Indirect Response of the Temperature, Humidity, and Rainfall on the Spread of COVID-19 over the Indian Monsoon Region

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Abstract—This article examines the role of the meteorological variable in the spread of the ongoing pandemic coronavirus disease 2019 (COVID-19) across India. COVID-19 has created an unprecedented situation for public health and brought the world to a standstill. COVID-19 had caused more than 1,523,242 deaths out of 66,183,029 confirmed cases worldwide till the first week of December 2020. We have examined the surface temperature, relative humidity, and rainfall over five cities: Delhi, Mumbai, Kolkata, Bengaluru, and Chennai, which were severely affected by COVID-19. It is found that the prevailing southwest (SW) monsoon during the pandemic has acted as a natural sanitizer in limiting the spread of the virus. The mean rainfall is 20–40 mm over the selected cities, resulting in an average decrease in COVID cases by 18–26% for the next 3 days after the rainfall. The day-to-day variations of the meteorological parameters and COVID-19 cases clearly demonstrate that both surface temperature and relative humidity play a vital role in the indirect transport of the virus. Our analysis reveals that most COVID-19 cases fall within the surface temperature range from 24 to 30 °C and relative humidity range from 50% to 80%. At a given temperature, COVID-19 cases show a large dependency on the relative humidity; therefore, the coastal environments were more prone to infections. Wavelet transforms coherence analysis of the daily COVID-19 cases with temperature and relative humidity reveals a significant coherence within 8 days.

Keywords: Temperature, Relative Humidity, Rainfall, Coronavirus, Health, India.

1. Introduction

Coronavirus disease 2019 (COVID-19) was first identified in Wuhan, China, in December 2019 as an infectious disease caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) (Li et al., 2020). SARS-CoV-2 is a single-stranded positive-sense ribonucleic acid (RNA) virus (Lu et al., 2020), with an extremely contagious nature; the number of registered cases across the globe to date (as of December 5, 2020) is 66,183,029 (https://www.worldometers.info/). SARS-CoV-2 belongs to the same family as Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS) of Coronavirus (CoVs) (Chen et al., 2020). These viruses cause common colds to severe respiratory disease and death (Huang et al., 2020). SARS-CoV-2 is transmitted primarily to a susceptible person through human-to-human, droplet, airborne, fomite, and animal-to-human contact (Li et al., 2020). The indirect transmission paths, such as aerosols, droplets, and contaminated fomites, are highly influenced by the surface temperature, relative humidity, ambient humidity, and solar radiation (Asyary & Veruswati, 2020; Nazari Harmooshi et al., 2020; Prata et al., 2020; Wang et al., 2020; Yuan et al., 2020; Zhu et al., 2020). However, due to limited data, the significance of airborne transmission and its different pathways is still uncertain (Jayaweera et al., 2020). In general, the infected person’s viral particles are spread through breathing, coughing, conversations, and sneezing (Yongjian et al., 2020). Setti et al. (2020) reported that SARS-CoV-2—RNA was identified in free atmospheric aerosols over Italy. The World Health Organization (WHO) postulated that
the viral particles $< 5 \mu m$ are aerosols and $> 5 \mu m$ droplets (Jayaweera et al., 2020). The larger droplets tend to fall on the surface because of the gravitational pull while the smaller particles linger and float in the air (Feng et al., 2020). Thus, aerosols pose a higher risk of widespread COVID-19 disease even far away from their point of origin (Van Doremalen et al., 2020).

The diameter of the SARS-CoV-2 virus ranges from 65 to 125 nm (Shereen et al., 2020), which can be blended with Aitken and accumulation modes of aerosol particles that may enhance the widespread of COVID-19 disease. In general, 80–90% of human respiratory particles are $< 1 \mu m$ (Papineni & Rosenthal, 1997); they can travel a maximum of 4.5 and 7 m during coughing and sneezing, respectively (Loh et al., 2020).

Numerous studies have correlated COVID-19 with meteorological parameters. Pani et al. (2020) reported that relative humidity and temperature favor the spread of COVID-19 disease, negatively correlated with atmospheric boundary layer height (ABL), wind speed, and ventilation coefficient. It has been observed that lower air temperature and higher humidity lead to prolonged viability of the virus in contaminated fomite (Kim et al., 2007). Xie and Zhu (2020) reported the spread of SARS-CoV-2 is positively correlated at 3 °C ambient temperature. Zhu et al. (2020) reported a positive correlation between absolute humidity and SARS-CoV-2. Yuan et al. (2020) reported that the mortality rate of COVID-19 disease is positively correlated with relative humidity. Notably, with temperatures $> 38 ^\circ C$ and relative humidity $> 95$%, viruses lose their viability in the tropical environment (Chan et al., 2011). It is reported that indirect transmission is more effective than direct transmission because of India’s unique geographical location and seasonal patterns (Neher et al., 2020). However, a few studies (Gupta et al., 2020) reported that SARS-CoV-2 spread is ineffective with temperature increases. Thus, the roles of the meteorological parameters on the spread of COVID-19 are under debate (Zaitchik et al., 2020).

Such contradictory findings on the role of the meteorological parameters mainly appear because of different analysis methods. These studies have performed primarily linear rank correlation analysis to establish the link between metrological variables and COVID-19 cases, with nonlinear variables leading to low confidence in statistical significance. Thus, an in-depth examination of the role of the meteorological parameters in the spread of SARS-CoV-2 transmission over the different regions of the globe is required for future projections to handle pandemics like COVID-19 faced today.

In response to the COVID-19 pandemic, India, the world’s second-most populous country, is severely affected, along with other Asian countries. Although India had overcome several outbreaks, such as SARS, swine flu, Nipah virus, etc., COVID-19 has been the most severe among them. As of December 5, 2020, India witnessed about 9,590,086 confirmed cases, 139,433 deaths, and 9,038,081 recovered cases. Although several studies have yielded a wealth of information on the link between meteorological parameters and COVID-19 cases, most of the studies suffer from inappropriate methodology and hypotheses (Zaitchik et al., 2020), as mentioned earlier. For example, Babu et al. (2020) reported a positive (negative) correlation between daily COVID-19 cases and temperature (relative humidity) from March to June over Delhi; however, Gupta et al. (2020) contradicted the results of Babu et al. (2020) and reported no correlation between COVID-19 cases with any weather parameters over Delhi and eight other affected major cities. Sasikumar et al. (2020) reported the cities with higher CO$_2$ emissions in India are vulnerable to COVID-19 infections. During the early phase of the COVID-19 cases during the Indian summer (March–May), the surface temperature increased linearly. It reached its maximum value, coinciding with increasing COVID-19 cases and showed a strong correlation. However, such seasonal variation in temperature is unlikely to be related to increasing CO$_2$ emissions attributed to causing COVID-19 cases. Though the increase in CO$_2$ is a major reason for warming, direct attribution of the higher CO$_2$ emissions to the increase in temperature within a season and increasing COVID-19 spread may misguide the public health regulations, e.g., imposing or lifting lockdowns. Notably, COVID-19 severely affected the Karnataka region, which is known to have lower CO$_2$ emission than other less affected regions, e.g., Gujarat (Garg et al., 2017). In
the present study, we hypothesize that Indian summer monsoon rainfall was an important factor in curtailing the spread of COVID-19 over the Indian region. Also, we have employed a non-linear wavelet approach to examine the link between surface meteorological variables such as temperature, relative humidity, and rainfall and COVID-19 spread over five severely affected metropolitan cities, Delhi, Mumbai, Kolkata, Bengaluru, and Chennai, as well as overall in India.

2. Datasets and Methodology

2.1. COVID-19 Cases Data

The pandemic COVID-19 data for Indian cities was obtained from the official website of the Ministry of Health and Family Welfare Government of India (https://www.mohfw.gov.in/, https://www.mygov.in/corona-data/covid19-statewise-status). We looked at information on detailed data from the cities available from 26 April 2020 to date. In this study, we have used daily reported COVID-19 case data for severely affected metropolitan cities (Delhi, Mumbai, Kolkata, Bengaluru, and Chennai) and over India from 26 April 2020 to 5 December 2020.

2.2. Weather Data

To understand the role and influence of temperature and relative humidity on COVID-19 spread over Indian cities, we obtained daily surface temperature and relative humidity data from the automatic weather station (AWS) from the India Meteorological Department (IMD) stations in Delhi, Mumbai, Kolkata, Bengaluru, and Chennai from 22 March 2020 to 5 December 2020. To investigate the role of the meteorological parameters on COVID-19 spread over the entire Indian region, we have used daily surface temperature and humidity data from ERA5 from March–December 2020.

2.3. GPM-IMERG-Rainfall Data

The daily rainfall data were obtained from Integrated Multi-satellitE Retrievals for Global Precipitation Mission (GPM) (IMERG). The GPM is a joint mission between the National Aeronautics Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA) that was successfully launched on 27 February 2014. The IMERG estimates the precipitation by using the Goddard Profiling Algorithm (GPROF2017) and Combined Ku Radar-Radiometer Algorithm (CORRA). The IMERG products are available as early, late, and final with a latency of 4 h, 12–14 h, and 3.5 months, respectively (Arshad et al., 2021; Huffman et al., 2015). IMERG early and late runs are used for real-time monitoring applications, such as floods and irrigation, and the final run is used for research purposes. In this study, we have used level 3 version 6 Daily (GPM_3IMERGDL) final data with a spatial resolution of 0.1° × 0.1°.

2.4. Particulate Matter (PM$_{2.5}$) Data

The PM$_{2.5}$ data were retrieved from the Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2) reanalysis data. The aerosol products in MERRA 2 are assimilated from the Goddard Global Ozone Chemistry Aerosol Radiation and Transport and used as primary input in Moderate Resolution Imaging Spectroradiometer aerosol optical depth products. Since 1980, the MEERA-2 has provided a mass concentration of five dominant aerosol species, including dust (DU$_{2.5}$), sea salt (SS$_{2.5}$), black carbon (BC), sulfate (SO$_4$), and organic carbon (OC), globally with a resolution of 0.5° × 0.625° and 73 vertical levels. More details about the MEERA aerosol products are available in Buchard et al. (2017). In the present study, the PM$_{2.5}$ data have been retrieved following Navinya et al. (2020) using the following equation:

$$PM_{2.5} = 1.375 \times [SO_4] + 1.8 \times [OC] + [BC] + [DU_{2.5}] + [SS_{2.5}]$$  \hspace{1cm} (1)

2.5. Methodology

We have obtained the daily reported new confirmed COVID-19 cases from the cumulative COVID-19 cases. Note that the daily number of cases from the cumulative cases is obtained by
successive differences. Figure 1 depicts the number of COVID-19 cases for 28 Indian states and 8 union territories (UTs). We have shown the total number of cases for each state and UTs as the color gradient. The highest number (between 1–2 million) of cases was reported over Mumbai in the Maharashtra state, followed by four of the South Indian States Andhra Pradesh, Karnataka, Tamil Nadu, and Kerala. Delhi (UT), Utter Pradesh, and West Bengal were the most affected in North India. The other States and UTs of India were less affected, and the number of confirmed cases was < 0.2 million. We have selected the five most affected metropolitan cities, Delhi, Mumbai, Kolkata, Bengaluru, and Chennai. The geographical location, population densities, cumulative COVID-19 cases, recovery cases, and deceased cases are given in Table 1.
2.6. Wavelet Transform Coherence (WTC) Analysis

To study the association between daily confirmed COVID-19 cases with daily average surface temperature and relative humidity, we have employed wavelet transform coherence (WTC) analysis instead of correlation analysis. The WTC technique is excellent for establishing a relationship between non-linear time series (Alola & Kirikkaleli, 2020). It allows the investigation of the co-movement between daily reported COVID-19 cases and meteorological variables in both the time and frequency domains. Therefore, this wavelet approach can simultaneously provide a lead-lag relationship and positive and negative associations between time series datasets. To perform WTC analysis, we utilized “Morlet wavelet” to transform the data to continuous wavelet as:

\[
\psi_{k,f}(t) = \frac{1}{\sqrt(h)} \psi \left( \frac{t-k}{f} \right), k, f \in \mathbb{R}, f \neq 0
\]

where \(k\) estimates the time function of the wavelet and \(f\) controls the variation in frequency from shorter to longer scale of the time series. From Eq. (2), the continuous wavelet transform is reconstructed for the time \(p(t)\), and frequency \(q(t)\) is denoted as:

\[
W_p(k,f) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{f(q)}} \psi \left( \frac{q-k}{f} \right) dt
\]

Finally, we employed the WTC analysis by the framework of Torrence and Compo (1998), given as follows:

\[
R^2(k,f) = \frac{\left| C(f^{-1}W_{pq}(k,f)) \right|^2}{C(f^{-1}|W_p(k,f)|^2)C(f^{-1}|W_q(k,f)|^2)}
\]

In Eq. (4), the time and smoothing process is captured by \(C\) with the values ranging between \(0 \leq R^2(k,f) \leq 1\), where zero represents no coherence and one refers to perfect coherence. To estimate the significance level of the coherence, we performed a Monte-Carlo simulation between daily reported COVID-19 cases with daily average temperature and relative humidity.

3. Results and Discussion

3.1. Daily Variations of Meteorological Parameters and COVID-19 Cases

Day-to-day variation of the COVID-19 cases, surface temperature, relative humidity, and rainfall over Delhi, Mumbai, Kolkata, Bengaluru, and Chennai are shown in Figs. 2, 3, 4, 5, and 6, respectively.

Over Delhi, the temporal pattern of COVID-19 cases shows three significant peaks during June, September, and November, which can be considered as three phases of COVID-19 outbreaks. During the...
first phase, the daily COVID-19 cases gradually increase from March and peak at ~ 3700 cases during the last week of June, falling to < 500 cases at the end of July (Fig. 2a). The temporal variation of the first phase covers both pre-monsoon (March–May) and monsoon months (June–August). During this period, the surface temperature (relative humidity) appears to be in phase (out of phase) with COVID-19 cases. Note that surface temperature reaches a maximum of up to 38 °C at the end of May and gradually falls during monsoon months because of the onset of the southwest (SW) monsoon season. The relative humidity is found to be ~ 40–50% during April–May, which increases to ~ 55–80% during June–July (Fig. 2c). At the higher temperature and lower humidity, the virus evaporates faster from respiratory droplets and forms bio-aerosols (Jayaweera et al., 2020), which can linger up in the air for a longer time and drift to a longer path in the presence of the higher wind speed (Yan et al., 2019). Thus, airborne transmission is dominant during March–May, which appears to be more vulnerable than droplet transmission.

Because the fine-mode aerosols can quickly reach the lung by inhalation, that could have been the primary reason for the higher number of COVID-19 cases during pre-monsoon months despite the complete lockdown, whereas a decrease in COVID-19 cases during June–July appears to be mainly associated with frequent rainfall events (Fig. 2d). The monsoon onset over New Delhi occurred on 24–25 June 2020. The wet removal from rainfall seems to act as a natural sanitizer, negatively affecting airborne transmission. Although during the rainfall season the drop in the surface temperature and rise in the relative humidity may allow droplet mode virus transmission (Marr et al., 2019), we observed that the COVID-19 cases remained sustained during June–July. In the second phase (August–mid-October), the daily COVID-19 cases gradually increase from August, reach the maximum during September, and decrease from mid-September to mid-October.
Figure 3
Same as Fig. 2 but for Mumbai

Figure 4
Same as Fig. 2 but for Kolkata
Figure 5
Same as Fig. 2 but for Bengaluru

Figure 6
Same as Fig. 2 but for Chennai
During this second phase, the surface temperature slightly increased, relative humidity started falling at dawn, and the SW monsoon withdrew, resulting in increased COVID-19 cases. The withdrawal date of the SW monsoon over New Delhi occurred on 25 September 2020. In general, the evaporation rate of the virus droplets is low at the lower temperature and intermediate relative humidity; thus, the virus remains either in a liquid or semi-solid phase resulting in its prolonged viability (Marr et al., 2019). Therefore, larger virus-laden droplets on the contaminated surface remain for a longer period and contribute to a higher probability of an increased number of cases evident during mid-August to mid-September. Brazilian cities also reported a similar situation (Auler et al., 2020). The decrease in COVID-19 cases from mid-September appears related to the reduction of relative humidity (RH < 40%) and drop in temperature in the post-monsoon months. Airborne transmission becomes favorable in the presence of low moisture content and high temperature in the atmosphere; however, viruses lose viability in a shorter time (~ 3 h) scale (Jayaweera et al., 2020). Therefore, it is evident that an increase in relative humidity plays a vital role in the spread of COVID-19. During the third phase (mid-October to November), the day-to-day variation of the COVID-19 cases is much higher compared to the previous two phases. In this phase, variation in the relative humidity appears similar to variability in the COVID-19 cases. Lowen et al. (2007) reported that cold and dry conditions favor many other infectious diseases like influenza, which increases the possibility of a higher number of COVID cases. Despite the droplet transmission, the massive rise in COVID-19 cases over a short period during October–November suggests overwhelming direct transmission (human-to-human contact, fomite) compared to indirect transmission. This indicates that human movement during cold and dry seasons increases the susceptibility to COVID-19 outbreaks.

Over Mumbai, the temporal pattern of COVID-19 cases indicates the two significant broad peaks during May–June and September–October, which are considered here as the two phases of COVID-19 outbreaks covering the period of pre-monsoon to SW monsoon months (March–August) and covering SW monsoon to northeast (NE) monsoon months (September–November). Similar to Delhi, an increase in the surface temperature with relative humidity ranging between 50%–60% (intermediate value) favors airborne transmission leading to a steep rise in COVID-19 cases over Mumbai (Fig. 3). A sudden drop in temperature (from 31 to 25 °C) and a rise in relative humidity (from 60% to 90%) are observed because of the heavy rainfall from the onset of the SW monsoon during the first week of June (~ 10 June 2020). Due to the SW monsoon rainfall, the COVID-19 cases were reduced and limited to ~ 2000 or fewer daily cases; otherwise, there could have been more cases. Thus, as mentioned earlier, rainfall acts as a natural sanitizer. It limits airborne transmission due to frequent wet deposition, leading to a decline in COVID-19 cases. However, the possible spread risk remains higher for Mumbai, a populous city, because of the sea breeze and strong wind during the SW monsoon season, as even a light breeze (1–3 m/s) can transport the virus droplets 1.8 m (Feng et al., 2020). This could be a possible reason why Mumbai does not show a significant reduction in COVID-19 cases even though frequent rainfall was observed during the SW monsoon season. As Mumbai is a coastal station while Delhi is a land-locked station, the former is more susceptible to the virus’s faster spread due to the sea breeze (Feng et al., 2020). During the withdrawal (~ 26 October 2020) of SW monsoon, the increasing surface temperature and intermediate relative humidity conditions favor the spread of the virus in the second phase of COVID-19. However, the sudden rise in COVID-19 cases during September is mainly associated with direct transmission. The second phase of COVID-19 cases was not as prolonged as the first phase over Mumbai. The sudden drop in COVID cases is observed during the month of October–November. It is known that decreasing relative humidity at high temperature results in a shorter timescale of virus viability and hence to fewer cases.

Over Kolkata, the day-to-day variation of the COVID-19 cases also shows two significant broad peaks during July–August and October–November (Fig. 4). The observed two peaks are considered here as the two phases of outbreaks similar to Mumbai. However, the number of COVID cases is smaller than
in the previous stations. Kolkata has significantly fewer day-to-day COVID cases (< 200) during the first phase from March to June. A rapid increase in cases was later observed, and the maximum number of cases was found at the end of July; however, it decreased soon within a month during August. The lower temperature and high humidity prevailed over Kolkata during the SW monsoon season (June–September). Such an environmental condition is unfavorable for airborne transmission; however, a sudden increase in cases was observed in July. This is strongly associated with direct transmission due to communities beginning to reopen further. It suggests poor monitoring of human mobility during the first un-lockdown period. During post-monsoon months, the environment was primarily dry and cold, which led to prolonged stability of the virus period and resulted in second-wave propagation. Notably, if the public isolation policy had lifted the lockdown, instead of June, it would have been continued till July. The massive increase in cases has been avoided in Kolkata. Therefore, this suggests the public health setting, e.g., imposing or lifting lockdowns, should be implemented based on the local conditions instead of nationwide.

Unlike previous cases, Bengaluru gives one extreme example of the COVID-19 spread (Fig. 5). When major metropolitan cities reported very high daily COVID-19 cases, Bengaluru remained less affected, and fewer cases were reported. However, unexpectedly, the cases started to pick up from mid-June and reached maximum daily cases of ~5000 at the end of September. Over Bengaluru, warm temperatures and low relative humidity during April–May favored airborne transmission. During this period, the daily reported COVID-19 cases were < ~200, similar to those observed in Kolkata. Later, during the months from June to September, the temperature was observed to be ~22–23 °C and relative humidity ~70–90%, suggesting that evaporation of virus droplets could be delayed because of the low temperature and high humidity, resulting in virus persistence for the longer duration leading to a higher number of cases over Bengaluru (Auler et al., 2020). Earlier studies also confirmed that higher relative humidity is prone to cause constructive health hazards (Auler et al., 2020) for any infectious outbreak. In addition, a strong low-level jet during the SW monsoon could have increased the spread of the virus over a larger scale. As the number of cases rapidly increased, direct transmission might have been one of the leading factors, as mentioned earlier. During the post-monsoon season, the COVID-19 cases suddenly start decreasing, and surface temperature and relative humidity also decreased to transition towards cold and dry weather. Though relative humidity shows a large fluctuation associated with isolated rainfall, it has not significantly affected the COVID-19 cases except for a little amplification.

Over Chennai, both SW and NE monsoons prevail, unlike in all the other cities mentioned earlier (Fig. 6). We observed a clear day-to-day variation of the COVID-19 cases associated with in-phase variation with surface temperature and out-of-phase variation with RH. During May–June, the temperature and humidity vary between 31 to 33 °C and ~60%, respectively. This environmental condition favors the production of more aerosol nuclei and spreads via the wind movement of longer tracks; these nuclei may drift farther. This results in a higher number of cases even during complete public isolation during the period of lockdown. Later, the onset of the SW monsoon (~4 June 2020) rainfall led to a decline in COVID cases. Noticeably, the maximum number of new cases was observed at the end of June. Later, there were heavy rainfalls for about 4–5 days, removing the infected bioaerosols from the atmosphere and reducing the chances of droplet mode transmission. It decreased to < 1000 cases per day; however, it remained prolonged till the end of September because of the warmer and intermediate humidity conditions. Similar to the SW monsoon, the NE monsoon rainfall leads to a further decrease in cases from October to December. In addition, strict implementation of the Government guidelines and the support of the public led to eradicating the virus infection to a low level.

We observed a decrease in COVID-19 cases after the rainfall events. To quantify the relationship between rainfall and COVID-19 cases, we have obtained the average number of cases for 3 days after each rainfall event over different stations. The rainfall was found to vary between 1 to 145 mm over different stations. We have further calculated the
percentage decrease in the number of COVID cases after each rainfall event. The overall mean rainfall and mean percentage decrease in the number of COVID cases are shown in Fig. 7. The mean rainfall over different stations varies from $\sim 20$–$40$ mm. The average decrease in COVID-19 cases after the rainfall is $\sim 18$–$24\%$ over different stations. The mean accumulated rainfalls at Delhi, Mumbai, Kolkata, Bengaluru, and Chennai are $19 \pm 11$ mm, $27 \pm 24$ mm, $16 \pm 10$ mm, $13 \pm 15$ mm, and $43 \pm 49$ mm, respectively. The corresponding mean percents of decrease in COVID cases are $18 \pm 09\%$, $21 \pm 15\%$, $24 \pm 10\%$, $26 \pm 20\%$, and $20 \pm 13\%$, respectively.

We have further examined the role of particulate matter (PM$_{2.5}$) in the spread of COVID-19 cases over the selected cities in India shown in Fig. 8. Several places reported the vulnerability of people residing in highly polluted areas to COVID-19 infection due to exposure to the prolonged high concentration of PM$_{2.5}$ (Sahu et al., 2021). It can be seen that during the country-wide lockdown period, PM$_{2.5}$ levels remained low over all the stations, consistent with the earlier report. However, after the end of the fourth unlocked phase ($\sim 5$ September), PM$_{2.5}$ increased over all the stations.

Over Delhi, the PM$_{2.5}$ varies between 30 and 270 $\mu$g/m$^{-3}$ during lockdown to unlocked periods. Like the surface temperature and RH, PM$_{2.5}$ also indicates three significant phases observed during June, September, and November. Initially, COVID cases grew linearly from April to June as PM$_{2.5}$ levels rose, while at the end of June, a substantial reduction in PM$_{2.5}$ and COVID cases is observed because of the intermittent monsoon rainfall between June and July. The PM$_{2.5}$ reduced from 100 to 20 $\mu$g/m$^{-3}$ because of the wet removal process, and it reflects in the COVID spread; the cases are reduced from $\sim 4000$ to $\sim 1500$. During August and September, the COVID cases progressively rise along with the PM$_{2.5}$ (from 30 to 100 $\mu$g/m$^{-3}$). Noticeably, during post-monsoon season the PM$_{2.5}$ and COVID cases increase nearly two-fold. This is mainly attributed to the prevalence of lower surface inversion over the Delhi region (Ganguly et al. 2009). It effectively traps surface pollutants within the shallow boundary layer, resulting in a higher spread of indirect transmission as the emissions are higher in the unlocked period.

Over Delhi, the PM$_{2.5}$ day-to-day variability is nearly coherent with COVID-19 cases. It indicates that PM$_{2.5}$ significantly influenced the COVID-19 spread over Delhi. However, over Mumbai, the relationship between the PM$_{2.5}$ variability and COVID-19 cases is not strongly related. Initially, a clear reduction in PM$_{2.5}$ levels was observed from April (50 $\mu$g/m$^{-3}$) to May (25 $\mu$g/m$^{-3}$). However, it remains at the same baseline, 25 $\mu$g/m$^{-3}$, with sporadic enhancement in September. Over Mumbai, the COVID cases gradually increased from May and
Figure 8
Day-to-day variation of the confirmed COVID-19 cases and PM 2.5 concentrations over a Delhi, b Mumbai, c Kolkata, d Bengaluru, and e Chennai from 22 March to 5 December 2020. The solid dashed line marks the lockdown (L1, L2, and L3; red) and unlocked (UL1-UL6; blue) periods.
Figure 9
The density plot of COVID-19 confirmed cases with the function of temperature and relative humidity observed over a Delhi, b Mumbai, c Kolkata, d Bengaluru, and e Chennai.
had a positive correlation of PM$_{2.5}$ until October. Similar to Delhi, PM$_{2.5}$ levels raised two-fold post-monsoon. However, the COVID cases are in the opposite phase, suggesting the indirect transmission damping is probably due to COVID health metric guidelines. PM$_{2.5}$ over Kolkata gradually decreases from $\sim 50$ to $\sim 25$ μg/m$^3$ during April–June. Later, the increments in COVID cases and PM$_{2.5}$ are observed to be in phase, suggesting that indirect transmission is dominant during the post-monsoon period. Thus, like Delhi, Kolkata also shows a strong coherence between the PM$_{2.5}$ and COVID-19 spread. However, COVID-19 cases in Bengaluru and Chennai are poorly related to PM$_{2.5}$ variability. Thus, pollution emission levels must be controlled during low-temperature conditions to curb COVID spread.

3.2. COVID-19 Cases as a Function of Surface Temperature and Relative Humidity

Figure 9 shows the density plot of the COVID-19 cases as the function of surface temperature and relative humidity for the two-land locked stations, Delhi and Bengaluru, and three coastal stations, Mumbai (west coast of India) and Kolkata and Chennai (east coast of India). We observed that the number of the cases generally follows as an inverse relationship between surface temperature and relative humidity, however, not always. Over Delhi, Mumbai, and Chennai, the COVID-19 cases were found roughy increasing with an increase in temperature and a decrease in relative humidity, whereas over Bengaluru and Kolkata, the COVID-19 cases were roughly increasing with a decrease in temperature and an increase in relative humidity. Over Delhi and Kolkata, maximum cases are found with low temperature (20–28 °C) and intermediate relative humidity (40–80%). Over Mumbai, many cases fall in relatively higher temperatures (28–31 °C) and intermediate relative humidity (40–70%). At the high surface temperature, virus structural proteins and the genomic structure may have been changed, which may cause the deactivation of the virus in a shorter time scale (~ 3 h) (Aboubakr et al., 2020), resulting in fewer COVID-19 cases over Bengaluru and Kolkata. More cases over these stations with high humidity could be due to the larger size of infected droplets that would have converted to a smaller size after evaporation and remain as aerosol nuclei and spread through the air.

The early phase of COVID-19 started in the pre-monsoon season (March–May) when high surface temperatures and low relative humidity prevailed throughout most of India. Since human mobility was entirely restricted because of the nationwide lockdown (since 22 March 2020), the spread of COVID-19 was mainly through airborne transmission. However, during June–October, after the lockdown lifted, a surge in COVID-19 cases appeared because of direct transmission. Note that relative humidity played a vital role in virus viability. Figure 9 clearly shows that more COVID-19 cases are reported at intermediate (55–80%) and higher RH (> 80%) with a temperature between 22–28 °C across all the cities. Aboubakr et al. (2020) reported that during low/moderate T with intermediate/high RH results, SARS COV 2 viruses remain on the surfaces longer (on stainless steel ~ 7 days, copper ~ 4 days, and glass ~ 5.8 days).

3.3. Role and Influence of Temperature and Relative Humidity on COVID-19 Spread

We observed that the relationship between the COVID-19 cases and meteorological parameters (surface temperature and relative humidity) is not linear. Hence, performing the linear regression and correlation analysis to derive their relationships will misdirect the results. To better understand the relationships between COVID-19 spread as a function of temperature and relative humidity, we have performed wavelet transformation coherence (WTC) analysis, which provides the correlation coefficients at an appropriate lag. Figure 10 shows the WTC analysis between daily COVID-19 cases and surface temperature and relative humidity for Delhi, Mumbai, Kolkata, Bengaluru, and Chennai. Color bar indicates the magnitude of the correlation coefficients. The right and left arrowheads indicate the positive and negative correlation with meteorological parameters. The thick black contour lines indicate a 95% confidence level. The right upward and left downward arrowheads suggest the time series of meteorological variables leading to the COVID time
The u-shaped curved line refers to the cone of influence where the wavelet power is affected because of discontinuity and is not considered for the analysis.

The time and frequency domain of the WTC analysis of the COVID-19 cases with the surface temperature over Delhi shows significant coherence within 0–4-day frequency bands during the first week of July, the first week of September, the last week of October, and the first week to mid-November. We also observed significant coherence within 4–8 days during the last week of May, the first week of July, and mid-September to the first week of October. During the last week of May and the first week of July, we observed a negative correlation (0.9) with the left arrow sign indicating COVID-19 cases leading to the temperature. Note that such a situation is not a plausible one. Though this result is mathematically correct, the physical interpretation would be rather difficult to explain because it has been understood that changes in the background meteorological condition play an indirect role in the spread of COVID-19 cases.
COVID-19 cases (Zaitchik et al., 2020). Notably, an indirect effect of the COVID-19 pandemic on the weather and climate cannot be ruled out because of the slow rate of anthropogenic activities during the worldwide lockdown. However, such analysis and interpretations are beyond the scope of the present study. From mid-September to the first week of October, we observed positive correlation coefficients (0.9) with the right upward arrow sign indicating temperature is leading the COVID-19 cases.

Over Mumbai, significant coherence was observed within the 0–8 day frequency band during the second week and end of May, end of June, the last week of July, the first and second week as well as the end of August, and mid-October. We observed positive correlations between temperature and COVID-19 cases, with temperature leading (right upward arrow sign) during the last week of July, the second week of August, and the end of August. In contrast, negative correlations between temperature and COVID-19 cases with temperature leading (left downward arrow sign) are observed during the first week of August. Note that a positive (negative) correlation between temperature and COVID-19 cases observed during the second week of May (mid-October) with COVID cases leading the temperature is not a possibility, as mentioned earlier. We also observed the coherence within 16–32-day frequency bands with a positive correlation where the temperature leads to COVID cases from mid-August to the end of October.

Over Kolkata, prominent coherence is observed within 4–8-day frequency bands during June and 8–16-day frequency bands during September. However, COVID is leading to temperature during June and hence discarded, as mentioned earlier. During September, a negative correlation is observed between temperature and COVID-19 cases with temperature leading (left downward arrow sign). Note that the second wave over Kolkata was initiated during September, indicating that the decrease in the surface temperature acted as a favorable condition for droplet transmission leading to a massive increase in COVID cases during October.

Over Bengaluru, significant coherence is observed within 4–8-day frequency bands during the first week of July and the first week of October. During the first week of July, the temperature is negatively correlated, leading to COVID-19 cases as expected. However, during the first week of October, the temperature is positively correlated with no leading to or lagging of COVID-19 cases. The in-phase coherence between temperature and COVID-19 cases means that suspected patients would have reported when the temperature was high even though they would have been affected earlier in contrast to the first week of July. We also observed coherence for 8–16 days during the second half of August, indicating that temperature and COVID-19 cases are negatively correlated, leading to COVID-19 cases. For an 8–32-day period during the first week of October to the first week of November, we observed a negative correlation with COVID leading for a lower period and a positive correlation with temperature leading to a higher period. However, such a long period may occur because of seasonal changes from SW monsoon to post-monsoon.

Over Chennai, significant coherence was observed for 0–8-day frequency bands during the last week of July, the first week of October and mid-October, and 32–64-day frequency bands during September–October. During the last week of July and the first week of October, we observed a downward and left downward arrow indicating the negative correlation with temperature leading to COVID-19 cases. However, during mid-October, we observed positive and negative correlations with COVID-19 leading to the temperature. As mentioned earlier, the temperature positively correlating to COVID-19 cases during September–October could be due to seasonal changes in the temperature.

Similarly, WTC analysis between COVID-19 cases and relative humidity for the five cities is also carried out, as shown in Fig. 11. The coherence between COVID-19 cases with relative humidity is mainly opposite to the coherence between COVID-19 cases and temperature, except for a few variation frequency bands and the significance level. Like the temperature, the relative humidity also shows significant coherence within 0–4-, 4–8-, and 8–16-day frequency bands. Notably, the observed periodicity falls within the clinical incubation period (~ 14–16 days) of COVID-19 cases (Dbouk &
Drikakis, 2020; Lauer et al., 2020; Qin et al., 2020) reported by earlier studies.

We have extended our analysis for overall India to understand the agreement and influence of meteorological parameters on COVID spread between regional and spatial scales. Figure 12a, b depicts the daily mean surface temperature and relative humidity, respectively, from 1 March–5 December 2020. It has been suggested that hot and dry regions of Indian territory are more susceptible to the COVID infection.
(Gupta et al., 2020; Sasikumar et al., 2020). However, we observed that the hot and highly humid regions like Kerala, Tamil Nadu, and Andhra Pradesh were severely affected by COVID spread compared to hot and dry regions, which are mainly observed in the northwestern and central part India (Fig. 12a, b).

Figure 12c, d shows the histogram of daily average surface temperature and relative humidity for the entire Indian state. The temperature ranges from 12–36 °C and relative humidity ranges from 40–96%. However, the maximum occurrence of COVID-19 cases falls between temperature ~ 26–30 °C and relative humidity ~ 84–92%, respectively. Figure 12e shows the density plot of the daily COVID cases with the temperature and close humidity function for overall Indian states. COVID-19 cases tend to increase with the decrease in temperature and increase in humidity; however, it does not have a perfect linear relationship. COVID-19 cases in conditions of very low temperatures (< 20 °C) and very high humidity (> 75%) are rare. Cold and semi-moist conditions (temperature ~ 18–22 °C and humidity 40–50%) as well as hot and humid (temperature ~ 24–32 °C and humidity ~ 60–85%) conditions are favorable for COVID-19 cases. These conditions are mainly associated with the transmission mechanism governed by evaporation rate and droplet size. As evaporation is minimal at the lower temperature (< 20 °C), the semi-moist air acts as an optimal route for the long-range transport of the smaller particles, leading to a higher risk of airborne transmission and vulnerability to the inhalation process. However, in dry and hot weather conditions, the evaporation rate is higher,
which significantly reduces the viability of the virus (Dbouk & Drikakis, 2020). Thus, we observe the dependency of the COVID-19 cases only for the intermediate values of the surface temperature and relative humidity (Auler et al., 2020; Ijaz et al., 1985; Ward et al., 2020).

Figure 12f shows the WTC analysis between daily COVID-19 cases and the surface temperature. The significant coherence between COVID-19 cases and the surface temperature is observed within 0–4- and 4–8-day frequency bands during mid-May, June, July, and mid-September.

During mid-May, June, July, and mid-September, we observed significant positive coherence with 0–4 with surface temperature leading to COVID-19 cases. In contrast, the first week of September shows negative coherence. Similarly, we observed positive (negative) coherence during the last week of July (mid-August). In the early phase (March to mid-June) of COVID-19 spread, most of the Indian states had dry and hot weather; thus, its transmission was mainly controlled by temperature fluctuations leading to positive coherence. However, later during June–December, the inhomogeneous distribution of the relative humidity due to changes in the seasons from monsoon to winter results in a negative effect on airborne transmission, and hence we observed both positive and negative coherence. A similar phenomenon is observed from WTC analysis between daily COVID-19 cases and relative humidity, as shown in Fig. 12g. From March to mid-June, COVID-19 spread was very slow, during which significant coherence was observed within 0–4-day frequency bands. However, during June–December, the frequency of significant coherence is ~ 2–8 days. During mid-June, the first week of July, and mid-September, positive coherence is observed in contrast to mid-August, the last week of October, and November.

4. Summary and Conclusions

The present study aims to understand the influence of surface temperature, relative humidity, and rainfall on COVID-19 spread over five severely affected cities and the Indian continent. In this study, we employed a non-linear wavelet approach to study the influence of meteorological variables on COVID-19 spread instead of linear, as most previous studies have demonstrated. The following conclusions and suggestions are drawn from the present study.

1. From the day-to-day variation of the COVID-19 cases, it is clearly observed that monsoon rainfall has played a vital role in sustaining the spread at a more or less constant level over all the cities.
2. The mean accumulated rainfalls received at Delhi, Mumbai, Kolkata, Bengaluru, and Chennai due to monsoons are 19 ± 11 mm, 27 ± 24 mm, 16 ± 10 mm, 13 ± 15 mm, and 43 ± 49 mm, respectively. This results in a decrease in COVID cases by 18 ± 09%, 21 ± 15%, 24 ± 10%, 26 ± 20%, and 20 ± 13%, respectively, for the next 3 days after rainfall.
3. The PM$_{2.5}$ levels vary coherently with COVID cases, especially over Delhi, Mumbai, and Kolkata, indicating that emission of pollutants must be controlled during low-temperature conditions to limit the spread of the virus.
4. Both surface temperature and relative humidity were the crucial factors in the mobility of the COVID-19 cases. Over Delhi, Mumbai, and Chennai, COVID-19 cases tend to increase with increasing temperature and decreasing humidity. In contrast, over Kolkata and Bengaluru, COVID-19 cases tend to increase with a decrease in surface temperature and an increase in relative humidity. Over all of India, COVID-19 cases tend to increase with a decrease in surface temperature and an increase in relative humidity.
5. The most COVID-19 cases are reported at warmer temperatures (24–30 °C) and intermediate relative humidity (50–80%), indicating that COVID-19 infections are prone to warmer and intermediate humidity conditions in India.
6. We observed that variability in the relative humidity was more critical than the temperature variability.
7. The time and frequency domains of the WTC analysis of COVID-19 cases have a significant coherence with the surface temperature and relative humidity within 0–8 days.
8. After lifting the lockdown over India, COVID-19 cases suddenly started to increase in all cities,
especially in Chennai and Kolkata (where the cases increased three-fold within a short time), except in Mumbai, indicating that a decision to unlock would have been based on the localized COVID-19 cases instead of overall COVID-19 cases.

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**Author Contributions** SKM Writing-Reviewing and Editing, Visualization, Investigation. AA Data curation, Writing-Original draft preparation, conceptualization, Methodology, Software, Investigation. TVRR Data curation, Software. SA Data curation, Methodology. SBM Data curation. SP Data curation. PP and KBB Data curation.

**Data availability**

COVID 19 data for Indian cities are available from the official website of the Ministry of Health and Family Welfare Government of India (https://www.mohfw.gov.in/, https://www.mygov.in/corona-data/covid19-statewise-status). The automatic weather station (AWS) data are from https://weather.uwyo.edu/surface/meteorogram/seasia.shtml. The daily rainfall data were obtained from the Global Precipitation Mission website https://gpm.nasa.gov/data/imerg. Particulate Matter (PM2.5) are taken from Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2) reanalysis (https://gmao.gsfc.nasa.gov/reanalysis/MERRA/). The entire study is analysed using Matlab software.

**Declarations**

**Conflict of Interest** The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.

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