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Random forest regression analysis on combined role of meteorological indicators in disease dissemination in an Indian city: A case study of New Delhi

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A R T I C L E   I N F O

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A B S T R A C T

Meteorological parameters show a strong influence on disease transmission in urban localities. The combined influence of factors such as daily mean temperature, absolute humidity and average wind speed on the attack rate and mortality rate of COVID-19 rise in Delhi, India has been investigated in this case study. A Random forest regression algorithm has been utilized to compare the epidemiological and meteorological parameters. The performance of the model has been evaluated using statistical performance metrics. The random forest model shows a strong positive correlation between the predictor parameters on the attack rate (96.09%) and mortality rate (93.85%). On both the response variables, absolute humidity has been noted to be the variable of highest influence. In addition, both temperature and wind speed have shown moderate positive influence on the transmission and survival of coronavirus during the study period. The synergistic effect of absolute humidity with temperature and wind speed contributing towards the increase in the attack and mortality rate has been addressed. The inhibition to respiratory droplet evaporation, increment in droplet size due to hygroscopic effect and the enhanced duration of survival of coronavirus borne in respiratory droplets are attributed to the increase in coronavirus infection under the observed weather conditions.

1. Introduction

Global pandemic crises have periodically caused havoc to mankind and have imposed threat to the lives of numerous humans (Hiscott et al., 2020). Spanish flu, swine flu, ebola and zika are some of the most dreaded epidemic eruptions of the past (Kamorudeen and Adedokun, 2020; Chowell et al., 2006; Calore et al., 2011; Nikookar et al., 2020). Coronaviruses were considered as relatively harmless pathogens until they caused three major outbreaks of severe respiratory disease in the last 20 years. So far, seven coronaviruses are known to cause human disease. Originating from animals, four of these human coronaviruses, HCoV 229E, HCoV OC43, HCoVNL63, and HCoVHKU1 have caused mild infections. However, three viruses, Severe Acute Respiratory Syndrome Coronavirus (SARS-CoV), Middle East Respiratory Syndrome Coronavirus (MERS-CoV), and the recently identified SARS-CoV2 have the potential to cause serious respiratory illnesses in humans (Djilali and Ghanbari, 2020; Gao et al., 2020). Since December 2019, the world is being challenged by the sudden and rapid spread of SARS-CoV2, alternatively called as COVID-19 or the novel coronavirus. The virus has infected millions of people and subsequently has led to the fatality of many around the globe. Owing to the rate of spread and the

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drastic increase in mortalities due to the infection, World Health Organization has declared COVID-19 as a global pandemic. The transmission of COVID-19 predominantly occurs through direct human-to-human contact (Paules et al., 2020). Studies have also shown evidence of propagation of the coronavirus through aerosols and large respiratory droplets (Wang et al., 2020; van Doremalen et al., 2020).

There are a variety of factors that affect the dissemination of COVID-19 pathogen. Both laboratory and epidemiological studies have shown significant influence of meteorological factors on the transmission of coronavirus (Qi et al., 2020; Fattorini and Regoli, 2020; Casanova et al., 2010). Abiotic parameters such as ambient temperature, humidity, precipitation, dew point, solar radiation, water vapor content, wind speed etc., have been evaluated as major driving forces for the transmission and survival of the virus (Auler et al., 2020; Chin et al., 2020; Sajadi et al., 2020). A strong dependence of viral transmission on ambient temperature has been demonstrated. The increase or decrease in temperature is a notable factor affecting the transmission of virus by influencing the duration of survival of coronavirus on surfaces (Bannister-Tyrrell and Meiqari, 2020; Zhu et al., 2020; Lin et al., 2020a, 2020b). Numerous studies have also confirmed that humidity is a potential driver in the spread of this infectious disease (Runkle et al., 2020; Bashir et al., 2020; Auler et al., 2020). The combined effect of low temperature and humidity has been declared to be detrimental to human health, as it favors the optimal condition for the survival of the coronavirus (Chen et al., 2020). Wind speed has also been reported to affect the viral attack rate in previous studies (Auler et al., 2020; Sahin, 2020). The dependence of COVID-19 transmission on meteorological parameters has been studied in countries including China, Norway, Turkey, USA and Italy (Zhang et al., 2020; Menebo, 2020; Sartor et al., 2020; Sahin, 2020; Bashir et al., 2020). The influence of climate factors has been reported to be different in tropical countries based on relevant studies that have been conducted in Brazil, Singapore and Indonesia (Prata et al., 2020; Pani et al., 2020; Tosepu et al., 2020). India is a tropical country in the northern hemisphere that enjoys four distinct climatological seasons. In the world’s second populous country, in spite of a countrywide lockdown, between April–July 2020, the COVID-19 cases rose continuously. In particular, the cities have become COVID-19 epicenters and are quite vulnerable to the infectious disease. The impact of COVID-19 pandemic in cities is dominated by a variety of factors such as environmental conditions, social impact, economy, governance and transportation (Sharifi and Khavarian-Garmsir, 2020). Hence it is logical to study the influence of climate factors in cities on the spread of novel coronavirus. Statistical analysis is one of the popular methods to assess the correlation between the climate-epidemic factors. In the recent years, machine learning models have become cost-effective alternatives to accurately analyze a wide variety of data (Malki et al., 2020; Smiti, 2020; Roohi et al., 2020; Hong et al., 2020).

The objective of this study is to utilize machine learning methodology to evaluate the influence of meteorological parameters on the transmission of COVID-19 and the associated fatality rate in Delhi. The climatic parameters considered in this study include daily mean temperature, wind speed and absolute humidity.

2. Materials and methods

2.1. Study area

Delhi, also referred to as the National Capital Territory (NCT) is a metropolitan city in northern India bordered by the states of Haryana and Uttar Pradesh. The capital city of India sprawls over an area of 1484 km². The population of the city is about 16.8 million (Census Population Data, 2015). During the investigation period, April–July, the city typically experiences a semi-arid climate with occasional dust storms.

2.2. Data collection

The COVID-19 data consisting of the numbers of the daily infected and deceased persons were collected from the official web portal of the Health and Family Welfare, Government of NCT of Delhi (HFW-Delhi, 2020). The period of collection of data was from 27th April 2020 to 10th July 2020. The meteorological data comprising of the daily mean temperature (°C), relative humidity (%) and daily average wind speed (m/s) during the same period were collected from the official website of the Indian Meteorological Department (IMD, 2020). The incubation period of a virus is defined as the duration between the exposure to the virus and the onset of symptoms such as cold, cough, fever, loss of smell etc. It has been reported that the incubation period of COVID-19 ranges from 1 to 14 days with a median of 5–6 days. Similarly, depending on the nature of the COVID-19 testing method, the results of the tests are declared in 1 to 7 days with a median of 3 days. Therefore, in this study, the epidemiological parameters were mapped with the meteorological parameters which were recorded eight days earlier.

2.3. Data pre-processing

The collected data were checked for missing values and outliers. The response variables utilized while building the machine learning model were the epidemiological parameters such as attack rate and mortality rate. They were calculated from the raw data using Eqs. (1) and (2).

\[
\text{Attack Rate} \% = \frac{\text{Number of persons suffering from infection}}{\text{Susceptible population}} \times 100 \tag{1}
\]
Mortality Rate (%) = \frac{\text{Number of death}}{\text{Confirmed Cases}} \times 100 \quad (2)

Daily mean temperature, absolute humidity and average wind speed were treated as independent variables in this study. The absolute humidity is a temperature independent physical quantity that represents the water vapor content in air. It was calculated using the Clausius-Clapeyron expression and represented in absolute unit (A.U) (Gupta et al., 2020; Pani, Lin, and Ravindra Babu et al. 2020) as given in Eq. (3).

\[
\text{Absolute Humidity} = \frac{6.112 \times e^{\left(\frac{17.67}{T} \times RH \times 2.1674\right)}}{(273.15 + T)} \quad \text{(A.U)}
\]  

(3)

where, RH is the relative humidity and T is the daily mean temperature.

Fig. 1. (a) Epidemic curve for COVID-19 data in Delhi between 27.04.2020–10.07.2020 (b) Plot between basic reproduction number (R_0) against number of COVID-19 infection (c) Variation of basic reproduction number (R_0) with number of days passed (d) Plot between attack rate and basic reproduction number (R_0).
2.4. Model building and performance metrics

Random forest regression algorithm is implemented in the R programming language environment to understand the non-linear relationship between the meteorological and epidemiological parameters (Breiman, 2001). It is an ensemble supervised learning model built by random sampling of many individual decision trees which subsequently reports the aggregate response of all the trees. The model was built using the “randomForest” package in R environment (version 3.4.2). Some of the key parameters that govern the performance of the model are the number of trees, number of input variables and the node size. By optimizing these parameters, the random forest regression model was further improvised. Statistical parameters, extracted from the “Metrics” package of R programming language, were used to assess the performance of the tuned model. Further, the graphical visualization of the results were implemented using the “ggplot2” package. The “R0” package was used to compute the epidemiological parameters presented in this study (Boelle et al., 2015).

3. Results and discussion

3.1. Data analysis

Fig. 1 shows the preliminary analysis on the transmission of COVID-19 cases recorded in Delhi during the selected duration. Fig. 1a reveals a steady rise in the number of confirmed and deceased cases. The behavior of the epidemic curve shall be further understood using the measures of viral transmission such as the attack rate and basic reproduction number ($R_0$) as shown in Fig. 1b–d (Marimuthu et al., 2020; Nikbakht et al., 2019). The basic reproduction number represents the number of secondary infections caused by an infected person during the course of a contagious disease. The reproduction number is calculated as a function of the attack rate using

![Fig. 2. Variation in the attack rate as a function of (a) Daily mean temperature (b) Absolute humidity (c) Average wind speed.](image-url)
the expression,

$$A = 1 - \exp(-R_0 A)$$

(4)

where A represents the attack rate and $R_0$ is the reproduction number. In general, when $R_0 > 1$, an epidemic outbreak occurs and when $R_0 < 1$, the susceptible population is immune to the infection.

The reproduction number shows a monotonous increase from 1.0 to 1.4, as noted in Fig. 1b and c, which marks the onset of an outbreak. Since $R_0 > 1$, Fig. 1a confirms a growing epidemic curve and that a significant proportion of the population is susceptible to the pathogen. Fig. 1d shows the typical exponential variation of attack rate as a function of the basic reproduction number which further confirms the growth of epidemic. During the period considered in this study, the Indian government had imposed a nation-wide lockdown. Hence the contribution of population density, interaction of people, migration and immunity level of individuals plays a minor role.

Fig. 2 shows the plots between the attack rate and the climatic parameters such as mean temperature, absolute humidity and average wind speed. Fig. 2a shows that the attack rate is high in the 33–40 °C temperature range. Fig. 2b reveals that the rate of increase in COVID-19 cases is high when absolute humidity is between 20 and 27 (A.U). In a similar manner, when the wind speed is between 1 and 4 m/s, attack rate is higher as noticed from Fig. 2c. The influence of the chosen meteorological parameters on the attack rate are studied using a multi-linear regression model. From Table 1, the probability of significance (P) for temperature and wind speed is noticed to be high.

Table 1 shows the Pearson (r) and Spearman correlation coefficients ($\rho$) for the predictor variables with the response variables. Except for absolute humidity, the other parameters show a weak negative correlation on the dependent variables.

Similarly, Fig. 3a–c show the relationship between the mortality rate and the selected meteorological parameters. Among the three parameters, high absolute humidity between 18 and 27 (A.U) shows a strong correlation with the mortality rate. For temperature between 30 and 40 °C and wind speed between 1 and 4 m/s, high mortality rate has been recorded. The mortality rate shows very poor linear correlation with each of the selected predictor variables as noticed from the values of the correlation coefficients presented in Table 1. In order to study the synergistic effect of the weather parameters, a non-linear random forest regression analysis has been conducted. The model considers the epidemic attack rate and mortality rate as response variables against the chosen meteorological parameters as the predictor variables. It has been reported in previous studies that temperature, humidity and wind speed have profound effect on COVID-19 caused infections (Chen et al., 2020; Lin et al., 2020a, 2020b). The random forest machine learning model would predict the attack and mortality rates as a combined influence of the meteorological factors.

### 3.2. Tuning of hyper-parameter in random forest regression model

The performance of the model has been improved by optimizing the number of trees in the random forest. Fig. 4a shows the plot of number of trees against the root mean square error (RMSE) for the random forest regression algorithm that predicts the attack rate. The RMSE, which is the standard deviation of the residuals, shows moderate variation initially and becomes almost a constant when the number of trees is around 200. In a similar manner, in Fig. 4b, it is observed that the correlation coefficient (R) reaches a maximum at around 150–200 trees; with further increase in the number of trees, it does not vary significantly. Based on the observations made from Fig. 4a and b, the regression model with low RMSE and high R has been selected by setting the number of trees to 150.

Fig. 5a and b represent the variation in RMSE and R for the random forest regression model that predicts the mortality rate. Here again, 150 trees has been selected to obtain the best correlation between the predictor and response variables.

### 3.3. Influence of meteorological factors on attack rate

Fig. 6a presents the plot between the actual attack rate and the random forest regression model predicted attack rate. The performance of the model has been evaluated using statistical parameters as shown in Table 2. The model shows a high correlation coefficient of 96.09% between the actual and predicted attack rates. The superior performance of the model is also evident from the low RMSE values.

Fig. 6b compares the relative importance of the individual meteorological parameters on the attack rate. It is evident from the bar graph that absolute humidity shows a strong influence (76.6%) on the attack rate. The results of the studies in literature that compares

| Response variables | Statistics | Predictor variables |
|--------------------|------------|---------------------|
| Attack rate        | P          | Temperature         |
|                    |            | < 0.001, 0.714      |
|                    | r          | 0.145               |
|                    | $\rho$     | 0.001               |
|                    |            | 0.726, 0.728        |
| Mortality rate     | P          | Absolute humidity   |
|                    |            | < 0.001, 0.943      |
|                    | r          | 0.006               |
|                    | $\rho$     | 0.008               |
|                    |            | 0.738, 0.035        |
Fig. 3. Plot comparing the mortality rate and (a) Daily mean temperature (b) Absolute humidity (c) Average wind speed.

Fig. 4. Tuning of the number of trees in the random forest regression model predicting the COVID-19 morbidity rate based on (a) RMSE (b) Correlation coefficient.
COVID-19 related epidemiological data with weather parameters so far are, to some extent, contradicting in nature as presented in Table 3. It has been reported that an increase in temperature has aided in reducing the transmission of the novel coronavirus (Prata et al., 2020). By treating the temperature or humidity as independent parameters, Ahmadi et al. (2020), Bannister-Tyrrell and Meiqari (2020) and Lin et al. (2020a, 2020b) have reported that low temperature and low humidity supports coronavirus survival. Yao et al. (2020) have reported the absence of correlation between the COVID-19 based epidemiological data and weather data. Studies have also reported that the increment in temperature and humidity aids in reducing COVID-19 transmission (Şahin, 2020; Wu et al., 2020). Similar studies have reported that coronavirus transmission is favored at low temperatures and dry conditions (Liu et al., 2020; Wang et al., 2020; Sun et al., 2020a, 2020b; Sajadi et al., 2020; Biktasheva, 2020; Goswami et al., 2020; Izurieta et al., 2020; Ma et al., 2020).

![Fig. 5. Optimizing the number of trees in random forest regression model predicting the COVID-19 mortality rate based on (a) RMSE (b) Correlation coefficient.](image)

![Fig. 6. Plot comparing the predicted and actual attack rates of the COVID-19 dissemination (b) Bar graph showing the relative importance of the meteorological parameters on transmission of COVID-19 pathogen.](image)

Table 2
Performance metrics of the optimized random forest regression model.

| Statistical parameters | Model prediction on attack rate | Model prediction on mortality rate |
|------------------------|--------------------------------|----------------------------------|
| MAE                    | 0.041                          | 0.251                            |
| MAPE                   | 0.743                          | 0.131                            |
| RMSE                   | 0.054                          | 0.337                            |
| R                      | 96.09%                         | 93.85%                           |
| R²                     | 92.32%                         | 88.07%                           |
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In the current study, it is observed that in addition to absolute humidity, temperature and wind speed are mild positive contributors for the spread of COVID-19 infection with a relative importance of 13.2% and 10.2% respectively. The results indicate that the three meteorological factors have a synergistic effect on the increase in COVID-19 cases. Chen et al. (2020) have also demonstrated a combined effect of meteorological parameters and have shown strong dependence of the increase in COVID-19 infections on the collaborative influence of temperature, relative humidity, wind speed and air visibility. In the present study, a significant increment in the attack rate with an increase in absolute humidity (analogous to 60–95% relative humidity) is noticed. Bu et al. (2020) and Chen et al. (2020) have also concluded that relative humidity between 50 and 90% favor the survival of COVID-19 pathogen. As observed by Chen et al. (2020), a minor influence of wind speed on COVID-19 attack rate is noticed when in combination with other weather parameters. Such a correlation was absent when the wind speed was treated as an independent predictor variable. At an ambient temperature of about 30–35 °C, the combined effect of high absolute humidity and wind speed is detrimental. High absolute humidity leads to an increase in coronavirus borne droplet size due to the hygroscopic environment. Large droplets are efficient in retaining their initial momentum, acquired by a cough or a sneeze, since they possess high Stokes number. The high absolute humidity coupled with high wind speed of about 1–3 m/s leads to larger deposition and faster transmission of the droplets (Feng et al., 2020). The synergistic effect of the meteorological variables considered in this study also play a critical role in delaying the evaporation of the respiratory droplets (Bhardwaj and Agrawal, 2020). This favors the prolonged survival of the COVID-19 pathogen which is quite stable on a variety of smooth surfaces under conducive environment (van Doremalen et al., 2020).

### 3.4. Influence of meteorological factors on mortality rate

Fig. 7a shows the actual mortality rate against the random forest regression model predicted value.

A high coefficient of determination ($R^2$), low mean absolute error (MAE) and low mean absolute percentage error (MAPE) stands as a testimony for the superior performance of the regression model as shown in Table 2. The non-linear nature of the model is appropriate to predict the behavior of the mortality rate as a function of meteorological factors. The behavior of a single meteorological parameter such as temperature, humidity or wind speed does not correlate with the observed mortality rate very well. However, the random forest regression model, unlike the single-parameter models, has been successful in providing a quantitative correlation between the combined meteorological factors and the COVID-19 mortality rate. Fig. 7b shows that absolute humidity is a predictor variable of supreme influence (62.7%) on the mortality rate. It is moderately influenced by the daily mean temperature (21.9%) and wind speed (15.4%). In the context of influence of weather parameters on mortality rate, the correlation coefficient of the present random forest regression model is noted to be better than any of the previously reported machine learning models. Experimental results collected across the globe show a strong influence of temperature and humidity on the fatality rate of COVID-19 infected patients. In particular, a strong negative correlation between humidity and COVID-19 mortality is reported (Ma et al., 2020). Similar to the current study, Malki et al. (2020) have reported the correlation between weather factors using machine learning models. They have shown a strong dependence of mortality rate on temperature, solar radiation, humidity wind speed etc. The increase in absolute humidity could influence supersaturation in human airways, which can aggravate respiratory illness such as asthma and chronic obstructive pulmonary disease (Grasmeijer et al., 2016). However, further study on the combined effect of high absolute humidity,

| Temperature | Absolute humidity | Wind speed | COVID-19 infection | References |
|-------------|-------------------|------------|-------------------|------------|
| High        | High              | Increase   | Increase           | (Auler et al., 2020; Bashir et al., 2020) |
| Low         | Low               | Increase   | Increase           | (Ahmadi et al., 2020) |
| High        | Low               | Decrease   | Decrease           | (Bashir et al., 2020; S¸ahin, 2020) |
| High        | Medium            | Increase   | Combined           | (Chen et al., 2020) |
| Low         | Medium            | Increase   | Decrease           | (S¸ahin, 2020) |
| Low         | High              | Increase   | Decrease           | (Pani et al., 2020) |
| Low         | Moderate          | Increase   | Decrease           | (Zhu et al., 2020) |
| High        | High              | Increase   | Decrease           | (Menebo, 2020; Bashir et al., 2020; S¸ahin, 2020) |

Poor immunity system, reduction in airway cilia cells, dry nasal mucosa, conjunctivitis and formation of droplet nuclei has been attributed as the main reasons for pathogen transmission. These results are in contradiction with the trend observed in the present study which may be due to the season and geographic location of the conducted study. However, similar to the results in this study, Runkle et al. (2020) have also observed absolute humidity as the most significant meteorological indicator. Further, the results of the current study match with the reports of Auler et al. (2020), Bashir et al. (2020), and Pani et al. (2020) wherein high temperature and humidity have positively correlated with the transmission of COVID-19. Bashir et al. (2020), Menebo (2020), and S¸ahin (2020) have reported negative influence of wind speed on number of COVID-19 cases. However, Ahmadi et al. (2020) and Pani et al. (2020) have reported negative influence of wind speed on number of COVID-19 cases. 

In the present study, Malki et al. (2020) have also reported the correlation between weather factors using machine learning models. They have shown a strong dependence of mortality rate on temperature, solar radiation, humidity wind speed etc. The increase in absolute humidity, coupled with high wind speed of about 1–3 m/s leads to larger deposition and faster transmission of the droplets (Feng et al., 2020). The synergistic effect of the meteorological variables considered in this study also play a critical role in delaying the evaporation of the respiratory droplets (Bhardwaj and Agrawal, 2020). This favors the prolonged survival of the COVID-19 pathogen which is quite stable on a variety of smooth surfaces under conducive environment (van Doremalen et al., 2020).
high temperature and moderate wind speed on mortality rate is required, to understand the influence better. The strong dependence of weather factors on the transmission and survival of COVID-19 pathogen is evident in this study. However, other social and economic factors that are not considered in this study also play a significant role. As predicted by previous research studies, a mere increase in temperature and humidity has not terminated the transmission of the virus. Policy makers should ensure other measures such as social distancing, contact tracing, home quarantine, isolation of infected personnel, compulsory wearing of face mask, hand hygiene etc., to overcome the spread of the virus.

4. Conclusions

The present study demonstrates the coordinated influence of meteorological parameters on the increase in COVID-19 attack and mortality rates in Delhi, India between 27 April 2020 and 10 July 2020. The study has been conducted by building a non-linear random forest regression model. This is one of the first studies that uses machine learning algorithms to correlate the weather factors and epidemiological parameters in the capital city of India, Delhi. The research corroborates the positive correlation of weather parameters such as daily mean temperature, absolute humidity and average wind speed on the COVID-19 caused attack rate and mortality rate. The regression model confirms that the predictor variables shows a high coefficient of determination with the response variables such as attack rate (92.32%) and mortality rate (88.07%). Among the predictor variables, absolute humidity showed a strong influence (~60%) followed by temperature (~22%) and wind speed (~18%). The study recapitulates the importance of climatic parameters on the transmission and survival of COVID-19 pathogens in a tropical city. The machine learning model built in this study holds the potential to provide more information for government’s future decisions on COVID-19 outbreak control. The research also reiterates that warm season and humid conditions are not sufficient to reduce COVID-19 dissemination. In addition, stringent measures to ensure social distancing, hand hygiene, isolation of infected persons and wearing of personal protection outfits are essential to reduce the transmission. The current study therefore, presents a preliminary analysis and poses certain limitations. Future studies should be conducted to provide an insight on the collective influence of social, economic, political and cultural factors in COVID-19 transmission.

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