Science of the Total Environment 762 (2021) 143161

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

How air quality and COVID-19 transmission change under different lockdown scenarios? A case from Dhaka city, Bangladesh

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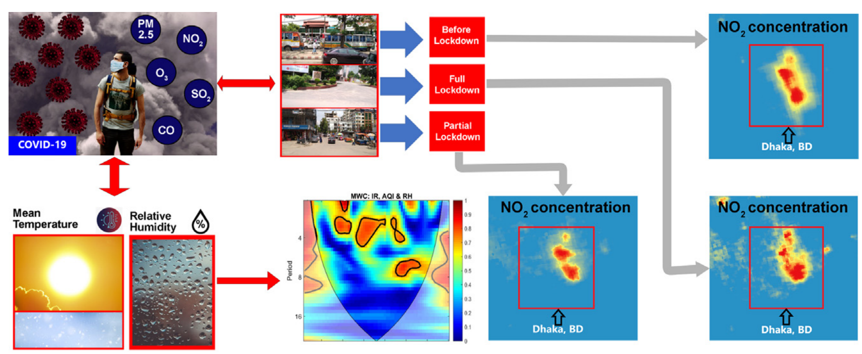
HIGHLIGHTS

- The lockdown policy triggered a sudden reduction of air pollution in Dhaka city.
- The containment policy did not play a crucial role to modulate COVID-19 infection.
- The air quality parameters can't be explained as COVID-19 transmission modulator.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 30 May 2020
Received in revised form 11 October 2020
Accepted 12 October 2020
Available online 21 October 2020

Keywords:
Air pollution
PM2.5
CO
Ozone
Humidity
COVID-19

ABSTRACT

The transmission of novel coronavirus (COVID-19) can be reduced by implementing a lockdown policy, which has also been proven as an effective control measure for air pollution in the urban cities. In this study, we applied ground- and satellite-based data of five criteria air pollutants (PM2.5, NO_2, SO_2, O_3, and CO) and meteorological factors from March 8 to May 15, 2020 (before, partial-, and full-lockdown). The generalized additive models (GAMs), wavelet coherence, and random forest (RF) model were employed to explore the relationship between air quality indicators and COVID-19 transmission in Dhaka city. Results show that overall, 26, 20.4, 17.5, 9.7 and 8.8% declined in PM 2.5, NO_2, SO_2, O_3, and CO concentrations, respectively, in Dhaka City during the partial and full lockdown compared to the period before the lockdown. The implementation of lockdown policy for containing COVID-19 transmission played a crucial role in reducing air pollution. The findings of wavelet coherence and partial wavelet coherence demonstrate no standalone coherence, but interestingly, multiple wavelet coherence indicated a strong short-term coherence among air pollutants and meteorological factors with the COVID-19 outbreak. Outcomes of GAMs indicated that an increase of 1-unit in long-term exposure to O_3 and CO (lag1) was associated with a 2.9% (95% CI: −0.3%, −5.6%), and 53.9% (95% CI: 0.2%, −107.9%) decreased risk of COVID-19 infection rate during the full-lockdown period. Whereas, COVID-19 infection and MT (mean temperature) are modulated by a peak during full-lockdown, which is mostly attributed to contact transmission in Dhaka city. RF model revealed among the parameters being studied, MT, RH (relative humidity), and O_3 were the dominant factors that could be associated with COVID-19 cases during the study period. The outcomes reported here could elucidate the effectiveness of lockdown scenarios for COVID-19 containment and air pollution control in Dhaka city.

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https://doi.org/10.1016/j.scitotenv.2020.143161
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1. Introduction

Dhaka, the capital city of Bangladesh has an area of 306.4 km^2, one of the most densely populated cities in the world is prone to high ambient air pollution due to smoke generating brick kilns, vehicle and traffic exhaust on fuel with an elevated level of sulfur and re-suspended dust from roads dust (Hoque et al., 2020; Islam et al., 2020a). The effects of the uncontrolled population growth pressurize on the environment along with unrestrained urban development, subsequent fast industrialization, and automobile traffic have created huge ambient air pollution in this megacity. Besides Dhaka has the ranked second highest particular matter (PM2.5) emitter followed by Delhi, the Capital city of India (AirVisual, 2018). Since the association between local emissions and PM pollution is non-linear which varies from city to city. Furthermore, average atmospheric PM2.5 concentration (80 $\mu g/m^3$) in the megacity is more than 5 times the Bangladeshi standard and 8 times the WHO guidelines (Rana et al., 2016; Islam et al., 2020a). The poor air quality threatens public health through cardiovascular and respiratory diseases, IQ loss, premature mortality, and cancer (World Bank, 2018). Besides, numerous ailments including eye irritation, severe headache, disruption of blood circulation, respiratory problem, and even premature death are seen in the Dhaka city dwellers due to present environmental disorder (Begum et al., 2011; Rizwan et al., 2013). However, air pollution remains a public health issue, accounting for an estimated 8.8 million premature deaths per year (95% CI 7.11 to 10.41%) and loss of life expectancy of 2.9 years (95% CI 2.3 to 3.5 years) (Lelieveld et al., 2020). Air pollution, and particularly high nitrogen dioxide (NO_2) concentration, may be of paramount importance in the context of respiratory tract infections.

COVID-19 is a highly infectious disease, which has influenced the life of humans in all aspects and the global economy as well, that is responsible for more than 4 million infections and 239,448 deaths in 187 countries around the globe (WHO, 2020). In Bangladesh, there are 44,608 infected cases confirmed, 9375 recoveries and 610 deaths have been reported up to May 30, 2020 (IEDCR, 2020; Bodrud-Doza et al., 2020). Apart from this, lockdown is a restriction on free public movement, and closing down the business and industrial institutions was first enforced on Wuhan, Hubei province of central China where the noxious virus was reported first and then followed by others (Wang et al., 2020). Due to the transmission of infectious coronavirus, Bangladesh experienced its first lockdown from March 26 to April 2, 2020, and is extended to May 17, 2020 as the third time. Due to this lockdown, nearly all industrial activities and transportation have been prohibited in Bangladesh. The goal of lockdown is to flatten the endemic curve of COVID-19, concurrently it can reduce urban traffic congestion and consequently metropolitan air pollution load. Thus, this research intends to assess the level of air quality variation before, partial and full lockdowns at a temporal scale in Dhaka city.

In recent time, a vivid number of studies have been carried out to reveal the impact of lockdown due to the COVID-19 pandemic on the restoration of air quality in different cities of the world (Kanniah et al., 2020; Chauhan and Singh, 2020; Bashir et al., 2020; Collivignarelli et al., 2020; Morawska and Cao, 2020; Bao and Zhang, 2020; Mahato et al., 2020; Dantas et al., 2020; Siciliano et al., 2020; Tobias et al., 2020; Hashim et al., 2020). For example, the megacities such as Bangkok, Quezon city, and Kualalumpur have reported a decline in PM2.5, deriving from vehicle use and industrial emissions, up to 80% during the COVID-19 lockdown scenarios (Atkin, 2020).

Data obtained by Tropospheric Monitoring Instrument (TROPOMI) onboard the Sentinel-5P satellite (ESA) have been extensively employed to show the decrease of tropospheric NO_2 associated with pollution after the executing of preventive measures (e.g. lockdown) in Spain and Brazil (Tobías et al., 2020; Nakada and Urban, 2020; ESA, 2020; Gautam, 2020). However, satellite remote sensing data have indicated a substantial reduction in air pollution concentration during the lockdown period. The open question remains to how and what extent these interferences affected the air quality indicators (Muhammad et al., 2020; Contini and Costabile, 2020). However, the COVID-19 spread is yet less understood during different lockdown scenarios and probably to have a pivotal role in the improvement of ambient air quality in the developing countries, particularly megacity like Dhaka. Since Dhaka is the most affected city and the epicenter of COVID-19 infection with over 58% of the total positive cases in Bangladesh. As of May 26, 2020, IEDCR (2020) has confirmed more than 8000 cases, including >410 deaths in Dhaka city (Fig. 1). Why is the city facing such a COVID-19 surge? It is a burning question and of course, there are many factors behind such a situation including population density, contact transmission, a single-entry point for international air route passengers, and so on. Are there any relationships between the high air pollution load with the COVID-19 infection rate in Dhaka city during COVID-19 lockdown scenarios? This information is imperative to report potential human health implications to enhance inhaled air quality. So

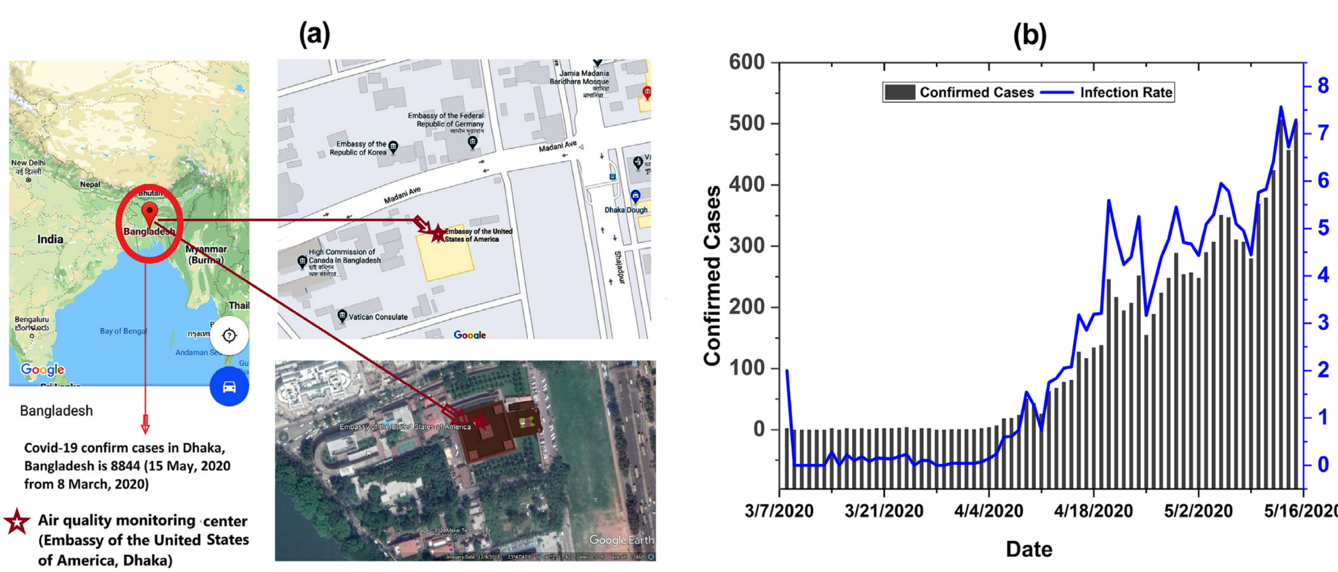

Fig. 1. (a) Map showing the study station and (b) total confirmed cases and infection rate from COVID-19 in Dhaka city.

far, the answer is we do not know and it warrants research. In addition, the lockdown during the COVID-19 outbreak provides a unique opportunity to do this research in the way. When the high level of pollution is a key human health issue in Bangladesh, it is crucial to understand the degree and the temporal extent of the reduction in air pollutants because of curb measures during the COVID-19 lockdown scenarios. Thus, this study intended to explore how COVID-19 induced-lockdown measures modulate the air quality, and disease transmission in Dhaka city using wavelet coherence transform, generalized additive models (GAMs) and random forest model for the first time in Bangladesh. The outcomes of this study do not only help the concerned authorities and decision-makers to improve the air quality but also its efficacy as a substitute measure for inhaled clear air quality of Dhaka with public participation in forthcoming years.

2. Data and methods

2.1. Study area

Dhaka is the 3rd most densely populated city in the world, which is situated along the east bank of the Buriganga River in the center of the Bengal Delta (Islam et al., 2020a). This city is highly congested with many private and public motorized vehicles but very little monitoring of air quality has been carried out in the city area (Fig. 1). Dhaka scores in the top 20 positions among 1100 cities of the world that have populations of more than 100,000 (WHO, 2016). High population density (8111 km^2) in Dhaka city may exert significant health impacts to the dwellings due to long-term exposure to huge air pollutants especially in winter (Hoque et al., 2020).

2.2. Data sources and quality control

To assess air quality status during the lockdown period of Dhaka city, we collected Particulate Matters (PM 2.5) data from the continuous air monitoring station of the US Embassy, Dhaka. The daily average concentration of four criteria air pollutants including Sulfur Dioxide (SO_2), Nitrogen Dioxide (NO_2), Carbon Monoxide (CO), Ozone (O_3) have been obtained from AirNow that is a one-stop source for air quality data (https://www.airnow.gov/about-airnow). Subsequently, the daily concentrations of these criteria air pollutants have been estimated with air quality index (AQI) conversion calculator (https://www.airnow.gov/aqi/aqi-calculator).We excluded PM10 in the present study due to scattering data neither significant correlation nor coherence and most fragile among six pollutants. They provide quality data through ensuring rigorous protocols for sampling, analysis, and calibration. The data was collected for Dhaka city as 3 time period from March 8 to May 15, 2020. The 3-time period was before lockdown (March 8 to March 25), full lockdown (March 26 to April 10), and partial lockdown (April 11 to May 15).

Satellite-based remote sensing NO_2 dataset, measured by the Copernicus Sentinel-5 Precursor Tropospheric Monitoring Instrument (S5p/TROPOMI) established by the European Space Agency (ESA, 2020), has been employed to appraise tropospheric NO_2 background levels in a high resolution (3.5 × 7 km) constant area (Veefkind et al., 2012). Then, the R script has been written to save, compute mean levels, and plot over a GIS-based map the NO_2 dataset employing Google Earth Engine (Tobías et al., 2020).

2.3. GAMs modeling approach

To determine the effects of meteorological variables and adjust for probable static and time-varying relationships, we applied the generalized additive models (GAMs) framework (Hastie and Tibshirani, 1999). The GAMs are capable of flexibly modeling the association between occurrence and weather, where a semi-parametric smooth function of time series as a proxy variable for the time-varying association. This model has been extensively employed as a standard model in air pollution studies, and epidemiology fields over the past decade (Hastie and Tibshirani, 1999; Almeida et al., 2010; Ma et al., 2020).

We used GAM (generalized additive model) to analyze the association between COVID-19 confirmed cases and the air quality index parameters (PM 2.5, O_3, CO, SO_2, NO_2) based on the quasi-Poisson link function (Almeida et al., 2010; Basu et al., 2008; Ma et al., 2020).

The result modeled is the daily number of the confirmed reported COVID-19 cases, Y_{jt} (where j = 1, …n represents the day, and $t = 1, \ldots, 12$ signifies the days within each month). The outcome Y_{jt} is modeled as a quasi-Poisson distributed random parameter with the mean μ_{jt}, where it is computed by the following Eq. (1):

$$\log\left(\mu_{jt}\right) = g(t) + X_{jt}\beta \tag{1}$$

Here, g(t) is a smooth function of time over the days that estimate the impacts of unobserved time-varying relationships, associated with the occurrence of COVID-19 and to the weather. The function g(t) is supposed to have the same shape each month. β is the intercept and co-variate matrix is X_{jt}.

The GAMs do not assume any prior specific relationship, which can be employed to estimate non-linear effects of the covariate on the dependent variables. The main advantage of this model is that it has flexibility to allow non-parametric fittings with relaxed assumptions on the actual association between response and predictor that provides the potential for better fitting to data than purely parametric models. Considering lag effects over the lockdown period, we choose 3 situations as 3 lags (lag 0–2; before, full and partial lockdown). The GAM analysis was made by the 'mgcv' package (v 1.8–31) in R v3.6.3. The effect of each parameter was expressed in percent change where a 95% confidence interval in changing confirmed cases was associated with a 1-unit increase in AQI parameters.

2.4. Wavelet analysis

To investigate the relationship between environmental parameters and the COVID-19 infection rate in Dhaka city, we have used 3 types of wavelet analysis including Wavelet Transform Coherence (WTC), Partial Wavelet Coherence (PWC) and Multiple Wavelet Coherence (MWC). These wavelet methods are widely used in the geophysical application, weather, environment, climatic relationship, finance-related field, etc. (Afshan et al., 2018; Ng and Chan, 2012; Wu et al., 2019). It can allow non-linear relationships amid multiple time-series datasets. Such a method has been hardly used in COVID-19 related studies until now (Iqbal et al., 2020). There are some benefits of employing the wavelet methods in multiple data analysis series such as 1) It is done from a time-frequency point of view and is very efficient understanding non-linear relationships. 2) It can work with non-stationary time series where the assumption of stationarity can be relaxed. 3) It can identify significant periods and their presented changes. 4) Different types of wavelet functions can be used depending upon the nature of data, allowing more efficient and accurate tracking of the co-movements. 5) It can also determine the strength and direction of the association and difference between short, medium, and long-term relationships. 6) It can allow lead-lag associations simultaneously among various time-frequency couplings (Grinsted et al., 2004; Ng and Chan, 2012; Sleziak et al., 2015; Iqbal et al., 2020).

2.4.1. Wavelet coherence

Linear correlation analyses can be improved by wavelet transform coherence (WTC) by which irregular correlations can be revealed between two phenomena (Gurley and Kareem, 1999; Gurley et al., 2003). First, we have transformed the time series datasets using "Morlet wavelet" approach and next used WTC to identify the co-movements. The WTC ranges from 0 to 1 ($0 \le R^2 \le 1$). 0 refers to no coherence at all whereas 1 denotes to perfect coherence. This range is defined as the cross-spectrum normalized square by the smoothed individual power spectrum (Torrence and Compo, 1998) which can simply be defined by the following Eq. (2):

$$R^2(m,n) = \frac{\left|S\left(s^{-1}W_{xy}(s)\right|^2}{S\left(s^{-1}\left|W_x(s)\right|^2.S\left(s^{-1}\left|W_y(s)\right|^2\right.\right.} \quad (2)$$

where x and y are two time series with their respective wavelet transforms $W_x(s)$ and $W_y(s)$. Monte Carlo simulation method was also employed to get the statistical significance of the outcomes. WTC was employed to check the co-movement between two parameters.

2.4.2. Partial wavelet coherence

In this method, the co-movements are examined between two time series variables whereas controlling for the common impacts of a third variable. The mathematical derivation of the partial wavelet coherence (PWC) is shown in the Eqs. (3)–(8):

$$R(x_1,x_2) = \frac{S[W(x_1,x_2)]}{\sqrt{S[W(x_1)]S[W(x_2)]}} \quad (3)$$

$$R^2(x_1,x_2) = R(x_1,x_2).R(x_1,x_2) \quad (4)$$

$$R(x_1,y) = \frac{S[W(x_1,y)]}{\sqrt{S[W(x_1)]S[W(y)]}} \quad (5)$$

$$R^2(x_1,y) = R(x_1,y).R(x_1,y) \quad (6)$$

$$R(x_2,y) = \frac{S[W(x_2,y)]}{\sqrt{S[W(x_2)]S[W(y)]}} \quad (7)$$

$$R^2(x_2,y) = R(x_2,y)\cdot R(x_2,y) \quad (8)$$

whereas "R" denotes the coherence between two series datasets whereas "x_1", "x_2" and "y" mean the variables of time series. Eqs. (3)–(7) characterize WTC between three likely integrations of variables x_1, x_2, and y. Eq. (8) exhibits the mathematical illustration of PWC which computes the WTC between two series y and x_1 whereas controlling for the common impacts of x_2 on the associations. The confidence level in WTC and PWC was computed through Monte Carlo simulation.

2.4.3. Multiple wavelet coherence

Alike to PWC, three time-series were also used in multiple wavelet coherence (MWC). To understand the MWC, it is compared with the coefficient of multiple relationship. But in this methodology, the effects of the third series were not minimized rather it is added with the second series to examine the coherence of the dependent series y with the combination of independent series $x_1$and x_2.For multiple wavelet coherence, the Eq. (9) is as follows:

$$RM^2(y,x_1,x_2) = \frac{R^2(y,x_1) + R^2(y,x_2) - 2\ Re[R(y,x_1)\cdot R(y,x_1) * R(x_2,x_1)*]}{1-R^2(x_2,x_1)} \quad (9)$$

whereas "RM^2" denotes the dependence of variable "y" on the linear relationship of two other variables of time series, "x_1" and "x_2" respectively (Ng and Chan, 2012).

2.5. Random forest model

The RF (random forest) algorithm, a widespread and extremely flexible supervised artificial intelligence, was applied to measure the importance degree of various contributing factors. This RF model is developed based on coupled bootstrap trained and multiple trees regressions for acquiring better predictive accuracy (Xavier et al., 2020). Variables of every node determine each split of trees during the RF modeling (Rahmati et al., 2016). Final outcome is derived from the average values of all trees (Cutler et al., 2007). It was essential to describe two variables: the number of variables to be utilized in each tree-building process (mtry) and the number of trees to be made in the forest to run the RF model (ntree). To lessen the generalization error, the mentioned two variables must be optimized. Breiman (2001) reported that even a variable (mtry = 1) can produce good precision, whereas At least two variables (i.e. mtry = 2, 3, 4, …., m) are needed for avoiding generalization errors based on weaker regressors as splitters (Grömping, 2009).

The RF model contains an integration of multiple trees, where each tree is generated by bootstrap samples, leaves about one-third of the overall samples for validation, using the out-of-bag (OOB) error. The OOB error is an unbiased approximation of the generalization error (Breiman, 2001). The variance and covariance between grid cells can be calculated using OOB error dataset (Rahmati et al., 2016). These components represent a measure of the uncertainty over the estimation of environmental variables at a grid cell. This model can analyze the features of complex relationships and is a suitably robust tool for the handling of datasets with missing cases (Breiman, 2001). The RF model has been extensively used as a feature-selection tool to detect parameter importance from time-series dataset, and has some advantages in studying parameter associations, as compared to other models like artificial neural networks and support vector machines (Rahman and Islam, 2019; Yang et al., 2020). In this model, the mean decrease in Gini values was used to determine the relative importance of different contributing factors. A higher Gini value denotes a more significant input parameter (Islam et al., 2020b). However, research scholars have employed a simple method like Principle Component Analysis (PCA) for importance degree analysis in climate-related studies (Amiri and Mesgari, 2017; Bethere et al., 2017). But now, most researchers have used the RF model for analyzing the importance degree because this model gives better, robust and comparatively accurate results than other methods (Rahman and Islam, 2019; Islam et al., 2020b; Salam and Islam, 2020). A detailed explanation of the mathematical equation of RF method is found in Breiman (2001) and Rahman and Islam (2019). In this work, the "randomForest" package of R software (R Development Core Team, 2015) was employed to perform the RF model. So, this study utilized the RF model for obtaining the better result of contributing environmental variables in COVID-19 transmission in Dhaka City.

3. Result

3.1. Status of air pollutants during COVID-19 induced lockdown over Dhaka city

The changes in trend for meteorological and air quality indicators during 3 lockdown scenarios are shown with linear fitting in Fig. 2. All the variables are significant except AP (Fig. 2j) ($r^2 = 0.03$, $p > 0.05$). We have observed an upward trend in all meteorological variables e.g., MT (Fig. 2g), RH (Fig. 2h), WS (Fig. 2i), AH (Fig. 2k), RainF (Fig. 2l) amid the lockdown period except for AP (Fig. 2j) which has a downward trend. All air quality indicators are significantly downward with time axes. AQI (Fig. 2a), CO (Fig. 2c), NO_2 (Fig. 2d), O_3 (Fig. 2e) and SO_2 (Fig. 2f) have the lowest decrease in Partial lockdown whereas PM 2.5 (Fig. 2b) has a slight decrease in that time than before and full lockdown. It is found that the highest values of all air quality indicators were in the day before full lockdown initiated (March 25, 2020). When the full lockdown started the indicators value suddenly started to decrease and the lowest value of all indicators was found on May 5, 2020 during the partial lockdown.

Fig. S1 describes the average concentration of different air quality indicators of Dhaka city before lockdown (March 8 to March 25), during full lockdown (March 26 to April 10) and partial lockdown (April 11 to May 15) stage in COVID-19 pandemic situation in 2020. All the six indicators AQI, PM2.5, O_3, CO, SO_2, NO_2 were high in concentration before lockdown.

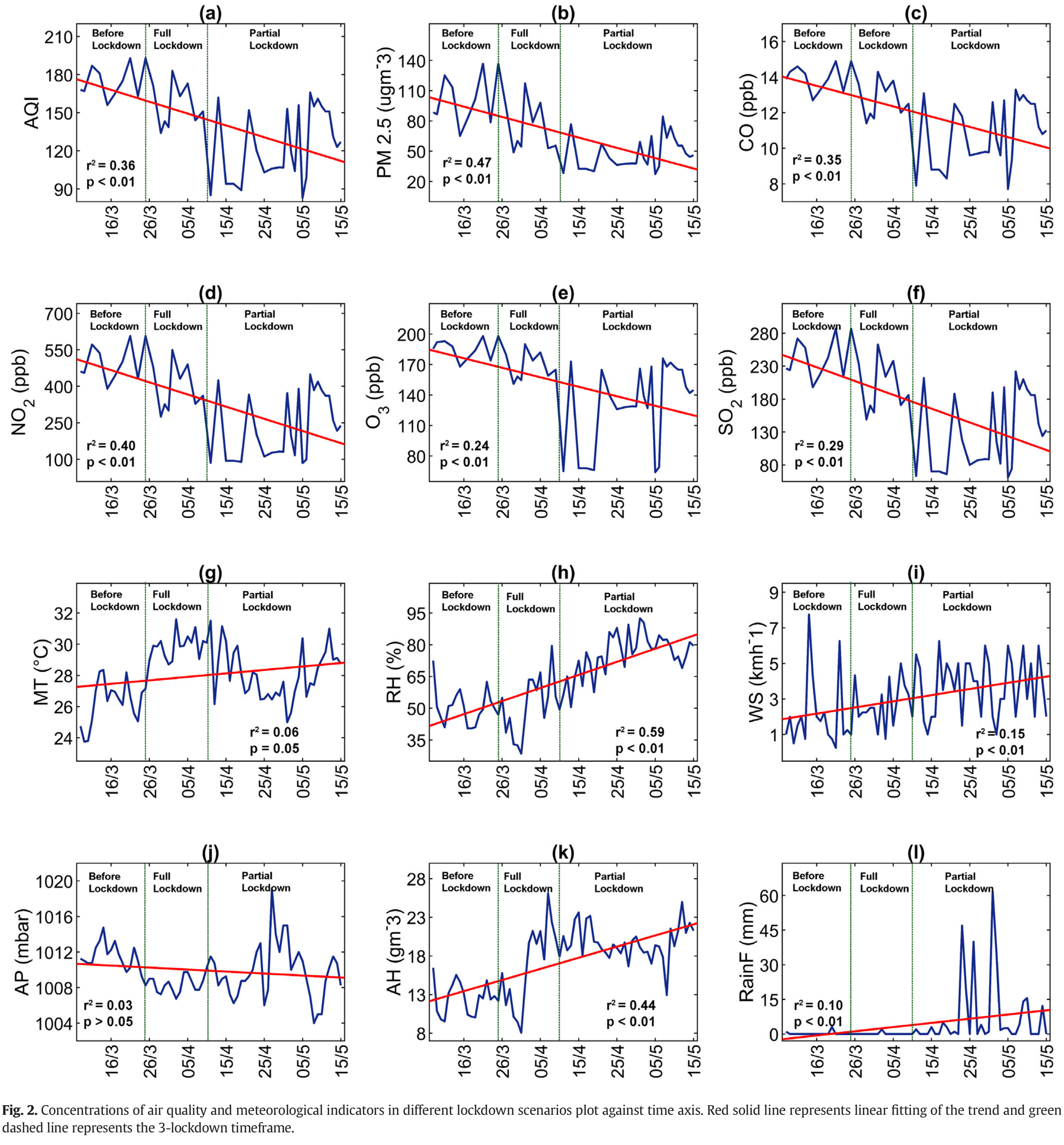

Fig. 2. Concentrations of air quality and meteorological indicators in different lockdown scenarios plot against time axis. Red solid line represents linear fitting of the trend and green dashed line represents the 3-lockdown timeframe.

During the full lockdown period, the concentrations of all the indicators were lower from the concentration of before the lockdown stage. During the partial lockdown, AQI, PM2.5, O_3, CO, SO_2, NO_2 concentrations were dramatically decreased from the concentration of before the lockdown period. Fig. S1 depicts that the mean concentration of AQI, PM2.5, O_3, CO, SO_2, NO_2 decreased during the full lockdown and partial lockdown phases indicating the air quality of Dhaka city has been improving during these lockdown situations compared to the normal situation.

During the partial lockdown, urban city air pollution declined with notable differences among five pollutants compared to full and before lockdowns (Table 1). PM 2.5averaged concentrations declined by −26%, −38.2% and −54.2% in the traffic city station, compared to the before lockdown (Table 1). In the lockdown period, the WHO Air Quality standard daily reference value of 20 μg/m^3 surpassed at the city station which in turn is two-three times greater than WHOAQG. For NO_2, the reduction was higher, −20.4%, −44.2% and −55.5% respectively in the Dhaka city, and similar to the one of SO_2 (−17.5–37.1, and −48.1% for the urban station respectively). The low CO concentrations found in the observation period and the noticeable reduction up to −8.8%, −16.2% and 23.5%, respectively. Concentrations of O_3 obviously

Table 1
Mean concentrations and variation of PM2.5 CO, NO_2, SO_2 and O_3 between 8 March to 25 March 2020 (before the lockdown), 26 March to 10 April 2020 (Full lockdown) and 11 April to 15 May 2020 (Partial lockdown) in Dhaka city, Bangladesh.

Air pollutant type	Before lockdown	Full lockdown	Partial lockdown	Variation					
				(Before-full)		(Full-partial)		(Before-partial)	
				μg/m^3	(%)	μg/m^3	(%)	μg/m^3	(%)
PM2.5	101.8	75.3	46.6	−26.4	−26.0	−28.8	−38.2	−55.2	−54.2
O_3	185.13	167.24	127.71	−17.9	−9.7	−39.5	−23.6	−57.4	−31.0
CO	13.96	12.73	10.67	−1.2	−8.8	−2.1	−16.2	−3.3	−23.5
SO_2	243.05	200.55	126.07	−42.5	−17.5	−74.5	−37.1	−117.0	−48.1
NO_2	500.97	399.08	222.84	−102.0	−20.4	−176.2	−44.2	−278.1	−55.5

declined by −9.7%, −23.6% and −31%, respectively. During lockdown scenarios, O_3 was recorded (167–127 μg/m^3), although higher than the WHOAQG (100 μg/m^3), compared with the before lockdown (185 μg/m^3).

The key changes elucidated above for NO_2, are clearly demonstrated by satellite-based remotes sensing measurements of background tropospheric NO_2 concentrations provided by TROPOMI-ESA (covering not only urban city area but also major highway) when comparing the before, full and partial lockdowns and the further with the similar period of 2019 (Fig. 3). Fig. 3 shows that there was an around300 μmol m^{-2} NO_2 pollution load in the Dhaka city during before lockdown period, while there were nearly 150–200 and 120–150 μmol m^{-2} NO_2 pollution loads, respectively during the full and partial lockdown periods. Mean TROPOMI NO_2 pollution loads over the Dhaka city area (306.4 km^2 with city and sub-urban area showed in Fig. 3) decreased during the lockdown by up to −20–30% and −55% in the full and partial lockdowns in comparison with the before lockdown period. The analogous comparison has been performed for the similar period for the reference period of 2019, about −20 and −50% was declined in the full and partial lockdown periods, in this circumstance, by meteorological impacts.

The air quality indicators are directly related to the gas emission of vehicles from mass transport and factories and the meteorological conditions. The COVID-19 epidemic brought the lockdown scenario which certainly played pivotal role in reducing the air pollutants in Dhaka city. The lockdown policy was implemented for the containment of the COVID-19 transmission through dramatic reduction of human activities. Thus, this disease containment policy become a trade-off between air quality indicators and human activities in Dhaka city.

In Fig. 4, different percentage limits were shown by red color due to variation of AQIs parameter ranges for visualization. It is surprisingly found that all of the six air criteria indicators (AQI, PM 2.5, O_3, CO, SO_2 and NO_2) have strongest rise in lag 2 during partial lockdown period [0.7% (95% CI: 1.3%, 0.04%); 0.7% (95% CI: 1.8%, −0.4%); 0.6% (95% CI: 1.1%, −0.2%); 10.7% (95% CI: 20.6%, 0.8%); 0.3% (95% CI: 0.6%, −0.01%); 0.1% (95% CI: 0.3%, −0.01%)] (Fig. 4). From this result, it is shown that each pollutant decreased initially in lag 1 during the full

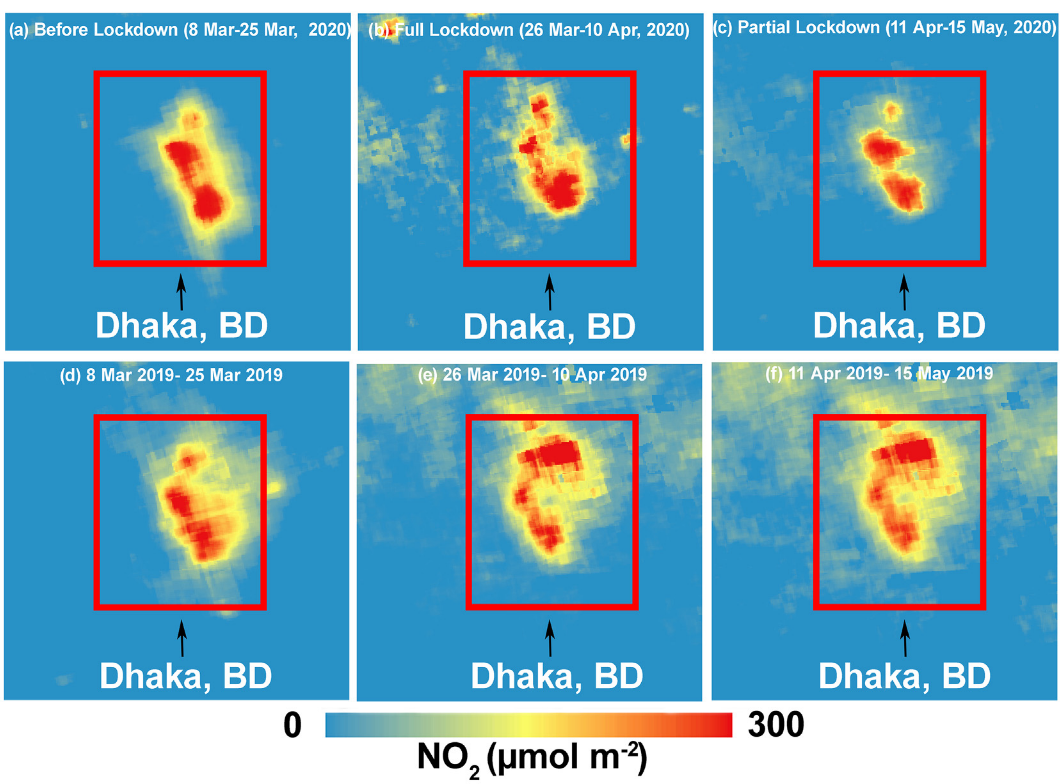

Fig. 3. Mean levels of background tropospheric NO_2 measured by TROPOMI-ESA in the capital Dhaka city, Bangladesh. (a) 8 March to 25 March 25, 2020 (before lockdown); (b) 26 April to 10 April 2020 (full lockdown); (c) 11 April to 15 May 2020 (partial lockdown); (d) 8 March to 25 March 25, 2019; (e) 26 April to 10 April 2019; (f) 11 April to 15 May 2019 same periods in 2019.

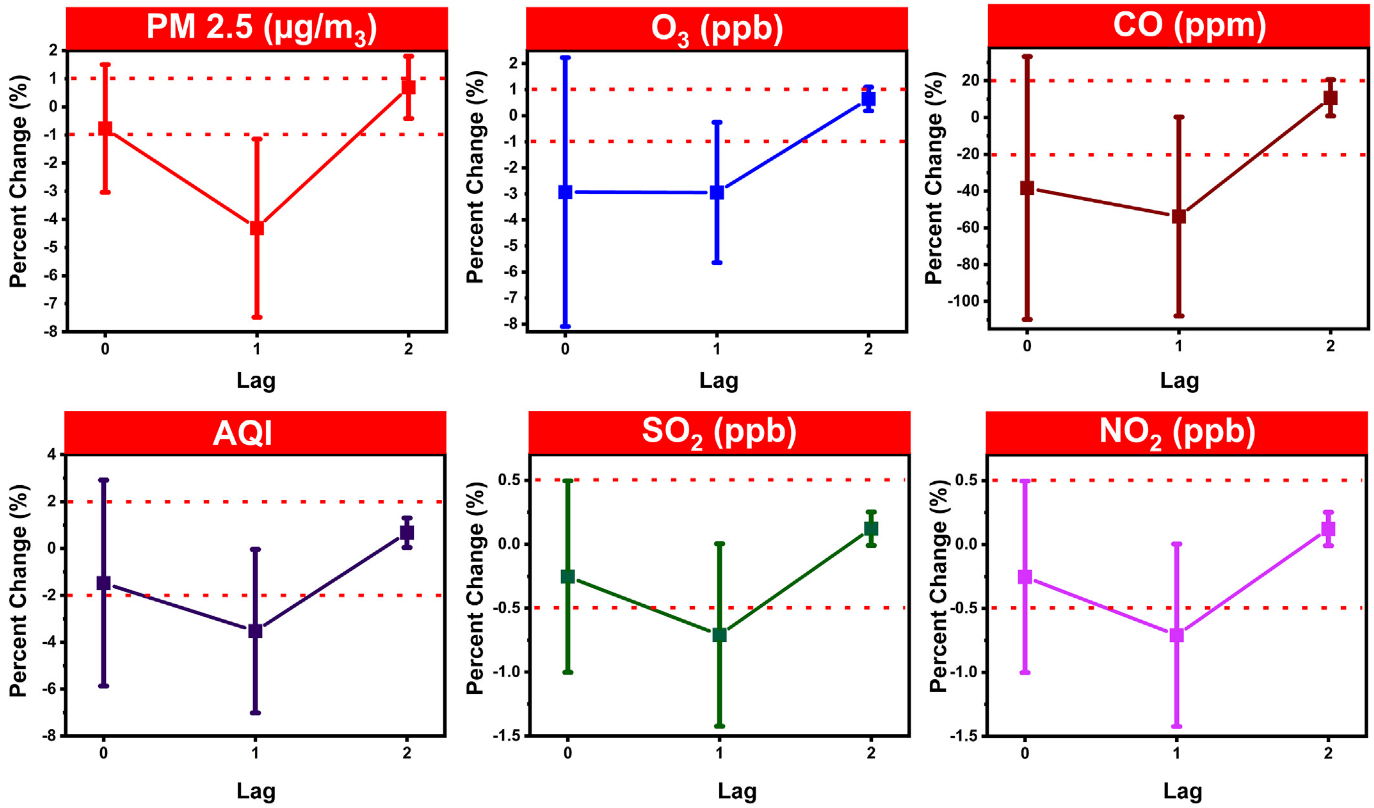

Fig. 4. Percent changes between COVID-19 daily confirmed cases with 1-unit increase with 5 air pollutants for the effects of lockdown-based lag days based on the GAM models in Dhaka City at 95% confidence interval. Trendline shows the increase or decrease in changing lag days. Red dotted line represents a certain percent change limit.

lockdown then highly increased in lag 2. The highest reduction of all 6 air pollutant indicators (AQI, PM 2.5, O_3, CO, SO_2 and NO_2) were found in lag 1. AQI, PM 2.5, SO_2 and NO_2 have the relatively higher decrease trending lag 1 [−3.5% (95% CI: −0.03%, −7.01%); −4.3% (95% CI: −1.1%, −7.5%), −1.7% (95% CI: 0.01%, −3.4%), −0.7% (95% CI: 0.004%, −1.4%)] than lag 0. Similarly, O_3 and CO have the greatest decrease [−2.9% (95% CI: −0.3%, −5.6%), −53.9% (95% CI: 0.2%, −107.9%)] in lag 1.

3.2. Modulations of the air quality indicators around Dhaka city

Fig. 5 exhibits the probability density functions (PDFs) of environmental indicators and COVID-19 infection rate within Dhaka megacity in the three different lockdown scenarios. The PDFs of environmental indicators and infection rates show noteworthy modulations that might play vital roles in controlling the variation of COVID-19 pandemics. The highest value in the PDF of the mean infection rate (IR) over the Dhaka city changes leftward from the peak toward low values from full to partial lockdown, i.e., 2.85 in full lockdown, nearly 2 in before lockdown, and about 0.25 in partial lockdown (Fig. 5a). The topmost value in the PDF of the air quality index (AQI) across the Dhaka city shifts right side from high to low values from before to partial lockdown, for instance, around 0.028, 0.016 and 0.012 in before, full and partial lockdowns, respectively (Fig. 5b). The PDF of PM2.5 around the Dhaka megacity during various lockdowns is comparatively smaller, for example, about 0.025, 0.015 and 0.012 in partial, before and full lockdowns respectively (Fig. 5c). The PDF of O_3, CO, SO_2 and NO_2 over the study station has an analogous pattern with that in the AQI and their differences of the peak PDF among different lockdowns are also similar fashions (Figs. 5d-g). Different from the other environmental indicators, the PDF in the mountainous O_3, CO, SO_2 and NO_2 show a steeper outline in the rightward side, with the peak value appearing at about 0.038, 0.55, 0.011 and 4.48×10^{-3}. The topmost value in the PDF of the relative humidity (RH) over the studied city shifts central to the right side from high toward low values, i.e., 0.055, 0.04 and 0.025 in before, partial and full lockdowns (Fig. 5h). The PDF of mean temperature (MT) across the Dhaka city has the same outline as that in the IR, but the differences of the high PDF are relatively smaller among various lockdowns shifting right side i.e., about 0.5, 0.3, and 0.2 in full, before and partial lockdowns respectively (Fig. 5i).

3.3. Nexus between air pollutant indicators, meteorological factors and COVID-19 transmission

To inquire about the teleconnection between COVID-19 infection rate (IR) and environmental indicators data series wavelet coherence was applied which elicited the association of the time-frequency band between the indices. Fig. S2a shows a single and tiny band of coherence between IR and AQI in the middle of the time series with a correlation value of around 0.7. The phase angles denote an in-phase association between the two signals while no association indicating band was observed between IR and PM 2.5 (Fig. S2b). Some right arrows appeared in Fig. S2c and Fig. S2d indicating an in-phase relationship of IR with CO and NO_2, respectively. For CO, a tiny coherence band of 2–3 periods appeared from April 11 to April 13, 2020 while no coherence band found for NO_2. In both cases, the right arrows prevail with 1–6 periods variation from April 4 to April 20, with a correlation value of 0.6 to 0.7. For O_3, A red island with the right arrows can be observed (Fig. S2e) with a variation of 1–7 periods from March 30 to April 20; indicating an in-phase relationship between IR and O_3 with a correlation of near about 0.70 to 0.75. A hot area with right arrows also appeared for SO_2 (Fig. S2f) denoting an in-phase relationship with IR having a variation of 2–4 period from April 5 to April 22. A clear red island with thick black contour showing a correlation value of 0.8 between IR and MT (Fig. S2g)

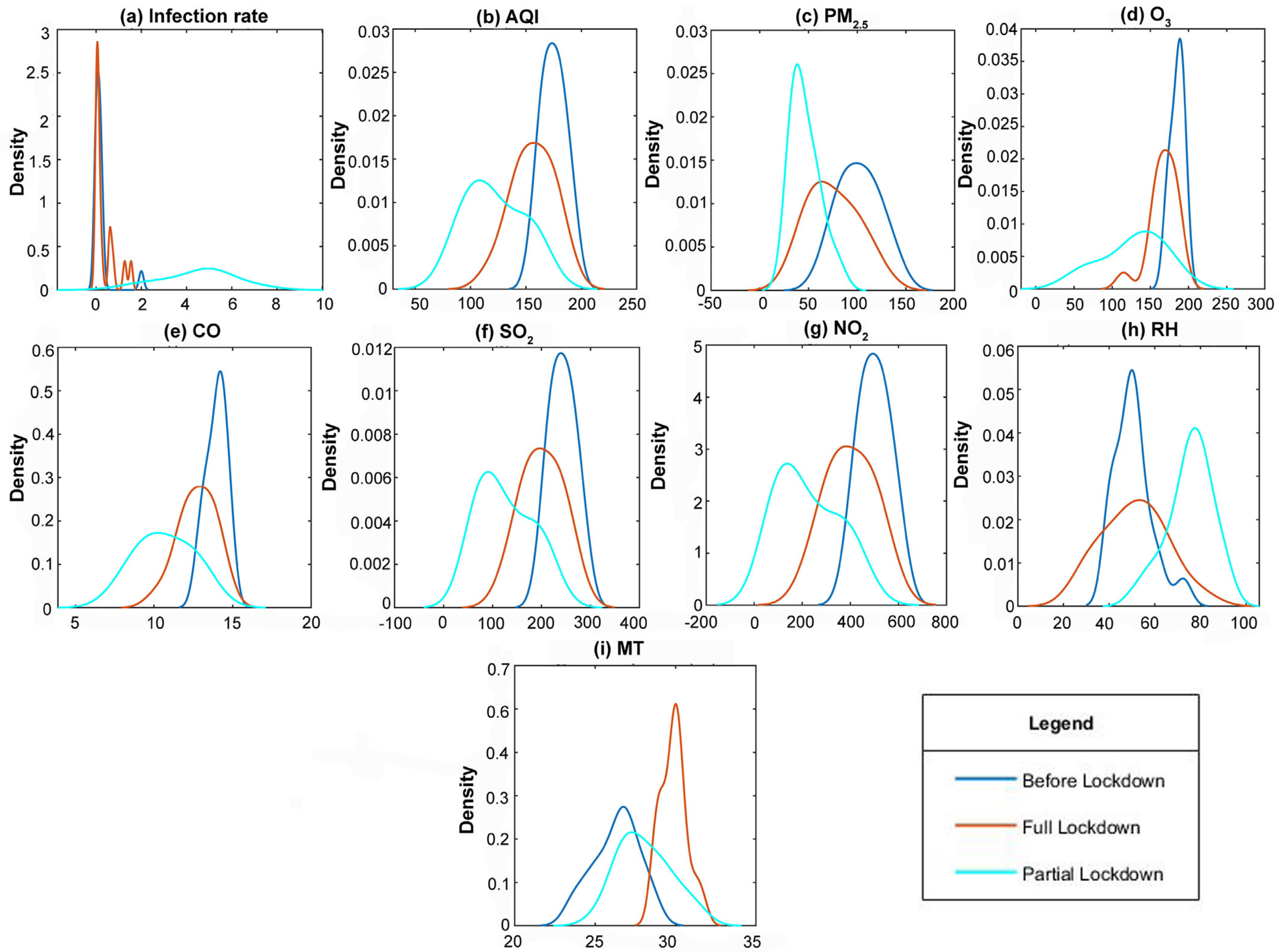

Fig. 5. Probability distribution functions (PDFs) of air quality indicators with climatic factors and COVID-19 infection rate over the Dhaka city under different lockdown scenarios.

occurred with a variation of 3–4 time periods from April 6 to April 14. The phase angle denotes that the COVID-19 infection rate series is approximately ahead of the mean temperature series during that period. Wavelet coherence between IR and RH (Fig. S2h) exhibits multiple conspicuous and significant bands of coherence with a variation of 2–3.7 period from March 22 to March 27, 2020. The phase angle delineates that the IR series is approximately lagged behind the RH series during this period. Another coherence band occurs with a variation of 3.3–4 period from April 4 to April 6. The phase angle hinted that the IR series is again lagged behind the RH series during this period. Another red island appeared in the time-frequency map which has a correlation value of near about 0.8 with a variation of 6–8 periods from April 20 to May 1, 2020. The arrow indicates that the IR series is approximately ahead of the RH series during this period. For all the data series some coherence bands seem to appear outside the cone of influence which is not significant.

Among the environmental indicators, both meteorological parameters (MT and RH) showed greater significance than the air quality parameters. So, we aimed to examine the independent influence of the air quality parameters while controlling one of the meteorological parameters at a time using Partial Wavelet Coherence (PWC). We also investigated the combined influence of the air quality and meteorological parameters on the COVID-19 infection rate through Multiple Wavelet Coherence (MWC).

Fig. 6a shows the Partial Wavelet Coherence (PWC) including IR, AQI and MT. It represents the wavelet coherence between IR and AQI series while controlling the common effect of mean temperature. One small yellowish spot can be detected with a frequency domain of 1.5–3 periods showing a correlation value of 0.6 approximately from April 16 to April 21, 2020. No coherence band appeared between IR and PM 2.5 (Fig. 6b) when the common effects of MT were minimized. PWC between IR and CO (Fig. 6c), IR and NO_2 (Fig. 6d), IR and O_3 (Fig. 6e) and IR and SO_2 (Fig. 6f) did not show any significant coherence band while the common effects of mean temperature were minimized. Although some yellow regions seem to appear, they were not significant enough. PWC between IR and RH (Fig. 6g) showed some clear coherence band while the effects of MT were controlled. The first one appeared from March 26 to March 30 with a variation of 2–3.5 periods; the second one had a frequency domain of 3.8–4.2 periods from April 2 to April 7 and the third one with a variation of 6–8 periods from April 21 to April 27, 2020. Fig. 6(h–n) elicits the PWC between IR-AQI, IR-PM 2.5, IR-CO, IR-NO_2, IR-O_3, IR-SO_2 and IR-MT respectively while the common influence of RH was controlled. Fig. 6h denotes a coherence band with a variation of 3–3.5 periods from April 14 to April 16 between IR and AQI. PWC between IR and PM 2.5 (Fig. 6i) did not reveal any significant coherence band while IR-CO (Fig. 6j), IR-NO_2 (Fig. 6k), IR-O_3 (Fig. 6l) and IR-SO_2 (Fig. 6m) denoted similar coherence band with a variation of 3–3.6 during April 14 to April 17. PWC of IR, MT and RH (Fig. 6n) elicited a red region with a correlation value of 0.6 to 0.7 in the middle of the given period, within it a little coherence band appeared with a variation of 3–3.5 period from April 13 to April 15, 2020. All the parameters

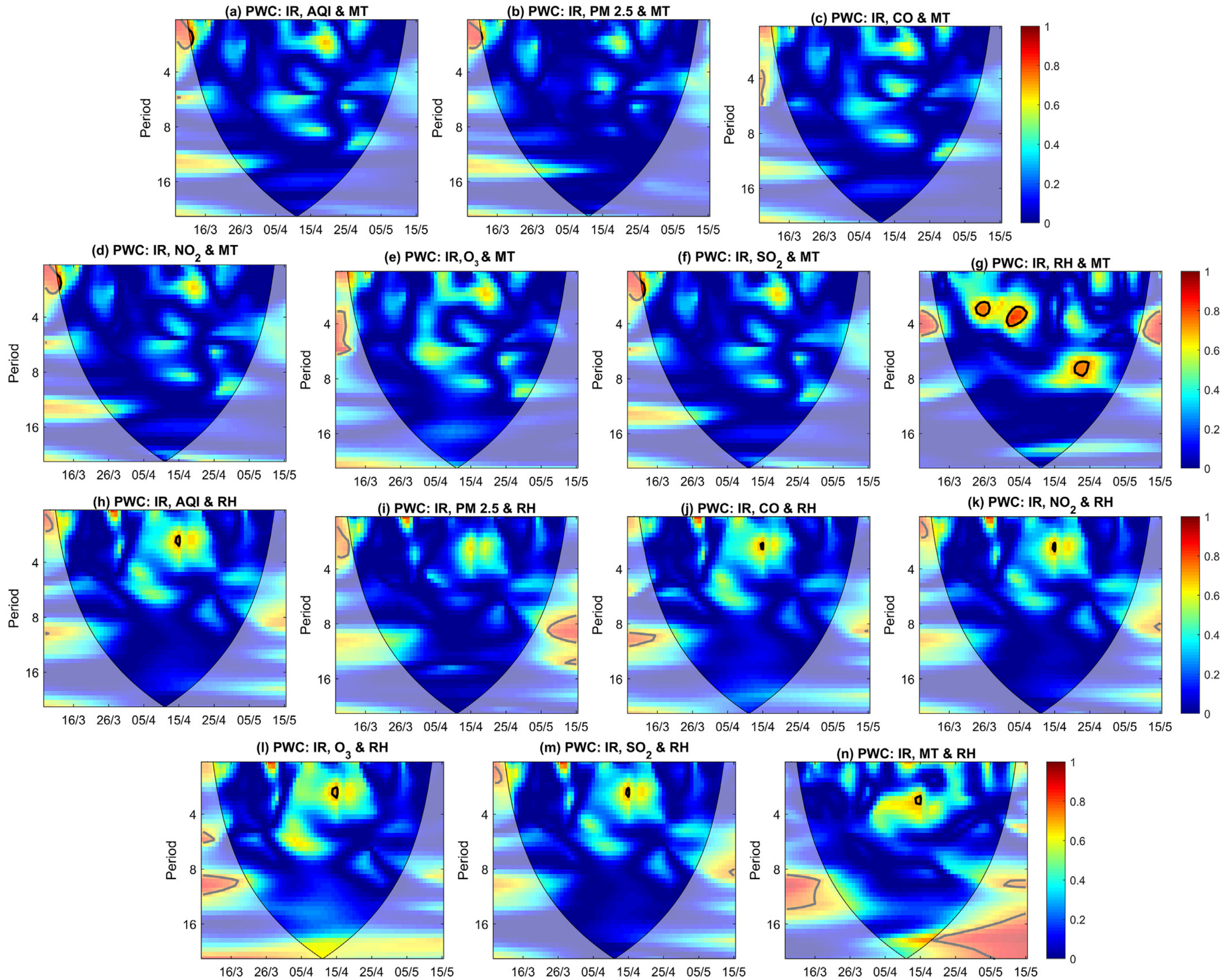

Fig. 6. Partial wavelet coherence between COVID-19 infection rate and air pollutant indicators with climatic factors (The thick black cone shaped contours show the 95% significance level, and the black line is the cone of influence. "→" denote that the two series are in-phase, while "←" means anti-phase relationship; "↓" indicate that the COVID-19 Infection Rate series is ahead of the environmental indicators, whereas "↑" means that the COVID-19 Infection Rate series is lagged behind the environmental indicators).

showed some coherence band outside the cone of influence which is insignificant.

MWC can reveal how the linear combination of two independent series moves with a dependent series. Fig. 7 presents the MWC results involving the COVID-19 infection rate as the dependent series when air quality parameters and mean temperature are used as an independent series. Some red islands with black contour line rise within the 0–4 frequency band when we took IR as a dependent variable and AQI and MT (Fig. 7a) and PM 2.5 and MT (Fig. 7b) as independent variables. The most visible island appeared from the April 5 to April 15, 2020 with a variation of 3–4.2 periods for both cases. A couple of red islands also appeared between IR and CO-MT combination (Fig. 7c). A little island appeared within the 0–4 frequency band during the March 23 to March 27 and a medium-sized island appeared from the April 5 to April 18 which exceeds the 0–4 frequency band. Some red islands also rose when we used IR as a dependent and NO_2-MT (Fig. 7d), O_3-MT (Fig. 7e), and SO_2-MT (Fig. 7f) combinations as independent variables. In all cases, a small island rose within the 0–4 frequency band from March 23 to March 26 and a notable coherence band of 3–4.3 periods appeared from April 5 to April 17. MWC between IR and AQI-RH combination (Fig. 7g) showed multiple red islands in both 0–4 and 4–8 frequency bands from March 21 to March 30, April 2 to April 15, and April 17 to April 30, 2020. MWC of IR and PM 2.5-RH (Fig. 7h) combination also denotes multiple short-term and long-term coherence in 0–4 and 4–8 frequency bands from March 20 to March 29, April 3 to April 10 and March 17, 2020 to continuing onwards to the end of the given period. MWC of IR with CO-RH (Fig. 7i), NO_2-RH (Fig. 7j), O_3-RH (Fig. 7k) and SO_2-RH (Fig. 7l) combinations exhibit a similar type of results like the result of MWC between IR and AQI-RH combination. All these air quality parameters showed significant short- and long-term coherence with the COVID-19 infection rate while combining with relative humidity. Among them, the O_3-RH combination showed larger coherence of 1–4.5 periods from March 28 to April 14. The combination of MT-RH also elicited significant coherence with IR (Fig. 7m). Multiple red-colored islands with thick black contour appeared in the time-frequency map within the 0–4 and 4–8 frequency bands. The first coherence band of 0–3.8 periods appeared from March 22 to March 29 while the second one occurred with a variation of 2–4.3 periods during the April 2 to April 16. The third and fourth coherence bands occurred with a variation period of 3–4.1 and 6–8 from April 18 to April 23 and April 19 to May 1, 2020 respectively. Some coherence bands also seem to occur outside the cone of influence for all the time-frequency maps.

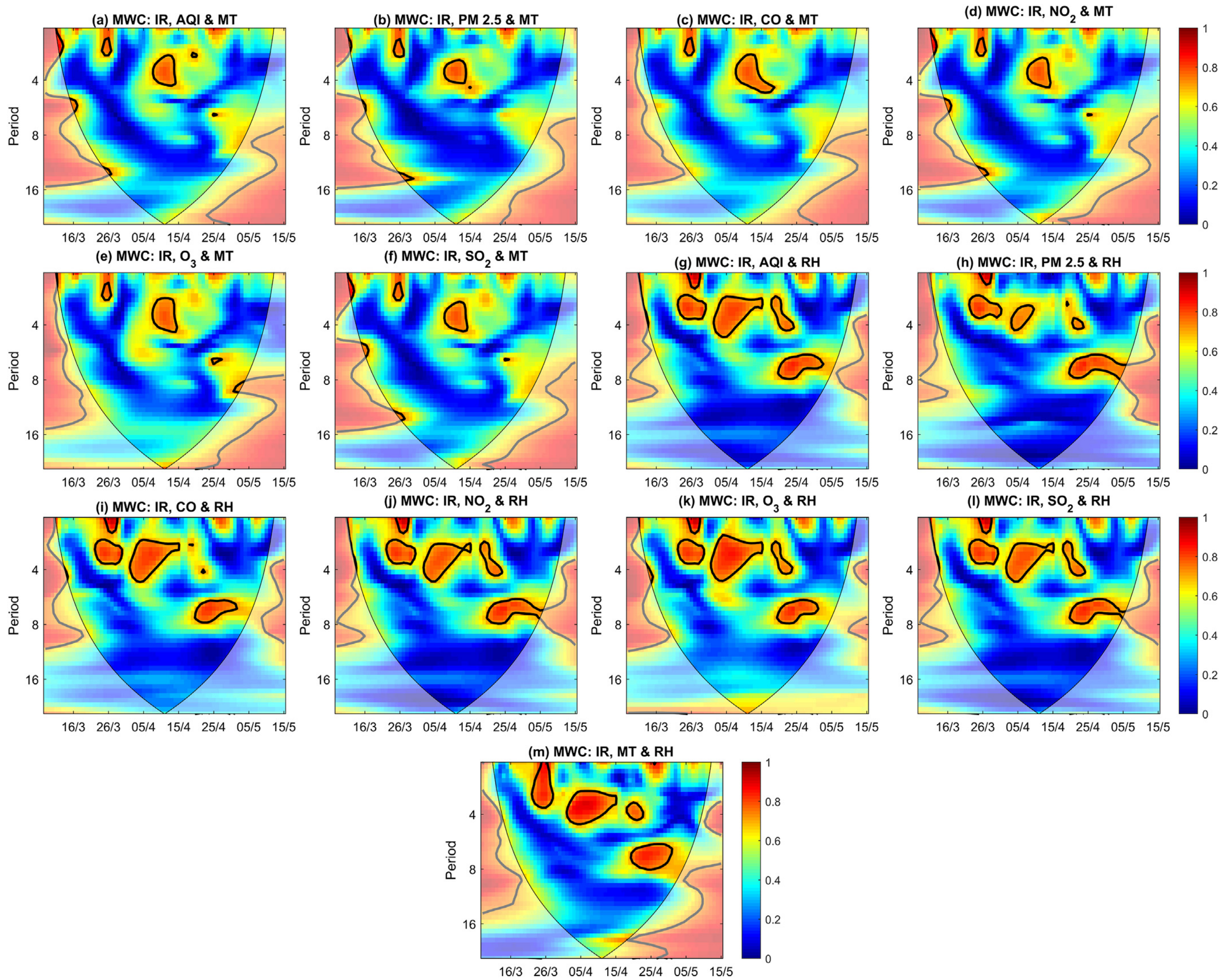

Fig. 7. Multiple wavelet coherence among COVID-19 infection rate, air pollutant indicators and climatic factors (The thick black cone shaped contours show the 95% significance level, and the black line is the cone of influence. "→" denote that the two series are in-phase, while "←" means anti-phase relationship; "↓" indicate that the COVID-19 Infection Rate series is ahead of the environmental indicators, whereas "↑" means that the COVID-19 Infection Rate series is lagged behind the environmental indicators).

3.4. Probable impact of different factors on the COVID-19 transmission in Dhaka city

The RF model was employed to assess the relative importance and the likely potential factors associated with the COVID-19 variations during lockdown measures in the Dhaka megacity. Fig. 8 reveals the relative importance degree of the contributing factors for COVID-19. MT and RH have the highest importance in the RF model for the COVID-19 outbreak (Fig. 8). The rankings of the most three important factors are MT, RH and O_3 and the COVID-19 transmission in the Dhaka city can be regarded as mean temperature-relative humidity (MT-RH)-driven type. Both MT and RH plays a pivotal role in changing the COVID-19 infection rate, followed by O_3, PM 2.5, SO_2, AQI, NO_2, AH, AP, CO, WS and RainF (Fig. 8). This change leads to high COVID-19 infection cases in partial lockdown compared to other lockdown scenarios. Although we did not get such a significant relationship between air quality indicator and COVID-19 cases, the result of the RF model indicates the importance of air quality indicators especially O_3, PM2.5 and SO_2 with the infectious disease. This clue further indicates the possibility of multi-factors involvement of environmental parameters to COVID-19 cases along with contact and person to person transmission. Thus, the meteorological parameters in combination with the air quality parameters produced the coupled impact in COVID-19 cases during the lockdown periods in Dhaka city.

4. Discussion

Due to the lockdown and movement restrictions after the COVID-19 outbreak, many articles have been published to established interactions between air pollution and coronavirus transmission (Dutheil et al., 2020; Tobías et al., 2020; Siciliano et al., 2020). It has been observed that the level of air pollutants reduced significantly after the COVID-19 emergence worldwide. The major reasons behind the reduction might be linked to cut off industrial emissions, lower traffic contributions, and no evidence from natural sources such as forest fires. Besides, the pollution trends might be explained from the local, regional, and global points of view regarding their sources and extent. This study particularly deals with the air pollution scenario of Dhaka city, Bangladesh one of the most polluted cities globally in terms of air quality. We have also focused on two meteorological parameters e.g. Mean Temperature (MT) and Relative Humidity (RH) rather than other meteorological parameters like wind speed, solar radiation, absolute humidity, air

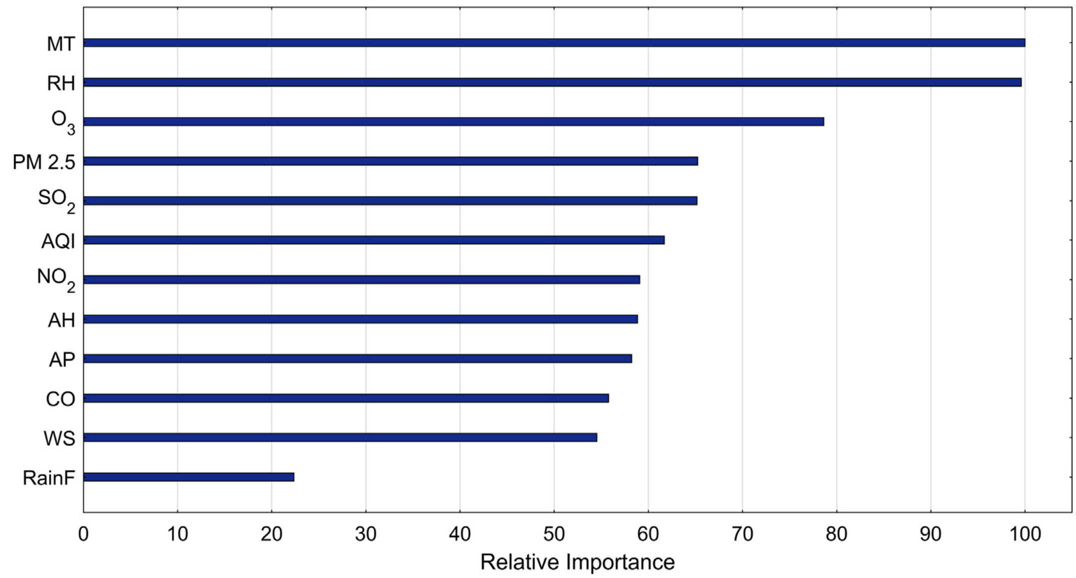

Fig. 8. Relative importance of the predictors in the Random Forest (RF) model for determining the COVID-19 infection rate.

pressure, etc. This is because many of the earlier studies (Wu et al., 2020; Bashir et al., 2020; Auler et al., 2020; Tosepu et al., 2020; Gautam, 2020; ESA, 2020) suggests that MT and RH are the most significant parameters which may be associated with COVID-19 transmission in different parts of the world.

This study aimed to visualize the air pollutants (PM2.5, O_3, CO, SO_2, and NO_2) along with the meteorological parameters such as MT, RH, and the COVID-19 situations in Dhaka city, the hotspot of pollution and COVID-19 infection in Bangladesh. Various important factors e.g., sources of emissions (vehicular exhaust, brake wear and road erosion; resuspension due to wheel-generated turbulence, emission from metal processing, urban waste processing and waste burning) (He et al., 2020), meteorology (i.e. temperature, rainfall, humidity, and wind pressure), and seasonal variations (Hoque et al., 2020) may affect changes in air quality and changes COVID-19 infection rate in Dhaka city. Besides the emission as mentioned above sources, the transboundary effect of pollutants may also play a pivotal role in worsening air quality in Dhaka city (Otmani et al., 2020). It is not surprising that such sources are the vital factors of air quality changes. However, different risk factors on spread of COVID-19 include patient demographics (Garg et al., 2020; Zhang et al., 2020a, 2020b), social isolation measures (Zhong et al., 2020), environmental variables (Bukhari and Jameel, 2020), housing and age distribution (Gardner et al., 2020) and health implication (Fang et al., 2020; Zhou et al., 2020).

Though wavelet coherence analysis revealed no actual coherence between the COVID-19 infection rate and the air quality parameters, IR has some coherences with the meteorological parameters, e.g., mean temperature and relative humidity. PWC revealed that air quality parameters do not have a standalone association with the COVID-19 infection rate. However, MWC unfolded that the COVID-19 infection rate has significant short-term coherence with air quality parameters, while combined with mean temperature and relative humidity. These findings present some exciting inklings that are different from the other related study which can provide valuable information for a better understanding of the varying characteristics of COVID-19. This issue needs further study on a regional or global scale with large datasets and rigorous statistical modeling.

A finding reported by Yongjian et al. (2020) suggested that the increase of PM2.5, PM10, NO_2, and O_3 were linked with the increase of COVID-19 confirmed cases in China. The previous study on other respiratory tract infections established a link between respiratory tract infection by microorganisms under polluted air (Mehta et al., 2013). However, considering the meteorological parameters (temperature, relative humidity, wind speed, rainfall, air pressure etc.) along with the air quality indicators, our study found very good coherence with COVID-19 IR in Dhaka city by the MWC analysis. This outcome provides new insights into the research dimension on the potential relations between environmental indicators and COVID-19 infections. Therefore, it is essential to identify each air quality and meteorological parameters' relative importance to draw a line between the implementation of lockdown policy and air quality indicators and the COVID-19 IR. The RF model's variable importance depicted that mean temperature and relative humidity are the most important parameter linked with the COVID-19 cases in Dhaka city followed by O_3 and PM2.5. From this study, it is clear that the spreading of COVID-19 has a complex association with the air quality parameters in Dhaka city. However, the meteorological parameters might play a straight and vital role in predicting COVID-19 infection rate which is supported by a recent study of Islam et al. (2020c).

It was also observed that the modulation of air pollution indicators and COVID-19 pandemic in the Dhaka city exhibits a clear distinction during the different lockdown scenarios. In fact, the AQI shows significant modulation in the rightward side in the city area, with peaking in before lockdown, followed by full and partial lockdown, which is mostly attributable to a set of controlling factors including industrial activities, construction projects, shut down educational institutions, mass transport, and non-essential services and restricted the movement of people and vehicles to tackle the spread of coronavirus. From the last week of April 2020, the government of Bangladesh ordered to reopen industrial activities (The Diplomat, 2020), the lockdown collapsed with the resume of industrial activities and the air quality started to become polluted again (Shammi et al., 2020a). Infection rates in Dhaka city are high may be due to lack of strict lockdown. Different precautionary measures like making people wash hands and wear facemasks, keeping social distancing, and implementing the infectious diseases law should be strictly followed to prevent infection in the city. Therefore, the measures to prevent COVID-19 transmission acted as a passive driver to regulate the air quality variation under different lockdown extent in Dhaka city. For instance, during the lockdown a complete shutdown of public transportation was observed which was one of the pivotal causes of air pollution in the city (Shammi et al., 2020b). Along with mass transportation major construction activities were also postponed, which eventually reduced air pollutants. Besides, most of the industrial activities such as readymade garments (RMG), textiles, leather, constructions and brick kilns were also under the shut-down policy at least until the beginning of the full lockdown phase which played a crucial role in the reduction of highest air quality indicators during the partial lockdown phase in Dhaka city.

The MT and IR exhibit higher modulation in the leftward side, associated mainly with meteorological effects. Unlike from these environmental indicators, the mountainous MT and PM2.5 exhibit distinct modulation with peaks in full lockdown, followed by the before and partial lockdowns. This may be due to the closing of traffic and industrial activities at the very beginning of Dhaka city lockdown. Several environmental risk factors have been identified for evolving the COVID-19 infection linked to the COVID-19 in this study. Although this study has excluded the contact transmission and population density, this might be due to the COVID-19 virus rapidly transmitted in the intimacy of urban city area people compared to rural areas.

The air quality of Dhaka city has been reported to be better after declaring the lockdown and closing of all business and economic activities including industries, transportation, construction, commercials, and educational institutions. The results of our study also reflected that by using the linear regression analysis, the lowest concentration of air quality parameters was found in partial lockdown, whereas the highest was before the lockdown in all the studied parameters. Like many other parts of the world, a similar association was explored in the Dhaka city. For instance, Sharma et al. (2020) reported the reduction of PM10 (−43%), PM2.5 (−31%), NO_2 (−18%), and CO (−10%) compared to previous years data in the lockdown period of in more than 20 cities in India. A line of evidence from China also stated a sharp reduction of air pollution loads due to the COVID-19 lockdown situation (Wang and Su, 2020). Moreover, Zhang et al. (2020a, 2020b) reported more than 50% reduction of NOx during the COVID-19 breakout compared to previous years. In Malaysia, the reduction effects of COVID-19 lockdown on air pollution were also reported along with other Southeast Asian countries (Kanniah et al., 2020). A huge air quality impact of COVID-19 was reported in Barcelona, Spain. Tobías et al. (2020) found a 45.4% lowering of BC levels and 47.0% and 51.4% reduction of the NO_2 concentrations from the background levels (Tobías et al., 2020; Hashim et al., 2020). In our study, the highest reduction effect was found in partial lockdown. During the partial lockdown, the greatest rate of COVID confirmed cases were found with a 1-unit increase of AQI variables where the lowest rate was found in full lockdown. It can be summarized, the restrictions on anthropogenic activities majorly triggered the lowering of the atmospheric pollution loads all over the world. However, the link between spreading COVID-19 and air pollution load is somehow varied depending on the local settings and there is a certain impact of meteorological parameters combined with the air quality parameters in the COVID-19 IR in Dhaka city, Bangladesh.

A recent study by Ogen (2020) integrated data on NO_2 concentration from the Sentinel-5 Precursor space-borne satellite and COVID-19 death rates across 66 regions in France, Germany, Italy and Spain and found that out of 4443 death, 3701 cases (83%) happened in the regions with the highest NO_2 concentration and only 51 cases (1.5%) in the regions with the lowest NO_2 concentration.

This study has found strong evidence that enhanced NO_2 concentration levels might be associated with detrimental results in the COVID-19 infection rate. However, the nature and strength of any direct relationships are still ambiguous. Although present lockdown scenarios have led to a substantial decline in air pollution levels, with the sharpest decreases in NO_2 (up to −20–30% and −55%) during full and partial lockdown periods. In this situation, major industrial activities (RMGs, textiles, tanneries, constructions, brick kilns etc.) and mass transportation were closed during the lockdown period and outside public gathering was also restricted along with the nation-wide general holidays, NO_2 exposure is anticipated to be declined by 55% compared to the before lockdown period (Shammi et al., 2020b). So, in addition to the drop in outdoor NO_2 pollution levels, this exposure reduction should be taken into consideration. The lockdown scenarios were unable to suppress the transmission of the COVID-19 pandemic. Similar to our findings, Gautam (2020) also confirmed NO_2 reduction up to −70% and 20–30% in India and China, respectively, indicating that there are substantial changes in the level of NO_2 recognized in Asian cities because of COVID-19 lockdown. More research is required into adjusting levels of pollution, exposure timing, and the potential association with COVID-19 pandemic, which can inform public health measures under the background of enabling lockdown actions.

5. Conclusion

In this research, a combination of aerosol (PM2.5) and gases (NO_2, SO_2, CO, and O_3) data along with meteorological datasets (MT, RH, AP, WS, and RainF) were collected from the ground and satellite-based stations during March–May 2020. Although wavelet coherence and partial wavelet coherence results show no actual or standalone relationships between air quality parameters and the COVID-19 infection rate, multiple coherence outcomes exhibit a strong coherence with the air quality parameters while combing them with meteorological parameters. A substantially higher reduction occurred in PM2.5 and NO_2 levels, which declined by 26–54.2% and 20.4–55.5% in the urban city area during full and partial lockdowns compared to the period before lockdown. These significant reductions in air pollutants were strongly associated with the effects of lockdown measures to restrict the people's movement and closing industrial activities, prohibiting mass gatherings, restricting religious activities and border closing, etc. The results of GAMs revealed that a 1-unit increase (lag2) in CO was associated with a 10.7% (95% CI: 20.6%, 0.8%) increased risk of COVID-19 infection rate during the partial lockdown. It was observed that modulation of air pollutants in this urban city exhibits COVID-19 induced lockdown differences with the peak before lockdown, which largely contributes to vehicle exhaust and industrial emissions. In contrast, IR and MT modulated by an analogous pattern peaked during full lockdown which is mostly attributed to contact transmission and high MT in the urban area. This research has identified the three potential factors including MT, RH and O_3 may contribute to the COVID-19 infection rate in the Dhaka city, and thus justifying further large-scale study. On the whole, our results provide some clues for further research to categorize the status of exposure efficacy and level of air pollution, particularly from the studies with the robust procedure familiar for vital confounders. The advantages of air quality constraint measures during COVID-19 lockdown scenarios appear to be a unique chance for pollution-control strategies.

CRediT authorship contribution statement

M.S.R., and A.R.M.T.I., designed, planned, conceptualized, drafted the original manuscript, and M.A.K.A., and M.H., was involved in statistical analysis, interpretation; R.S., and M.M.M.H., contributed instrumental setup, data analysis, validation; M.M.R., contributed to editing the manuscript, literature review, proofreading; M.A.K.A., M.H., and A.R.M. T.I., were involved in software, mapping, and proofreading during the manuscript drafting stage.

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.

Acknowledgement

We would like to acknowledge all the frontline doctors fighting this COVID-19 pandemic and all the research scholars cited in the references.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.143161.

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