperion and Landsat data. Ecological Indicators, 106, 105471. <https://doi.org/10.1016/j.ecolind.2019.105471>.

Khan, R., Saxena, A., Shukla, S., Sekar, S., Goel, P., 2021. Effect of COVID-19 lockdown on the water quality index of River Gomti, India, with potential hazard of faecal-oral transmission. Environ Sci Pollut Res. <https://doi.org/10.1007/s11356-021-13096-1>.

Lal, P., Kumar, A., Kumar, S., Kumari, S., Saikia, P., Dayanandan, A., Adhikari, D., Khan, M.L., 2020. The dark cloud with a silver lining: Assessing the impact of the SARS COVID-19 pandemic on the global environment. Science of The Total Environment 732, 139297. <https://doi.org/10.1016/j.scitotenv.2020.139297>.

Lele, N., Nigam, R., Bhattacharya, B.K., 2021. New findings on impact of COVID lockdown over terrestrial ecosystems from LEO-GEO satellites. Remote Sensing Applications: Society and Environment 22, 100476. <https://doi.org/10.1016/j.rsase.2021.100476>.

Li, X., Xiao, J. 2019. Mapping photosynthesis solely from solar-induced chlorophyll fluorescence: A global, fine-resolution dataset of gross primary production derived from OCO-2. Remote Sensing, 11(21), 2563; <https://doi.org/10.3390/rs11212563>.

Li, X., Xiao, J., He, B., Arain, M.A., Beringer, J., Desai, A.R., Emmel, C., Hollinger, D.Y., Krasnova, A., Mammarella, I., Noe, S.M., Ortiz, P.S., Rey-Sanchez, C., Rocha, A.V., Varlagin, A. 2018. Solar-induced chlorophyll fluorescence is strongly correlated with terrestrial photosynthesis for a wide variety of biomes: First global analysis based on OCO-2 and flux tower observations. Global Change Biology, 24, 3990-4008.

Long, H.W., Feng, W.J., 2020. Research Report on Companies’ Survival and Development Strategy During a Novel Coronavirus Epidemic. UIBE Press, Beijing.

Lu, X., Chen, M., Liu, Y., Miralles, D.G., Wang, F., 2017. Enhanced water use efficiency in global terrestrial ecosystems under increasing aerosol loadings. Agricultural and Forest Meteorology 237–238, 39–49. <https://doi.org/10.1016/j.agrformet.2017.02.002>

Lyapustin, A., Wang, Y. 2018. MCD19A2 MODIS/Terra+Aqua Land Aerosol Optical Depth Daily L2G Global 1km SIN Grid V006. <https://doi.org/10.5067/MODIS/MCD19A2.006>.

Mahato, S., Pal, S., Ghosh, K.G., 2020. Effect of lockdown amid COVID-19 pandemic on air quality of the megacity Delhi, India. Science of The Total Environment 730, 139086. <https://doi.org/10.1016/j.scitotenv.2020.139086>.

Maithani, S., Nautiyal, G., Sharma, A., 2020. Investigating the Effect of Lockdown During COVID-19 on Land Surface Temperature: Study of Dehradun City, India. J Indian Soc Remote Sens 48, 1297–1311. <https://doi.org/10.1007/s12524-020-01157-w>.

Mehdipour, V., Memarianfard, M., 2017. Application of Support Vector Machine and Gene Expression Programming on Tropospheric ozone Prognosticating for Tehran Metropolitan. CivileJournal 3, 557. <https://doi.org/10.28991/cej-030984>.

Mishra, M., Kulshrestha, U.C., 2021. A Brief Review on Changes in Air Pollution Scenario over South Asia during COVID-19 Lockdown. Aerosol Air Qual. Res. 21, 200541. <https://doi.org/10.4209/aaqr.200541>

Mofijur, M., Fattah, I.M.R., Alam, M.A., Islam, A.B.M.S., Ong, H.C., Rahman, S.M.A., Najafi, G., Ahmed, S.F., Uddin, Md.A., Mahlia, T.M.I., 2021. Impact of COVID-19 on the social, economic, environmental and energy domains: Lessons learnt from a global pandemic. Sustainable Production and Consumption 26, 343–359. <https://doi.org/10.1016/j.spc.2020.10.016>

Motesaddi, S., Hashempour, Y., Nowrouz, P., 2017. Characterizing of air pollution in Tehran: comparison of two air quality indices. Civil Engineering Journal 3 (9), 749–758. <https://doi.org/10.21859/cej-030911>.

Motesaddi, S., Hashempour, Y., Nowrouz, P., 2017. Characterizing of Air Pollution in Tehran: Comparison of Two Air Quality Indices. cej 3, 749–758. <https://doi.org/10.21859/cej-030911>.

Muhammad, S., Long, X., Salman, M., 2020. COVID-19 pandemic and environmental pollution: A blessing in disguise? Science of The Total Environment 728, 138820. <https://doi.org/10.1016/j.scitotenv.2020.138820>.

Nigam, R., Pandya, K., Luis, A.J., Sengupta, R., Kotha, M., 2021. Positive effects of COVID-19 lockdown on air quality of industrial cities (Ankleshwar and Vapi) of Western India. Sci Rep 11, 4285. <https://doi.org/10.1038/s41598-021-83393-9>

Niyogi, D., 2004. Direct observations of the effects of aerosol loading on net ecosystem CO 2 exchanges over different landscapes. Geophys. Res. Lett. 31, L20506. <https://doi.org/10.1029/2004GL020915>

Nowak, D.J., Hirabayashi, S., Bodine, A., Greenfield, E., 2014. Tree and forest effects on air quality and human health in the United States. Environmental Pollution 193, 119–129. <https://doi.org/10.1016/j.envpol.2014.05.028>

Parida, B.R., Bar, S., Roberts, G., Mandal, S.P., Pandey, A.C., Kumar, M., Dash, J., 2021. Improvement in air quality and its impact on land surface temperature in major urban areas across India during the first lockdown of the pandemic. Environmental Research 199, 111280. <https://doi.org/10.1016/j.envres.2021.111280>

Parida, B.R., Pandey, A.C., Patel, N.R., 2020. Greening and Browning Trends of Vegetation in India and Their Responses to Climatic and Non-Climatic Drivers. Climate 8, 92. <https://doi.org/10.3390/cli8080092>.

Pokhariyal, S., Patel, N.R., Rana, R.S., Chauhan, P., 2021. Environmental Impact of Lockdown Amid COVID-19 Over Agricultural Sites in Himalayan Foothills. J Indian Soc Remote Sens. <https://doi.org/10.1007/s12524-021-01343-4>.

Ranjan, A.K., Patra, A.K., Gorai, A.K., 2020. Effect of lockdown due to SARS COVID-19 on aerosol optical depth (AOD) over urban and mining regions in India. Science of The Total Environment 745, 141024. <https://doi.org/10.1016/j.scitotenv.2020.141024>.

Rodgers, W.A., & Panwar, S.H. 1988. Biogeographical classification of India. New Forest, Dehra Dun, India

Saha et al. 2010. The NCEP Climate Forecast System Reanalysis. Bull. Amer. Meteor. Soc. 91, 1015–1058. <https://doi.org/10.1175/2010BAMS3001.1>

Sahani, N., Goswami, S.K., Saha, A., 2020. The impact of COVID-19 induced lockdown on the changes of air quality and land surface temperature in Kolkata city, India. Spat. Inf. Res. <https://doi.org/10.1007/s41324-020-00372-4>.

Saxena, S., Rabha, A., Tahlani, P., Ray, S.S., 2021. Crop Situation in India, Before, During and After COVID-19 Lockdown, as Seen from the Satellite Data of Resourcesat-2 AWiFS. J Indian Soc Remote Sens 49, 365–376. <https://doi.org/10.1007/s12524-020-01213-5>.

Sekhar, P.H., Mohan, S.K. 2014. Assessment of Impact of Opencast Mine on Surrounding Forest: a Case Study From Keonjhar District of Odisha, India. J. Environ. Res. Dev. Vol. 9, 249–254.

Shi, H., Han, X., Jiang, N., Cao, Y., Alwalid, O., Gu, J., Fan, Y., Zheng, C., 2020. Radiological findings from 81 patients with COVID-19 pneumonia in Wuhan, China: a descriptive study. The Lancet Infectious Diseases 20, 425–434. <https://doi.org/10.1016/S1473-3099(20)30086-4>.

Singh, R.K., Drews, M., De la Sen, M., Srivastava, P.K., Trisasongko, B.H., Kumar, M., Pandey, M.K., Anand, A., Singh, S.S., Pandey, A.K., Dobriyal, M., Rani, M., Kumar, P., 2021. Highlighting the compound risk of COVID-19 and environmental pollutants using geospatial technology. Sci Rep 11, 8363. <https://doi.org/10.1038/s41598-021-87877-6>

Sulla-Menashe, Damien, Josh M. Gray, S. Parker Abercrombie, and Mark A. Friedl. 2019. Hierarchical Mapping of Annual Global Land Cover 2001 to Present: The MODIS Collection 6 Land Cover Product. Remote Sensing of Environment 222 (March): 183–94. <https://doi.org/10.1016/j.rse.2018.12.013>.

Tarek, M., Brissette, F.P., Arsenault, R., 2019. Evaluation of the ERA5 reanalysis as a potential reference datasetfor hydrological modeling over North-America (preprint). Catchment hydrology/Modelling approaches. <https://doi.org/10.5194/hess-2019-316>

Teufel, B., Sushama, L., Poitras, V., Dukhan, T., Bélair, S., Miranda-Moreno, L., Sun, L., Sasmito, A.P., Bitsuamlak, G., 2021. Impact of COVID-19-Related Traffic Slowdown on Urban Heat Characteristics. Atmosphere 12, 243. <https://doi.org/10.3390/atmos12020243>.

Xiao, J., Chevallier, F., Gomez, C., Guanter, L., Hicke, J.A., Huete, A.R., Ichii, K., Ni, W., Pang, Y., Rahman, A.F., Sun, G., Yuan, W., Zhang, L., Zhang, X., 2019a. Remote sensing of the terrestrial carbon cycle: A review of advances over 50 years. Remote Sensing of Environment 233, 111383. <https://doi.org/10.1016/j.rse.2019.111383>

Xiao, J., Li, X., He, B., Arain, M.A., Beringer, J., Desai, A.R., Emmel, C., Hollinger, D.Y., Krasnova, A., Mammarella, I., Noe, S.M., Ortiz, P.S., Rey-Sanchez, C., Rocha, A.V., Varlagin, A. 2019b. Solar-induced chlorophyll fluorescence exhibits a universal relationship with gross primary productivity across a wide variety of biomes. Global Change Biology, 25, e4–e6, <https://doi.org/10.1111/gcb.14565>

Yunus, A.P., Masago, Y., Hijioka, Y., 2020. COVID-19 and surface water quality: Improved lake water quality during the lockdown. Science of The Total Environment 731, 139012. <https://doi.org/10.1016/j.scitotenv.2020.139012>.

Yunus, A.P., Masago, Y., Hijioka, Y., 2020. COVID-19 and surface water quality: Improved lake water quality during the lockdown. Science of The Total Environment 731, 139012. <https://doi.org/10.1016/j.scitotenv.2020.139012>

1. In India, from 25 March 31 May 2020, there was country-wide complete shutdown, hereafter we will use this phase as LD (**Table 1**). [↑](#footnote-ref-1)
2. From 1 June 2020 onwards, some services were resumed and this phase was termed as unlock phase. Similarly, every month some services were resumed with more ease of restrictions. Hereafter this phase will be used as UL (till 30 November) (**Table 1**). [↑](#footnote-ref-2)