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Effect of weather on COVID-19 spread in the US: A prediction model for India in 2020

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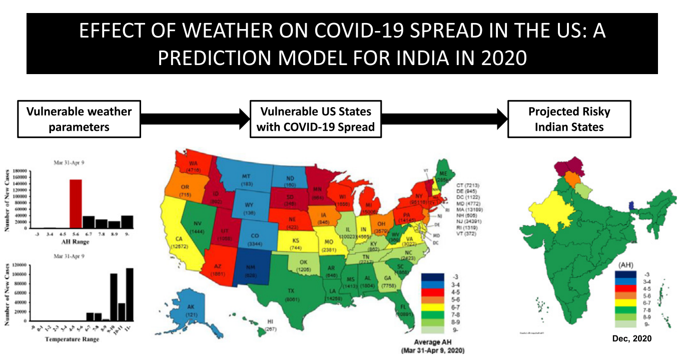
HIGHLIGHTS

- First study that clarifies the relationship between weather parameters and COVID-19 spread
- Distribution modeling of new cases in the US with respect to temperature and absolute humidity
- Vulnerable absolute humidity range identified for COVID-19 spread in US states
- US based vulnerable weather parameters used to predict risky states in India in the upcoming months in 2020

GRAPHICAL ABSTRACT



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ABSTRACT

The effect of weather on COVID-19 spread is poorly understood. Recently, few studies have claimed that warm weather can possibly slowdown the global pandemic, which has already affected over 1.6 million people worldwide. Clarification of such relationships in the worst affected country, the US, can be immensely beneficial to understand the role of weather in transmission of the disease in the highly populated countries, such as India. We collected the daily data of new cases in 50 US states between Jan 1–Apr 9, 2020 and also the corresponding weather information (i.e., temperature (T) and absolute humidity (AH)). Distribution modeling of new cases across AH and T, helped identify the narrow and vulnerable AH range. We validated the results for 10-day intervals against monthly observations, and also worldwide trends. The results were used to predict Indian regions which would be vulnerable to weather based spread in upcoming months of 2020. COVID-19 spread in the US is significant for states with $4 < AH < 6$ g/m^3 and number of new cases > 10,000, irrespective of the chosen time intervals for study parameters. These trends are consistent with worldwide observations, but do not correlate well with India so far possibly due the total cases reported per interval < 10,000. The results clarify the relationship between weather parameters and COVID-19 spread. The vulnerable weather parameters will help classify the risky geographic areas in different countries. Specifically, with further reporting of new cases in India, prediction of states with high risk of weather based spread will be apparent.

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1. Introduction

COVID-19 or the novel coronavirus is a rapidly spreading global pandemic, which as of April 14, 2020 has affected about 2.1 million people and claimed over 126,000 deaths globally (Johns Hopkins, 2020). After originating in Wuhan, China, it led to a massive loss of life and work in European countries such as Italy, France, and Spain. While there is no treatment available, the focus has been to contain the spread through national lockdowns and quarantines (Hamzelou, 2020). The current epicenter of COVID-19 is the US with over 600,000 cases and 26,000 deaths till April 14, 2020, with a rate of increase in reported new cases of over 30,000/day. While China has been able to effectively control the spread since the end of Feb, 2020 (Kupferschmidt and Cohen, 2020), the entire world has the eyes on the second most populated country, India, which houses about 17.7% of the world population. Till 14th April, there has been a total of 11,490 cases and 398 reported deaths all over India, with increase in reported new cases of over 1000/day. This worsening situation warrants immediate study of the

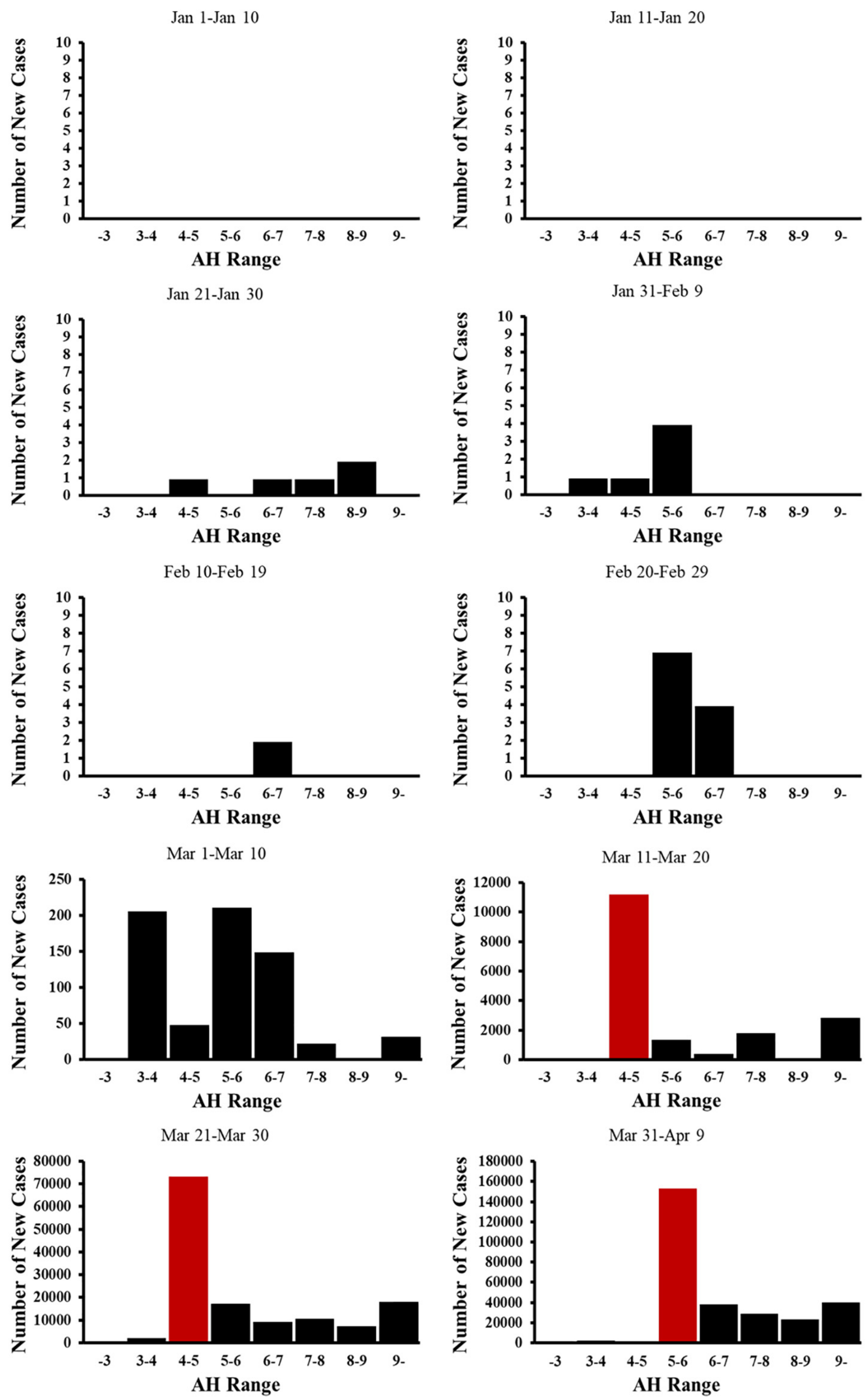

Fig. 1. Number of new cases of COVID-19 versus AH across 10-day intervals between Jan 1 and Apr 9, 2020 in the US. The vulnerable AH ranges are in red color. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

emerging evidence and patterns about the disease to contain it effectively, and to also be prepared for future outbreaks.

Recent studies have suggested that the spread of COVID-19 is expected to be more in the cold and temperate climate as compared to the warm and tropical climate, consistent with the behavior of a seasonal respiratory flu virus (Bloom-Feshbach et al., 2013). Multiple viruses from the Coronaviridae family, including the SARS CoV-1 and MERS CoV, also demonstrate seasonality and preference for low temperature and humidity (Casanova et al., 2010). The stability of SARS CoV-2, which is responsible for COVID-19, has been reported to be similar to that of SARS CoV-1 on various types of inanimate surfaces in specific weather conditions (van Doremalen et al., 2020). Sajadi et al. (2020) investigated the average monthly temperature and relative humidity in different parts of the world from Nov, 2019 to end of Feb, 2020

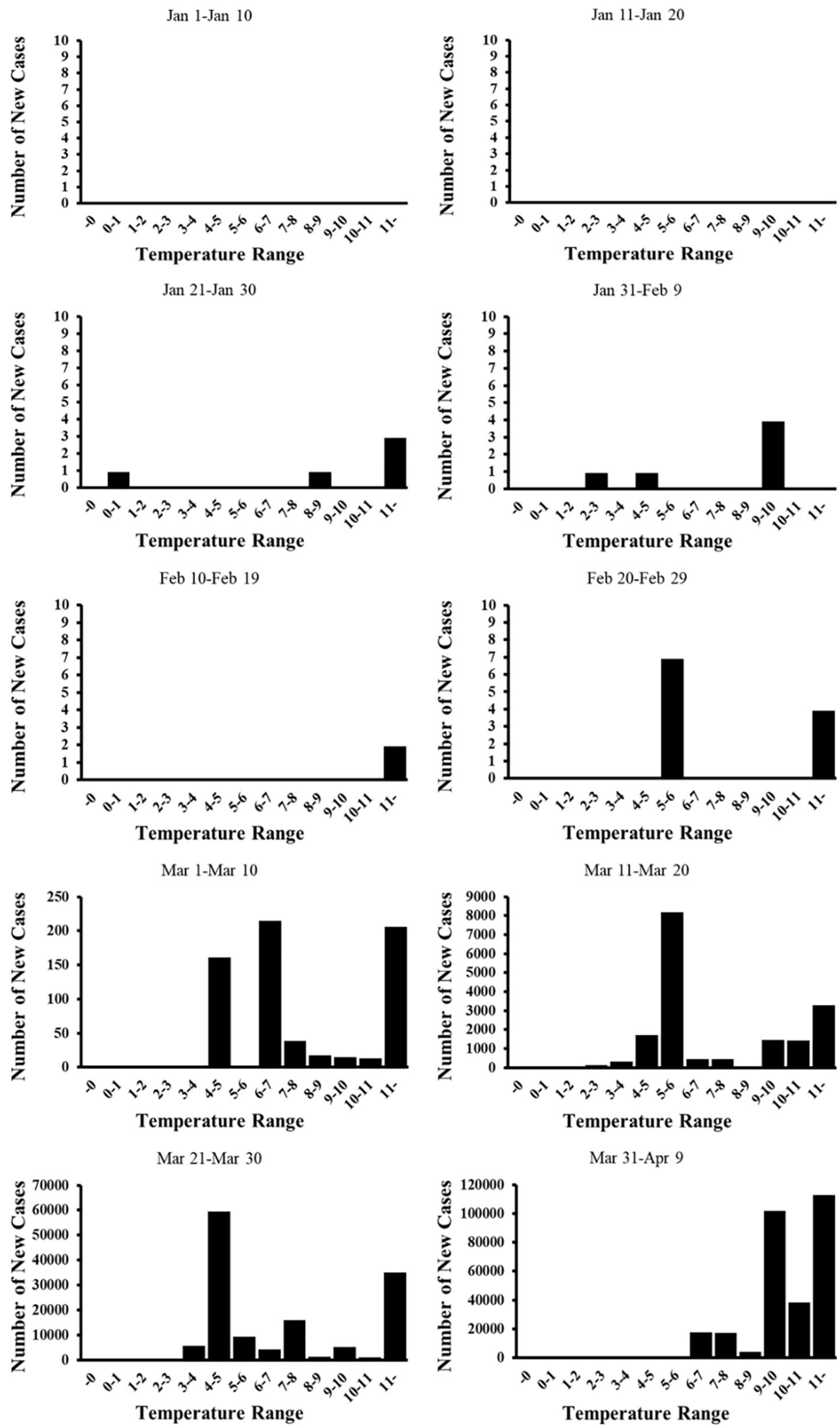

Fig. 2. Number of new cases of COVID-19 versus T (°C) across 10-day intervals between Jan 1 and Apr 9, 2020 in the US.

and observed the spread mainly in the countries lying in between latitudes 30–50° North, and having relatively similar weather patterns (temperature in the range of 5–11 °C and relative humidity in the range of 47–79%). In another study, Oliveiros et al. (2020) investigated the effect of temperature, humidity, precipitation, and wind speed on the rate of COVID-19 spread in China between Jan 23 to Mar 1, 2020. The rate of increase and doubling time of the number of cases were determined and compared with the weather variables using linear regression analysis. The results indicated that the doubling time of the number of cases was positively correlated with temperature and negatively correlated with humidity. However, these correlation values were very low ($R^2 < 0.18$) to draw any strong conclusion. Precipitation and wind speed were found to exhibit no correlation with the doubling time of the number of cases. Bukhari and Jameel (2020) studied the effect of humidity and temperature on the emerging worldwide cases of COVID-19 between Jan 20 and Mar 19, 2020. The results indicated absolute humidity (AH) to be a better metric than relative humidity (RH) and temperature (T) to study the spread. It was also observed that 90% of the new cases until 21 Mar 2020 had occurred within a specific range of AH (4 to 9 g/m^3) and T (3 to 17 °C). While this information on the global trend is valuable, to date, no relationships between weather and COVID-19 spread have been established for any specific country. Further studies at the local level may help improve our understanding on the realistic effect of weather on the viral spread.

In the current work, we attempted to clarify the role of weather parameters on the possible viral spread in the US. We characterized the distribution of new cases reported between Jan 1 and Apr 9, 2020 across all US states marked with varying daily weather parameters. Through statistical analysis, we were able to identify the vulnerable ranges of weather parameters and validate them for different time intervals, and against worldwide findings. Using our results, we predicted the risky states in India, which could possibly be more vulnerable for the transmission of COVID-19 in the recent and upcoming months in 2020. We anticipate our findings to not only be beneficial to the policymakers in US and India, but also countries which are going to experience vulnerable weather conditions in 2020, to prepare medically, socially, and financially against mass spreading of COVID-19.

2. Data and methods

2.1. Weather data

Daily Temperature (T) in °C and Relative Humidity (RH) in % were obtained from Visual Crossing Corp., Hamburg, Germany, which uses the National Centers for Environmental Information (NCEI) library (National Oceanic and Atmospheric Administration, 2019) from Jan 1 to Apr 9, 2020. T and RH data were extracted for 50 US states. Absolute Humidity (AH) in g/m^3 was calculated using the Clausius Clapeyron equation (Herrmann and Bucksch, 2014) described as follows:

$$AH = \frac{6.112 * e^{\left(\frac{17.67 * T}{T + 243.5}\right)} * RH * 2.1674}{273.15 + T} \quad (1)$$

The average of AH and T were estimated for each US state for 10-day intervals (e.g., Jan 1–Jan 10, 2020) and also monthly for further analysis. Additionally, the available and projected monthly averages of AH and T across Indian states were estimated from Jan till Dec, 2020 from the daily data using the NCEI repository (National Oceanic and Atmospheric Administration, 2019).

2.2. Covid-19 cases

Dataset on the number of daily new cases around the world were obtained from the John Hopkins University Coronavirus Resource Center repository (Johns Hopkins, 2020) until April 9, 2020. The state wise total number of new cases in the US was extracted for 10-day intervals and monthly starting Jan 1, 2020.

2.3. Data analysis

For all US states, the AH versus new cases and T versus new cases, across all 10-day intervals were sorted and rearranged to obtain the sum of new cases versus specific AH ranges (i.e., <3, 3–4, 4–5, 5–6, 6–7, 7–8, 8–9, and 9>) and also the sum of new cases versus specific T ranges (i.e., <0, 0–1, 1–2, 2–3, 3–4, 4–5, 5–6, 6–7, 7–8, 9–10, 10–11, and 11>), respectively. These specific ranges were selected based on earlier claims of weather based worldwide spread (Bukhari and Jameel, 2020), and to compare our results with existing literature

Table 1
Average and standard deviations of the AH, and new cases reported in different US states in the months of Jan, Feb, and Mar, 2020.

US state	AH						Total new cases		
	Jan, 2020	Dev (±)	Feb, 2020	Dev (±)	Mar, 2020	Dev (±)	Jan, 2020	Feb, 2020	Mar, 2020
Alabama	7.60	1.76	8.22	2.00	12.13	2.79	0	0	899
Alaska	3.58	1.71	5.13	0.21	4.02	0.46	0	0	114
Arizona	5.60	0.82	5.12	1.35	7.06	1.74	1	0	1156
Arkansas	6.18	0.52	5.93	0.85	9.15	1.48	0	0	473
California	7.36	1.07	6.25	0.62	7.13	0.20	2	10	7126
Colorado	2.43	0.45	2.57	0.19	3.88	0.47	0	0	2311
Connecticut	3.85	0.55	3.70	0.30	4.44	0.39	0	0	2571
Delaware	4.97	0.89	5.07	0.81	6.62	1.33	0	0	264
District of Columbia	4.99	0.92	4.91	0.74	6.55	1.50	0	0	401
Florida	9.12	2.84	9.81	2.31	13.24	2.84	0	0	5473
Georgia	6.55	1.93	7.00	1.52	9.85	2.19	0	0	2808
Hawaii	14.82	0.71	13.49	0.52	14.74	1.26	0	0	175
Idaho	4.34	0.93	3.53	0.59	4.42	0.33	0	0	340
Illinois	4.71	0.34	4.46	0.24	7.28	1.53	1	1	5054
Indiana	4.46	0.41	4.03	0.64	6.24	0.95	0	0	1786
Iowa	3.05	0.74	3.02	0.27	5.21	0.86	0	0	424
Kansas	3.80	0.36	3.65	0.30	6.15	1.37	0	0	372
Kentucky	5.01	0.66	4.74	0.74	7.01	1.39	0	0	479
Louisiana	9.49	1.97	9.51	2.45	13.87	2.63	0	0	4025
Maine	7.29	2.35	7.53	1.77	10.64	2.60	0	0	275
Maryland	4.85	0.70	4.96	0.72	6.46	1.10	0	0	1413
Massachusetts	3.71	0.50	3.52	0.28	4.23	0.50	0	1	5751
Michigan	3.58	0.24	2.95	0.41	4.46	0.48	0	0	6498
Minnesota	2.51	0.67	2.31	0.43	4.14	0.66	0	0	576
Mississippi	7.81	1.62	7.56	1.55	11.79	2.41	0	0	847
Missouri	4.25	0.58	4.02	0.38	6.46	1.26	0	0	1051
Montana	2.77	0.66	2.70	0.12	2.85	0.46	0	0	171
Nebraska	3.19	0.83	3.20	0.36	5.18	0.99	0	0	145
Nevada	8.08	0.52	7.70	1.32	8.65	0.40	0	0	1012
New Hampshire	7.44	1.10	6.29	0.54	7.12	0.31	0	0	314
New Jersey	4.24	0.69	4.29	0.78	5.38	0.72	0	0	16,636
New Mexico	2.89	0.60	3.17	0.41	4.01	0.87	0	0	237
New York	3.39	0.46	3.08	0.27	4.03	0.36	0	0	66,665
North Carolina	6.61	2.19	6.71	1.03	8.63	2.13	0	0	1313
North Dakota	2.28	1.09	2.62	0.61	3.61	0.51	0	0	109
Ohio	4.39	0.50	3.95	0.61	6.10	1.01	0	0	1933
Oklahoma	5.44	0.16	4.73	0.13	8.18	1.91	0	0	481
Oregon	6.70	0.94	5.76	0.52	5.67	0.58	0	1	605
Pennsylvania	4.04	0.64	3.98	0.64	5.33	0.91	0	0	4155
Rhode Island	4.13	0.66	3.96	0.33	4.66	0.58	0	0	408
South Carolina	7.37	2.39	7.51	1.63	10.36	2.23	0	0	925
South Dakota	2.75	1.17	2.97	0.49	4.21	0.55	0	0	101
Tennessee	5.71	0.85	5.48	0.83	8.02	1.71	0	0	1917
Texas	8.19	1.02	7.38	1.40	12.61	1.74	0	0	3147
Utah	3.99	0.83	3.35	0.35	4.52	0.19	0	0	798
Vermont	3.03	0.23	2.63	0.12	3.43	0.02	0	0	256
Virginia	5.66	1.23	5.58	0.71	7.25	1.92	0	0	1020
Washington	6.57	1.08	5.84	0.61	5.48	0.86	1	6	4916
West Virginia	8.89	2.51	8.88	2.17	12.10	2.83	0	0	145
Wisconsin	3.14	0.52	2.59	0.46	4.53	0.58	0	0	1230
Wyoming	2.42	0.45	2.17	0.08	3.36	0.34	0	0	94
Total monthly cases							**5**	**19**	**161,395**

(Bukhari and Jameel, 2020; Sajadi et al., 2020). The vulnerable ranges of AH (in g/m^3) and T (in °C), which led to the highest number of new cases, were identified and compared with worldwide trends. Based on our findings, AH was employed as a superior prediction metric, and its relationship with the monthly average number of new cases was studied across all US states, to understand if the time interval of studied parameters has any effect on the weather and spread relationship. Finally, the vulnerable AH range determined for the US states was used to predict which Indian states would be more vulnerable for the transmission of the disease. The available and projected AH and T data of each Indian state was averaged over each month starting Jan 1, 2020 and ending Dec 31, 2020, and the vulnerable states across 12 months in 2020 were identified.

3. Results

3.1. Absolute humidity (AH) versus new cases reported in the US

Between Jan 1 and Feb 29, 2020, in any of the first six 10-day intervals, the number of new cases in the US states, lying in any of the AH ranges, was <10 (Fig. 1). The total number of new cases reported during this time were only 24, all lying in states with $3 < AH < 9$ g/m^3 and no specific distribution trend. Between Mar 1 and Mar 10, 2020, 95% of the 684 new cases were still reported in the US states within the broad AH range of 3–9 g/m^3. The number of new cases increased exponentially from Mar 10, 2020 to Apr 9, 2020, by 298,893. Over 50% of these new cases were observed in states with a narrow range of AH between 4 and 6 g/m^3, and <15% were in states with AH > 9 g/m^3. Less than 0.5% of the new cases were reported in states with AH < 3 g/m^3. Additionally, it was observed that during this time period, the minimum number of new cases reported for any 10-day study interval was over 10,000.

3.2. Temperature (T) versus new cases reported in the US

Among the 24 cases reported within US between Jan 1 and Feb 29, 2020 (i.e., first six 10-day intervals), their distribution as per the ranges of T in different states did not follow any trend (Fig. 2). During Mar 1–Mar 30, 2020, over 70% of the new cases were in states with temperatures between 4 and 11 °C. In the recent Mar 31–Apr 9, 2020 interval, approximately 60% new cases were in the states within 4 °C–11 °C range. No cases were reported in any state with temperatures below 4 °C throughout. As any narrow vulnerable range of temperature could not be identified, we considered temperature to be a poor metric to study the weather based spread in the US.

3.3. Absolute humidity (AH) versus new cases reported across different US states monthly

The average and standard deviations of the AH reported for different US states in Jan, Feb, and Mar in 2020 were determined, along with the total number of new cases in these months (Table 1). In Jan, 2020, the total number of first few cases reported across all US states were 5, with 2 cases in California (with AH = 7.36 ± 1.07 g/m^3), and 1 case each in Arizona (with AH = 5.60 ± 0.82 g/m^3), Illinois (with AH = 4.71 ± 0.34 g/m^3), and Washington (with AH = 6.57 ± 1.08 g/m^3). Except California, all states had $4 < AH < 6$ g/m^3 in Jan, 2020. In Feb, 2020, 19 new cases were reported in total, with 10 lying in California (with AH = 6.25 ± 0.62 g/m^3), and 6 in Washington (with AH = 5.84 ± 0.61 g/m^3). One new case each were in Illinois, Massachusetts, and Oregon, with average $4 < AH < 6$ g/m^3. The number of new cases increased exponentially by end of Mar, 2020 up to 161,807. Over 40% of these new cases were reported in New York (with AH = 4.03 ± 0.36 g/m^3) followed by 10% in New Jersey (with AH = 5.38 ± 0.72 g/m^3). This finding is consistent with the observation of over 50% new cases in states with $4 < AH < 6$ g/m^3 in 10-day blocks when total number of new cases reported were >10,000. Also, both these states did not have any cases till end of Feb, 2020. Out of the states which already had cases by end of Feb, 2020, cumulatively, they shared <15% of the total new cases reported in Mar, 2020. On excluding New York, if all the new cases in states with $4 < AH < 6$ g/m^3 were summed for Mar 1–Mar 30, 2020, they still represented >50% of the new cases. Thus, the time interval for which parameters were studied was observed to not affect the relationship between AH and number of new cases from the viral spread.

Between Mar 31, 2020 and Apr 9, 2020, the total new cases reported were 299,601 (i.e., 1.85 times of the total new cases reported between Mar 1 and Mar 30, 2020). Fig. 3 shows the distribution of the new cases during Mar 31–Apr 9, 2020 across different US states. Each state was color coded based on the AH range which they fell into in this 10-day block. 52.7% of the new cases were reported in states with $4 < AH < 6$ g/m^3. These vulnerable zones included New York, Connecticut,

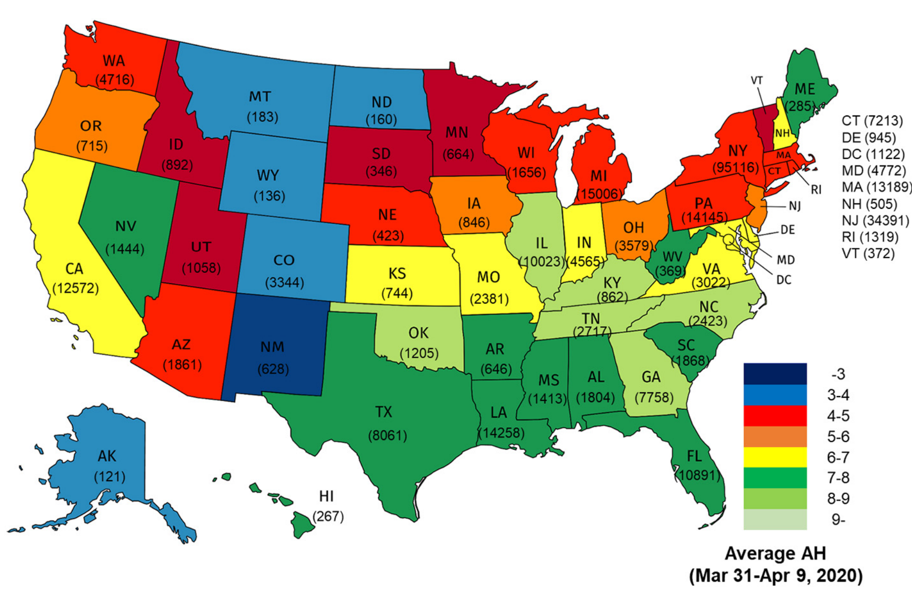

Fig. 3. Number of new cases of COVID-19 during Mar 31–Apr 9, 2020 in different US states, categorized as per absolute humidity (AH) ranges.

Idaho, Massachusetts, Michigan, Minnesota, Rhode Island, South Dakota, Utah, and Wisconsin. States with average AH > 9 g/m^3 (i.e., Nevada, Texas, Arkansas, Louisiana, Mississippi, Alabama, Florida, South Carolina, West Virginia, Hawaii, and Maine) had 14% of the total new cases. States with AH < 4 g/m^3 (i.e., New Mexico, Alaska, Colorado, Wyoming, Montana, and North Dakota) had only 1.5% of the total new cases.

3.4. Prediction of weather based spreading risk in Indian states

The AH ranges studied for the US states were used to classify the Indian states across the different months in 2020 (Fig. 4), and to predict the states lying in vulnerable AH range between 4 and 6 g/m^3. A majority of the Indian states were reported, based on the available and

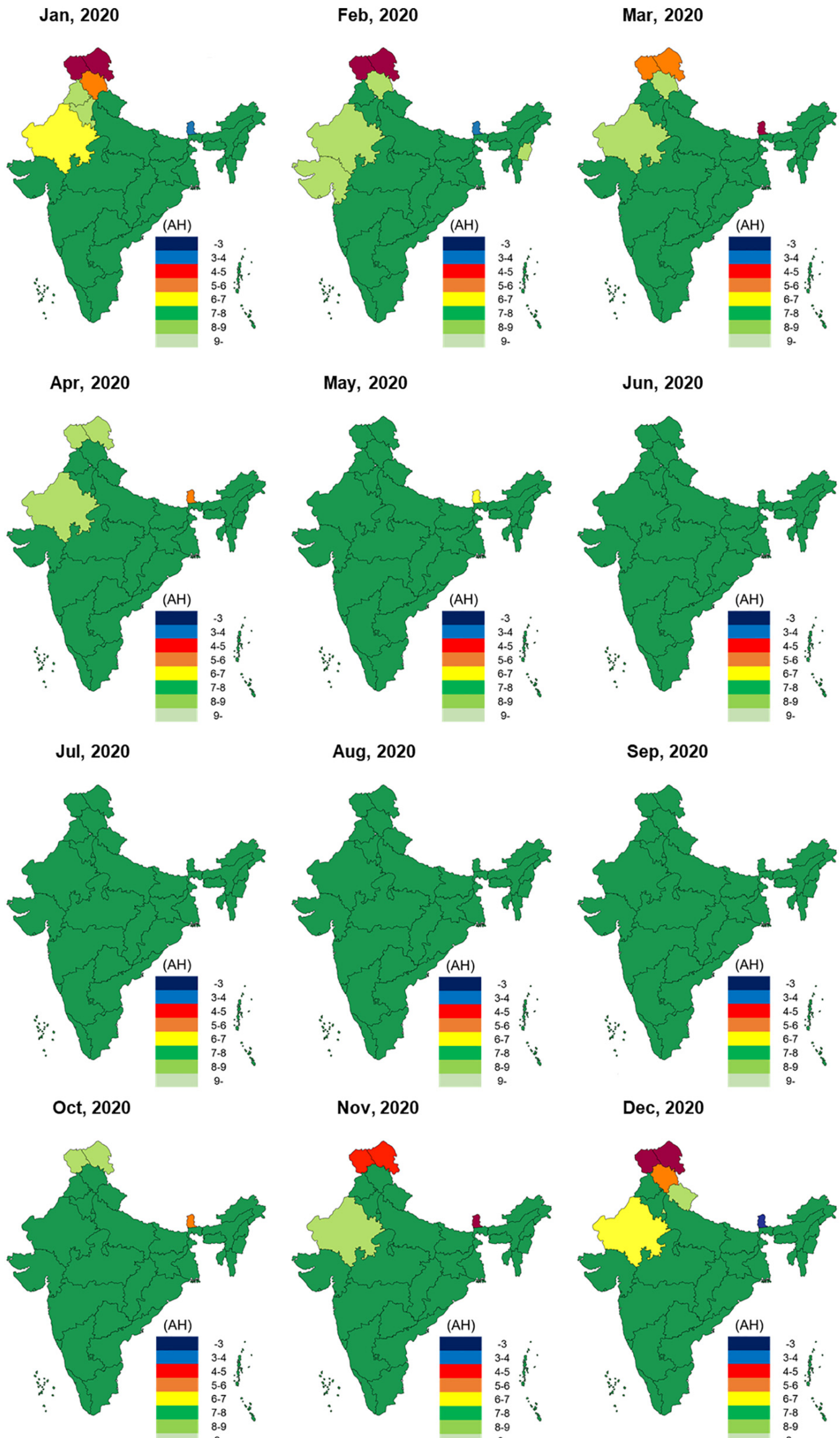

Fig. 4. Classification of Indian states in different AH ranges for Jan–Dec, 2020 as per the US based observations.

projected weather data, to experience AH > 9 g/m^3 throughout 2020. In Jan, 2020, the states namely Sikkim, Jammu and Kashmir, Himachal Pradesh, and Rajasthan were found to lie in the ranges of 3 < AH < 4 g/m^3, 4 < AH < 5 g/m^3, 6 < AH < 7 g/m^3, and 7 < AH < 8 g/m^3 respectively. Chandigarh and Haryana were in the same range of 8 < AH < 9 g/m^3. Based on the vulnerable AH range identified for the US, Jammu and Kashmir was found to be the only Indian state to lie in such a range. Going from Jan, 2020 to Feb, 2020, Jammu and Kashmir was still found to be in the vulnerable AH range of 4 to 6 g/m^3. Also, Sikkim stayed within 3 < AH < 4 g/m^3. Himachal Pradesh and Rajasthan were found to move to an 8 < AH < 9 g/m^3 range, and the new state Gujrat also lied in this same range. In Mar, 2020, Jammu and Kashmir moved to 6 < AH < 7 g/m^3 range and Himachal Pradesh and Rajasthan still lied in 8 < AH < 9 g/m^3 range. However, Sikkim moved from previous 3 < AH < 4 g/m^3 range into vulnerable 4 < AH < 6 g/m^3 range. In Apr, 2020, none of the states were projected to be in the vulnerable 4 < AH < 6 g/m^3 range. In May 2020, except Sikkim, all other states will experience AH > 9 g/m^3. In Jun, 2020 through Sep, 2020, AH across all Indian states are expected to be above 9 g/m^3. In Oct, 2020, Jammu and Kashmir is again expected to come back to 8 < AH < 9 g/m^3 range, and Sikkim to 6 < AH < 7 g/m^3 range. Further in Nov, 2020, Jammu and Kashmir will be again in vulnerable 4 < AH < 6 g/m^3 range along with Sikkim. Finally, in Dec, 2020, Jammu and Kashmir will stay in vulnerable 4 < AH < 6 g/m^3 range and Sikkim will move to AH < 3 g/m^3 range. As the total new cases reported, as of Apr 9, 2020, in India are low (i.e., 6725) and majorly in states with AH > 9 (e.g., Maharashtra and Tamil Nadu), we did not attempt to identify any relationship between AH and new cases within the study timeline.

4. Discussion

This study generated novel findings on the relationship of COVID-19 spread with weather parameters. In the US, once the number of new cases in a 10-day interval went over 10,000, the majority of the cases were found to be reported in states experiencing absolute humidity (AH) in a narrow range of 4 to 6 g/m^3, and temperature (T) in a wider range of 4 °C–11 °C. Considering AH as a better parameter than T to study the relationship between weather and COVID-19 spread, we found that the vulnerable 4 < AH < 6 g/m^3 range for 10-day intervals were generalizable to monthly study intervals. Also, our results lied within the literature reported AH ranges worldwide (Bukhari and Jameel, 2020; Chan et al., 2011). Assuming the US model to represent the world findings, we classified risky Indian states with expected 4 < AH < 6 g/m^3 through all months of 2020.

The distribution of new cases in the US in 10-day intervals across the AH and T ranges, are very similar to recent findings from studies investigating worldwide trends (Araujo and Naimi, 2020; Bukhari and Jameel, 2020; Cowling and Aiello, 2020; Hunter, 2020; Le Page, 2020; Sajadi et al., 2020). Sajadi et al. (Sajadi et al., 2020) observed that the COVID-19 spread was majorly supported by weather parameters in the ranges 5 °C < T < 11 °C and 3 < AH < 8 g/m^3. The vulnerable ranges identified in the current study lie within these ranges. In another study by Bukhari and Jameel (2020), majority of the new cases around the world were found to be in countries with 3 °C < T < 17 °C and 4 < AH < 9 g/m^3. These US based findings from our study are consistent with these worldwide observations.

Extension of this investigation to other countries may further our understanding on generalizability of the vulnerable weather parameters. With respect to India, the predictions for the states exhibiting vulnerable weather conditions cannot be correlated with the number of new cases in these states. It is possible that due the very low number of total cases reported, as of April 9, 2020 (i.e., 6725), the effect of any weather based spread is not apparent. This observation is consistent with our study results, where we did not see any correlation between weather parameters and the cases in the US until the number of new cases per interval was over 10,000.

This study has a few limitations which should be acknowledged. Out of a large number of possible weather parameters experienced around the globe, only a few were considered specific to the US. Caution should be utilized when extrapolating these results beyond the US based weather parameters considered in this study. It should be mentioned that the role of weather in affecting the transmission rates can only be termed as correlation and not causation at this point in time. Several other factors might have also acted as confounding factors in our correlational observations such as demographic variations, healthcare infrastructure, and social policies like lockdowns. Future studies will investigate the combined effect of such variables to fully understand the transmission dynamics.

In conclusion, this study provides important information on the effect of weather on COVID-19 spread. This information can lead to a better understanding of weather parameters which are vulnerable for spread of the virus in the US. Lastly, the results can help predict vulnerable regions with high chances of weather based spread in already effected countries, and countries with high population, such as India, with recent and rapidly rising spread.

CRediT authorship contribution statement

Sonal Gupta: Conceptualization, Data curation, Software. **Gourav Singh Raghuwanshi:** Writing - original draft, Software, Validation. **Arnab Chanda:** Supervision, Visualization, Investigation, Writing - review & editing.

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.

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