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Role of Climate on SARS-CoV-2 transmission

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Foreword

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Climate change can facilitate zoonotic spillovers and have an effect on transmission chains. These effects, alongside human behavior and awareness, need to be integrated in pandemic forecasting models. After it emerged in China and rapidly ravaged Europe and the USA in a catastrophic first wave, it seemed a matter of time before the COVID-19 pandemic would harmfully strike low and middle-income countries with limited resources. Despite its deadly toll in places such as India or Brazil, where nonetheless the disease did not spark as rapidly as it did in Europe—i.e., the effective reproduction number remained low—tropical countries remained relatively untouched compared with those in temperate regions.

In this Newsletter the role of environmental factors and conditions such as temperature, humidity, and wind speed are highlighted in COVID-19 transmission with the help of Spatio Temporal Variability. Temperature increase and sunlight can facilitate the destruction of SARS-COV-2 and the stability of it on surfaces. When the minimum ambient air temperature increases by 1°C, the cumulative number of cases decreases by 0.86%. The distribution of human population, migration, social interactions, climate change (deforestation, habitat invasion), agricultural growth, and direct contact with domestic and wild animals fall into this category.

Dealing with COVID-19 and preventing its rapid and dangerous spread is a global challenge. Therefore, the fight against this disease requires global management. However, due to the potential variability of this disease, according to the type of climate and other environmental factors, its prevention and control should be investigated quickly and seriously.

Nevertheless, a hierarchy to deal with SARS-CoV-2 transmission involves three steps such as : 1) Self Care (Face mask, Hand wash/Hand Sanitizer and Social Distance) 2) Test, Trace and Treatment and 3) Vaccination. I am sure this Newsletter is aimed to inform the readers about the effect and role of various climatic factors on COVID-19 transmission .

The World Health Organization (WHO) has declared the novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the causative agent of coronavirus disease 2019 (COVID-19) a pandemic on 11th March 2020 due to its rapid spread across the world[1]. As of 10th August 2021, there have been over 204 million confirmed cases with more than 4.3 million deaths reported due to COVID-19[2]. Scientists across the globe have been fighting to restrain the spread of the disease in various approaches such as the development of vaccines, nasal sprays, sophisticated masks, oral medicines, sanitizers and many more. Alongside, many researchers are also trying to explore the links between climatic conditions and the coronavirus transmission to develop a better understanding the impact of climate on the virus and how it spreads.

Environmental factors can affect the epidemiological transmission of many infectious diseases. Several studies have revealed that climate and weather conditions could influence the spatial and temporal distribution of infectious diseases.[3,4] The coronaviridae family viruses SARS CoV-1 and MERs CoV have also shown seasonal variations and prefer low temperature and humidity[5]. A team of researchers from the Brazil has reported that weather plays an important role in determining the transmission rate of SARS-CoV-2 infection. They have additionally specified that after controlling parameters such as age, population, and urbanization, the climatic variables are highly significant for predicting mortality rates of a region. During the initial days of COVID-19 outbreak during early 2020, it was wrongly hypothesized that the virus transmission would be great in cold climates consistent with the behaviour of a seasonal flu respiratory virus[6]. However, the rapid spread of the coronavirus in countries with hot and humid weather such as Brazil and India have challenged this misconception.

Earlier studies have suggested that relative humidity plays an important role in the survival and transmission of the virus in a closed or indoor environment[7] and lower relative humidity contributes to increase in virus transmission[8]. Similar studies conducted in various regions of the world such as New York City[9] and Chinese provinces[10] showed that relative humidity and temperature have significant adverse impacts on new cases of COVID-19. The study conducted in South American regions indicated that a significant correlation between the daily incidence of COVID-19 cases and absolute humidity[11]. Similarly, scientists have also reported that maximum and minimum temperatures positively influencing COVID-19 transmission rates[12]. In the same way, the researchers also found that temperature, wind speed, and solar radiation increases are potential climatic factors that gradually reduce the effects of the pandemic[13]. In many studies, wind speed showed a positive correlation with the incidence of COVID-19. Researchers have further reported that daily accumulated rainfall and COVID-19 infection are not correlated. However, an another study conducted in Oslo, Norway, researchers found a significant correlation between lack of precipitation and increased COVID-19 cases. Meanwhile a study conducted in the United States reported that lower air temperature (within the 20-40°Crange), lower specific humidity, and lower ultraviolet radiation were significantly associated with increased SARS-CoV-2 reproduction number (Rt)[14].

India, with its tropical climate, is one of the worst affected countries in the world with the second highest number of COVID-19 infection cases. Almost 428,715 deaths were caused by Covid-19 since its emergence. Studies on climate data and COVID-19 cases can provide important information on transmission behaviour of the virus, and offer potential improvements for controlling the spread of the disease[12]. Here, we examined the possible correlations among the cases and climatic factors and forecasted the cases using deep learning approach.

Case study: Prediction of COVID- 19 cases using the weather integrated deep learning approach for India.

Abstract: Advanced and accurate forecasting of COVID- 19 cases plays a crucial role in planning and supplying resources effectively. Artificial Intelligence (AI) techniques have proved their capability in time series forecasting non- linear problems. In the present study, the relationship between weather factor and COVID- 19 cases was assessed, and also developed a forecasting model using long short- term memory (LSTM), a deep learning model. The study found that the specific humidity has a strong positive correlation, whereas there is a negative correlation with maximum temperature, and a positive correlation with minimum temperature was observed in various geographic locations of India. The weather data and COVID- 19 confirmed case data (1 April to 30 June 2020) were used to optimize univariate and multivariate LSTM time series forecast models. The optimized models were utilized to forecast the daily COVID- 19 cases for the period 1 July 2020 to 31 July 2020 with 1 to 14 days of lead time. The results showed that the univariate LSTM model was reasonably good for the short-term (1 day lead) forecast of COVID- 19 cases (relative error <20%). Moreover, the multivariate LSTM model improved the medium- range forecast skill (1-7 days lead) after including the weather factors. The study observed that the specific humidity played a crucial role in improving the forecast skill majorly in the West and northwest region of India. Similarly, the temperature played a significant role in model enhancement in the Southern and Eastern regions of India.

Machine learning and deep learning techniques are the branches of Artificial Intelligence (AI) and provide powerful predictive capabilities and superiority over conventional statistical modelling[15]. Despite the high predictive power these algorithms are not widely exposed in public health data analysis. Here, we aim to apply a deep learning algorithm on integrated data sets (epidemiology and climate data) and deployed the multivariate long short-term memory (LSTM) modelling framework used to forecast COVID- 19 trends in India. Previously, the LSTM has been successfully used to forecast dengue and influenza[16,17]. Moreover, previous studies have used relative humidity and absolute humidity to understand their role in COVID-19 transmission. But, studies on the influenza virus showed that specific humidity is an important factor for disease transmission. Hence the present study used the specific humidity along with other climatic factors to understand COVID- 19 transmission and forecast in India.

Data analysis: All the states and Union Territories of India covering latitude (8°N– 38°N) and longitude (68°E–98°E) were considered for the study. Daily counts of laboratory-confirmed COVID- 19 cases of all the states of India were collected from the Ministry of Health and Family Welfare (MoHFW), Government of India from 1 April to 31 July 2020. Similarly, the daily meteorological parameters of a specified period consisting of temperature (minimum, maximum and mean) and specific humidity (SH) were extracted from NCEP/NCAR reanalysis data (https://psl.noaa.gov/). To understand the weather impact on COVID- 19 cases, the cross correlation analysis was carried out to identify the similarities between the lagged meteorological parameters (X) and daily count of COVID-19 cases (Y). The cross- correlation coefficient analysis helps to identify whether the antecedent (lagged) meteorological parameters are useful predictors for modelling the COVID- 19 cases over different states in India. The proposed work was carried out using the Keras implementation of an LSTM network. The computed average relative error was utilized to verify the performance of each model with different lags in predicting the future COVID- 19 cases for the selected states in India.

Spatio-Temporal variability of COVID- 19 cases and climate in India:

Figure-1 elucidates the spatial distribution of monthly COVID-19 cases for different states of India, from which a geographical heterogeneity of cases was observed. Before the onset of the Southwest monsoon (i.e. April and May), there were only 182,143 cumulative cases observed in India, and the majority of the cases were reported from the Western (Maharashtra, Gujarat, Rajasthan), Northern (Madhya Pradesh, Uttar Pradesh, Delhi) and Southern states of India (Tamil Nadu). After the onset of the monsoon, there was a rapid growth in cases (cumulative cases during June and July >1.4 million) and by the end of July, more than 1.6 million cases were reported in India (Figure-1). The maximum number of cases were reported from Maharashtra, Andhra Pradesh, Tamil Nadu, and Karnataka, and moderate cases from the states located in Central, East, and Western parts of India. Similarly, a low number of COVID- 19 cases were reported from the North and Northeast states of India. Figure-2 depicts the Spatio-temporal variation of 2m specific humidity (SH), 2m-maximum temperature (Tmax), 2m-minimum temperature (Tmin), and 2m-mean temperature (Tmean) during April, May, June and July of year 2020 over India. It was observed that the monthly average SH values were very low over Central India (CI), Northwest India (NWI), and North India (NI); moderate SH values over the East and West coast of India; and high over Kerala and Tamil Nadu during the early stage (April and May) of the pandemic. However, the SH has slowly increased from South to North during the monsoon season (June and July) and the high values were observed in July over the Central and East India region. The spatial map of maximum temperature show that most of the regions in Central and Northwest India record more than 40°C during the pre-monsoon season and it is reduced to <30°C during the monsoon progress over the South and Northeast India. Similarly, the minimum temperature ranges between 20 and 30°C during the pre-monsoon period and reduced to 20 and 24°C during the onset of monsoon.

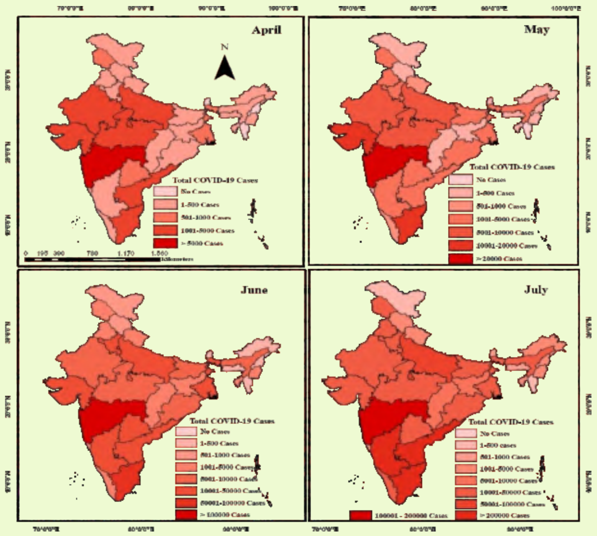


Figure-1:Spatial maps of monthly cumulated COVID- 19 cases over different states in India during pre- monsoon (April and May) and monsoon season (June and July) of the year 2020.

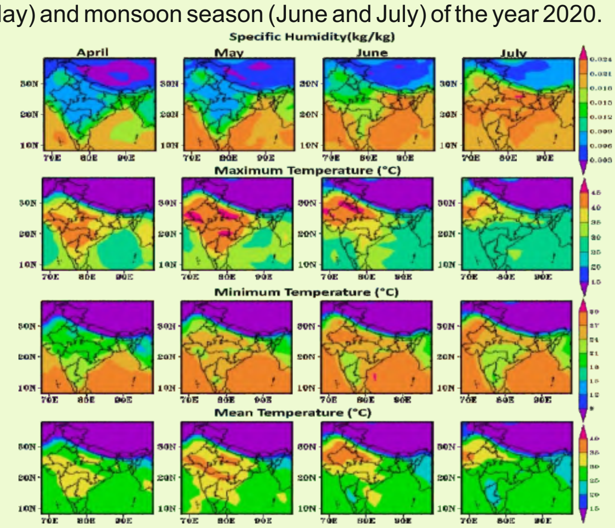
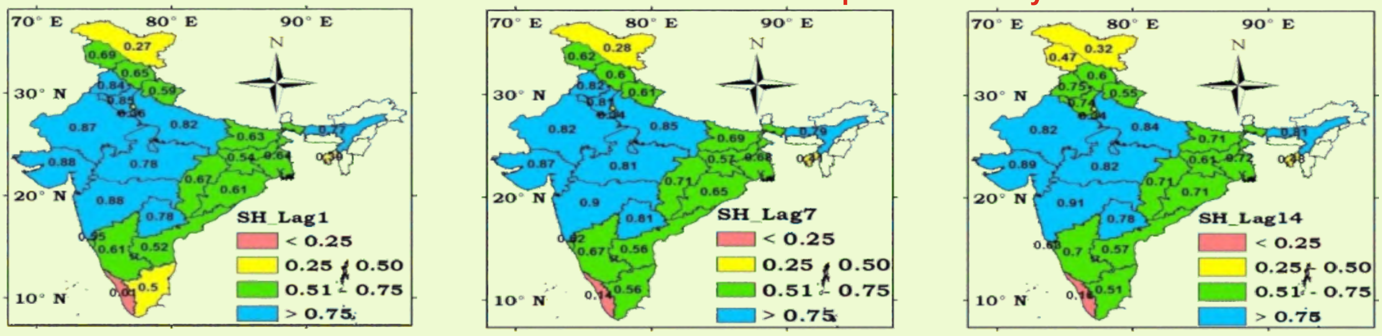


Figure-2 Spatial-temporal variation of surface meteorological parameters (2m- specific humidity, 2m- mean temperature, 2m- maximum temperature, and 2m- minimum temperature) during the pre-monsoon and monsoon season over India

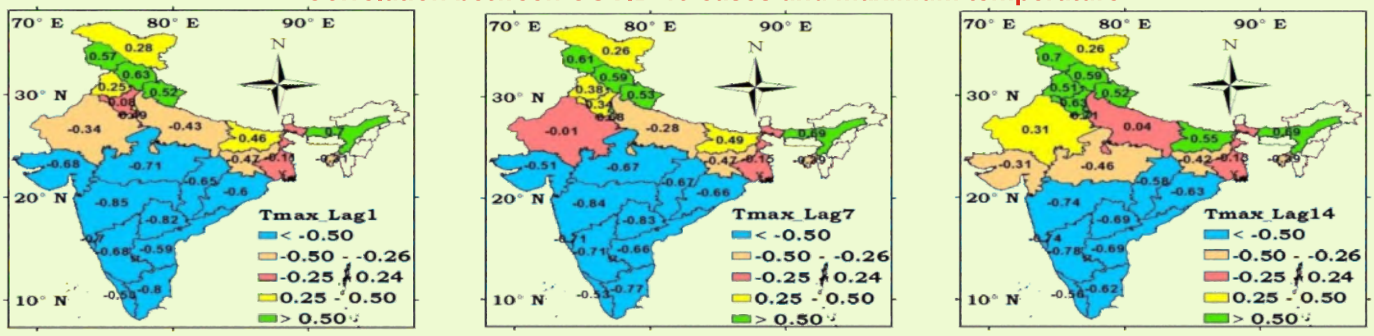
Association between weather and COVID-19:

To understand the weather effect on COVID-19 cases, the lag (0-14 days) correlation coefficients (CC) were computed between daily COVID-19 cases and surface meteorological parameters (SH, Tmax, Tmin, Tmean) for the period 01 April to 31 July 2020. The correlation coefficient values for lag1, lag7, and lag14 over different states of India shown in Figure-3. The correlation maps describe that the specific humidity has a strong positive association with COVID- 19 cases for most of the states in India. Maximum correlation (>0.75) values were found in Central and Northwest India, and moderate correlation (0.5-0.75) values were found in the East coast and some parts of North India (Figure-3). The mean temperature and maximum temperature have a strong negative association with COVID- 19 cases over South India and a positive association with foothills of the Himalayas region. Similarly, minimum temperature also has a strong positive association over the North, Northwest, and Northeast India but a weak negative association was found over the South India region (Figure-3).

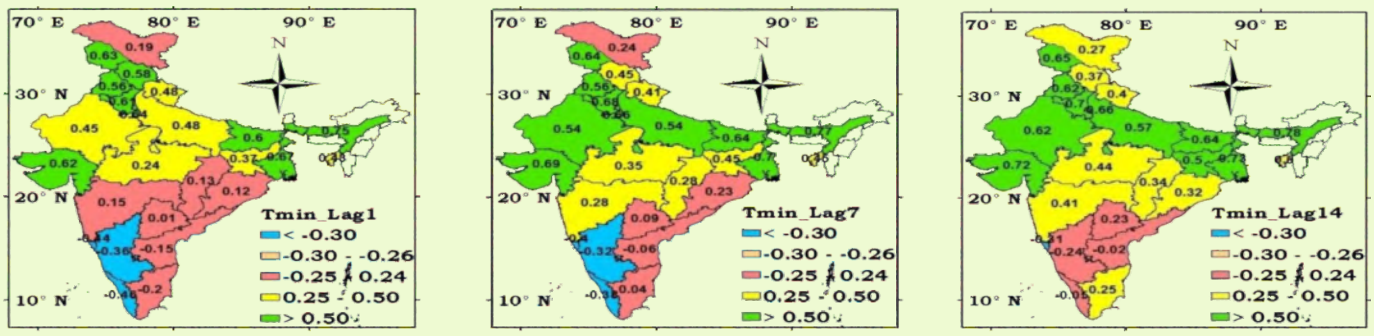
Correlation between COVID-19 cases and specific humidity



Correlation between COVID-19 cases and maximum temperature



Correlation between COVID-19 cases and minimum temperature



Correlation between COVID-19 cases and mean temperature

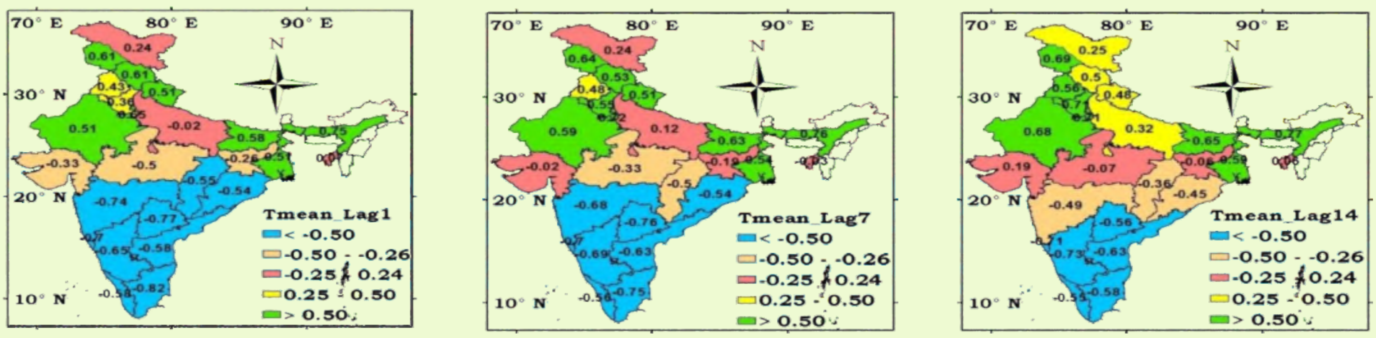


Figure-3: Correlation between confirmed COVID- 19 cases and meteorological parameters (2m-specific humidity, 2m-maximum temperature, 2m-minimum temperature and 2m-mean temperature) during the period 01 April to 31 July 2020.

Univariate LSTM model: The present study utilized the three months (01 April to 30 June 2020) data for training and one month data (01 July to 31 July 2020) for testing the model. The results show that the average relative error (31 days) for univariate LSTM (CTL) is reasonably good (<20%) with lag1 (short term forecast, i.e. 24-hr forecast) for most of the states in India. It is also noticed that the univariate LSTM model outperformed and captured the trend very well for both estimated and observed cases compared to the multivariate LSTM model for the states of Andhra Pradesh, Karnataka, Delhi, Bihar, Odisha, and Uttar Pradesh (Figure 4&5). The COVID-19 cases in Andhra Pradesh and Karnataka were very low during the pre-monsoon season, however more than 0.1 million cases were reported in July from these states in monsoon. The univariate LSTM model which is optimized with the confirmed case data performed well (relative error <15% for Lag1) in capturing the exponential growth of the pandemic. The LSTM model has shown its capability not only in increasing the trend but also in capturing the decreasing trend in Delhi (relative error =15%). Similarly, the multivariate LSTM model optimized with minimum temperature has shown slight improvement than univariate LSTM in lead 2, 3, and 4 days lead forecasts in Delhi (Figure-4c). It is also observed that the exponential growth of cases in Uttar Pradesh and Bihar states and the univariate model well captured the observed values and weather integrated multivariate LSTM model underestimate observed cases (Figure-4d&f).

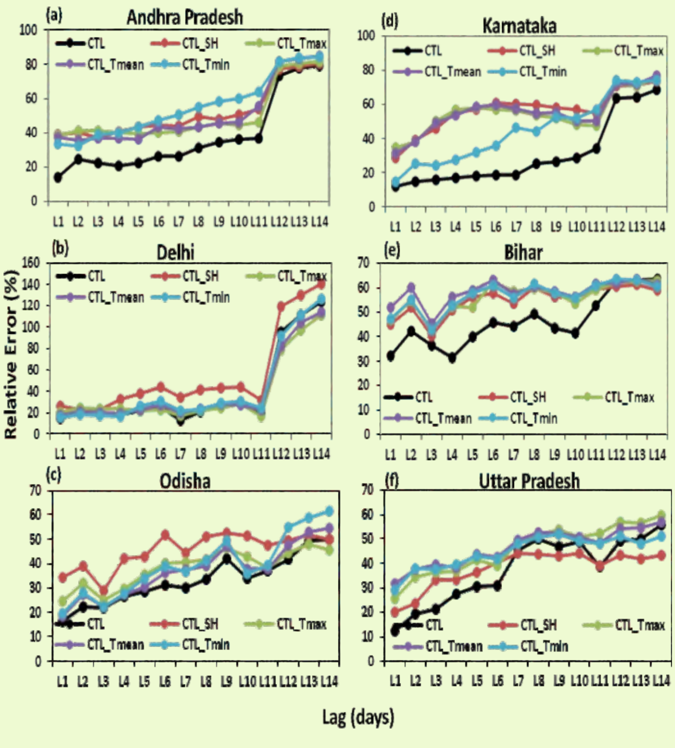


FIGURE-4: Skill (Average relative error) of univariate (CTL) and multivariate (CTL_SH, CTL_Tmax,CTL_Tmin, CTL_Tmean) LSTM models during test period (1 to 31 July 2020) for states of Andhra Pradesh, Karnataka, Delhi, Bihar, Odisha and Uttar Pradesh. L1 to L14 signifies 1 to 14 days of lag data utilized for

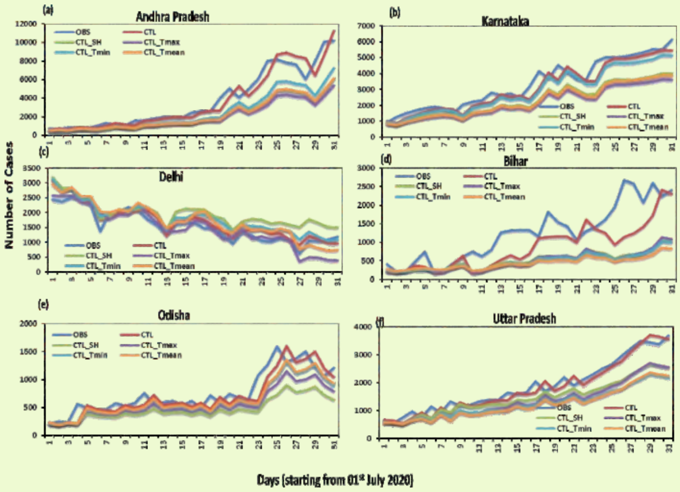


FIGURE-5: Time series data of COVID- 19 cases forecasted by univariate (CTL) and multivariate (CTL_SH, CTL_Tmax, CTL_Tmin, CTL_Tmean) LSTM models during the test period (1 July to 31 July 2020) for the states of Andhra Pradesh, Karnataka, Delhi, Bihar, Odisha and Uttar Pradesh.

Multivariate LSTM model: The states (Maharashtra, Madhya Pradesh, Gujarat, Rajasthan, Haryana, and Punjab) located in West, Northwest India, shown excellent forecasting skill for the multivariate LSTM model compared to the univariate LSTM model. It was observed that the correlation coefficient between specific humidity and COVID- 19 cases was significant in these states. Among all the states, Maharashtra reported the highest number of COVID- 19 cases in India. The multivariate LSTM model (CTL_SH) with specific humidity shown better performance (relative error <8%) with lag7 data (Figure 6a). The forecasting plot (with one-week advance data) shows that the models with other weather variables (CTL, CTL_Tmax, CTL_Tmin, and CTL_Tmean) were overestimating the daily cases whereas the specific humidity (CTL_SH) followed the observed trend and close to the observed data (Figure 8a). Similarly, the forecast skill was adequate with the specific humidity for the states of Gujarat (lag1), Madhya Pradesh (lag3), Rajasthan (lag3), Haryana (lag1), and Punjab (lag5) (Figure- 7b-f).In the case of high humid regions (Kerala, Tamil Nadu, and West Bengal) the forecast skill is improved with the multivariate LSTM model which is optimized with the temperature data. The forecast skill was outperformed with lead 1 (relative error <10%) for Tamil Nadu and West Bengal states and the skill is improved with the maximum and mean temperature. However, in Kerala, the forecast skill was slightly low (relative error between 20% and 30%) with all variables, and a slight improvement was observed in the model which was optimized with the minimum temperature.

Thus the current newsletter helps the general public to understand the relationship between climatic factors and the spread of SARS-CoV-2 in different regions of India. The evaluations and research outcomes discussed in this newsletter support the scientists in designing preventive measures and framing of appropriate mitigation policies, against the spread of SARS-CoV-2, on basis of local climatic profiles.

Univariate LSTM model: The present study utilized the three months (01 April to 30 June 2020) data for training and one month data (01 July to 31 July 2020) for testing the model. The results show that the average relative error (31 days) for univariate LSTM (CTL) is reasonably good (<20%) with lag1 (short term forecast, i.e. 24-hr forecast) for most of the states in India. It is also noticed that the univariate LSTM model outperformed and captured the trend very well for both estimated and observed cases compared to the multivariate LSTM model for the states of Andhra Pradesh, Karnataka, Delhi, Bihar, Odisha, and Uttar Pradesh (Figure 4&5). The COVID-19 cases in Andhra Pradesh and Karnataka were very low during the pre-monsoon season, however more than 0.1 million cases were reported in July from these states in monsoon. The univariate LSTM model which is optimized with the confirmed case data performed well (relative error <15% for Lag1) in capturing the exponential growth of the pandemic. The LSTM model has shown its capability not only in increasing the trend but also in capturing the decreasing trend in Delhi (relative error =15%). Similarly, the multivariate LSTM model optimized with minimum temperature has shown slight improvement than univariate LSTM in lead 2, 3, and 4 days lead forecasts in Delhi (Figure-4c). It is also observed that the exponential growth of cases in Uttar Pradesh and Bihar states and the univariate model well captured the observed values and weather integrated multivariate LSTM model underestimate observed cases (Figure-4d&f).

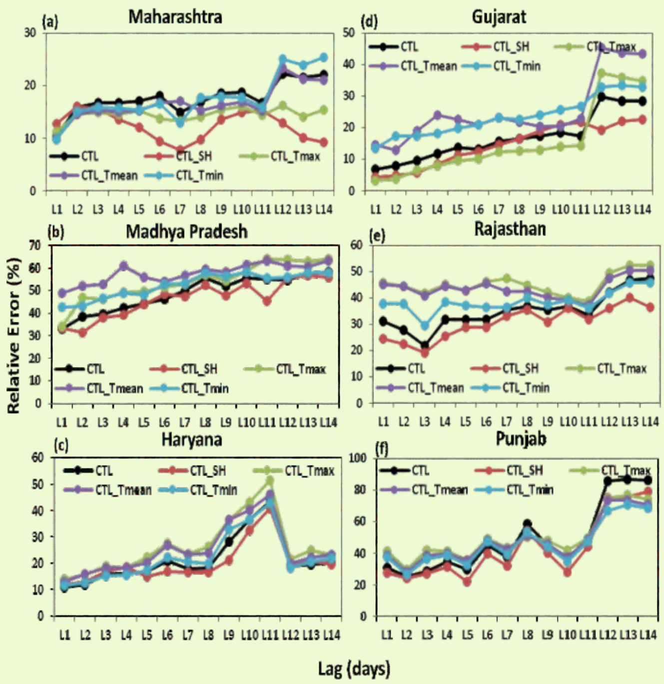


FIGURE-6: Skill (Average relative error) of univariate (CTL) and multivariate (CTL_SH, CTL_Tmax,CTL_Tmin, CTL_Tmean) LSTM models during test period (1 to 31 July 2020) for Maharashtra, Gujarat, Madhya Pradesh, Rajasthan, Haryana and Punjab. L1 to L14 signifies 1 to 14 days of lag data used for forecasting of next day COVID-19 cases

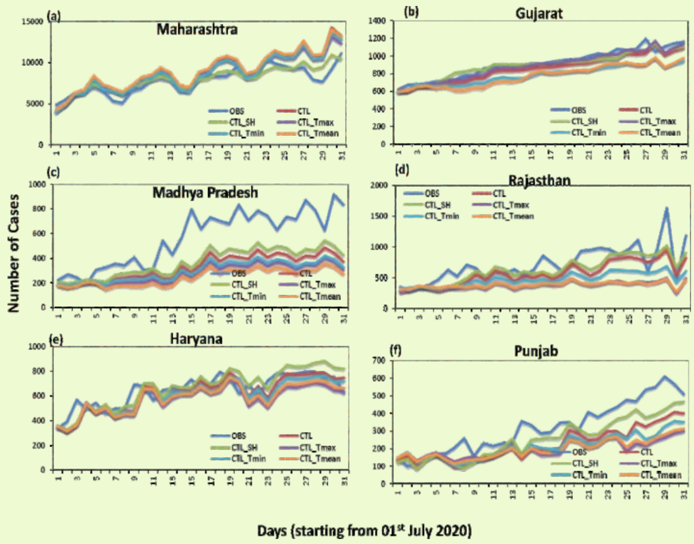


FIGURE-7: Time series data of COVID- 19 cases forecasted by univariate (CTL) and multivariate (CTL_SH, CTL_Tmax, CTL_Tmin, CTL_Tmean) LSTM models during the test period (1 July to 31 July 2020) for Maharashtra, Gujarat, Madhya Pradesh, Rajasthan, Haryana and Punjab

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CSIR-Indian Institute of Chemical Technology (CSIR-IICT) - Hyderabad is an ISO 9002 certified R & D institute in India. The institute had its origin as Central Laboratories for Scientific and Industrial Research (CLSIR), established in 1944 by the then Government of Hyderabad State. In 1956, CLSIR came under the aegis of the CSIR and was renamed as Regional Research Laboratories - Hyderabad (RRL-H). RRL-H was rechristened as Indian Institute of Chemical Technology (IICT), in 1989, recognizing multi-disciplinary activities and the expertise developed by the institute in the area of Chemical Technology.

Major areas of research are drugs, organic intermediates, oils organic coatings and polymers, coal, chemical engineering, design engineering and biology.

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