Geospatial Health 2023; volume 18:1213

Geospatial analysis in the United States reveals the changing roles of temperature on COVID-19 transmission

Ruiwen Xiong,[1] Xiaolong Li[2]

[1]Buchholz High School, Gainesville, FL; [2]Department of Environmental and Global Health, College of Public Health and Health Professions, University of Florida, Gainesville, FL, USA

Abstract

Environmental factors are known to affect outbreak patterns of infectious disease but their impact on the spread of COVID-19 along with the evolution of this relationship over time and in different regions is unclear. This study utilized three years of data on COVID-19 cases in the continental United States (US) from 2020 to 2022 together with the corresponding weather data. We used regression analysis to investigate the weather impact on COVID-19 spread in mainland US and estimated the change over space and time. It was found that temperature exhibited a significant and negative correlation for most of the US while relative humidity and precipitation showed either positive or negative relationships. By regressing temperature factors with the spreading rate of COVID-19 waves, we found the temperature change can explain over 20% of the spatial-temporal variation, with a significant and negative response between temperature change and the rate of spread. The pandemic in continental US during the 2020-2022 period was characterized by seven waves, with different transmission rates and wave peaks concentrated in seven time periods. When repeating the analysis for waves in the seven periods and nine climate zones, we found that the temperature impact changed over time and space, possibly due to virus mutation, changes in population susceptibility, social behaviour and control measures. This impact became weaker in 6 of 9 climate zones from the beginning of the pandemic to the end of 2022, suggesting that COVID-19 increasingly adapted to weather conditions.

Correspondence: Ruiwen Xiong, Buchholz High School, 32606 Gainesville, FL, USA
Tel.: +1.352.614.8957
E-mail: rywn.xiong@gmail.com

Key words: COVID-19, meteorological factors, spatial and temporal evolution, statistical analysis, continental United States.

Conflict of interest: the authors declare no potential conflict of interest, and all authors confirm accuracy.

Availability of data and materials: all data generated or analyzed during this study are included in this published article.

Acknowledgements: the work was supported by the Advanced Placement (AP) Capstone program of the United States.

Received: 12 May 2023.
Accepted: 30 June 2023.

Geospatial Health 2023; 18:1213
doi:10.4081/gh.2023.1213

Introduction

A severe acute respiratory syndrome coronavirus (SARS-CoV-2), known as COVID-19, was declared as a global public health emergency by the World Health Organization (WHO) on 30 January 2020 (WHO 2020). During the growth phase of the pandemic, the virus' fast spread disrupted daily lives, health systems and economies, receiving global concern, with countries applying various interventions, such as public health and social measures. The first COVID-19 patient reported in the United States (US) was occurred in Washington State on 15 January, 2020. Soon after, the virus spread quickly throughout the country (Davis *et al.*, 2021). This rapid transmission was captured in a large dataset, enabling researchers to conduct analyses to develop suitable policies.

Similar to other commonly circulating human coronaviruses (Nickbakhsh *et al.*, 2020) and influenza viruses (Petrova & Russell 2020; Shamn *et al.*, 2010), the transmission of COVID-19 exhibits plausible dependence on seasonal and geographic climate variations. Laboratory observations support the epidemiological hypothesis that weather patterns may affect the survival and spread of viruses (van Doremalen *et al.*, 2020). Empirical studies reported close relationships between meteorology factors and confirmed cases of COVID-19 (Chien & Chen 2020; Chin *et al.*, 2020). Prior studies suggested that cold, dry conditions may increase the transmission of the virus, in which temperature and relative and specific humidity appear to be the key climatic factors affecting the transmission of SARS-CoV-2 (Baker *et al.*, 2020; Bashir *et al.*, 2020; Liu *et al.*, 2020; Runkle *et al.*, 2020). However, with limited data on the current pandemic, these early-state results are inevitably inconclusive. Furthermore, it is especially important to understand how COVID-19 spread changes with weather considering the high volume of cases in the US (WHO Coronavirus Dashboard, 2022). The relative importance of climate drivers and how they may evolve over time and regions due to changes in virus mutation, human intervention, and social behaviour adjustment have also not been fully investigated. With the three years long COVID-19 time-series data spanning from 2020 to 2022 and the corresponding environmental dataset, we used a simple statistical approach to investigate the importance of temperature and precipitation on COVID-19 transmission, particularly its evolution over time and space. The analysis examined the climate drivers from a temporal and geospatial perspective. The results of this study could help inform and strengthen the management of the COVID-19 pandemic as well as other similar diseases in the future.

Materials and Methods

COVID-19 dataset

A time series of confirmed COVID-19 cases was downloaded from a unified global dataset that integrates and implements quality checks of the data from numerous leading sources of COVID-19 epidemiological and environmental data (Badr *et al.*, 2023). The dataset is disseminated through the Center of Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU), the source of the widely accessed JHU Coronavirus Dashboard (https://github.com/CSSEGISandData/COVID-19/) (Dong *et al.*, 2020). It contains daily COVID-19 case data since 22 January 2020, hydro-meteorological, air quality, information on COVID-19 control policies and key demographic characteristics, all aligned to a global consistent hierarchy of administrative units. From this dataset, we selected data for the continental US in which local outbreaks were detected up to 31 December 2022.

Data processing

The multi-step methodological approach applied to different sources of data was illustrated in Figure 1. We only considered counties in the continental US in this study. Because of the recurrent low reported case count each weekend, we first aggregated the daily new confirmed COVID-19 cases to the weekly sum. To avoid the biases arising because of the incomplete spread of the pathogen, such as a limited number of records due to connections with other affected areas, we only included counties experiencing local COVID-19 outbreaks. By adopting the method used by Ficetola and Rubolini (2021), the onset of a local COVID-19 outbreak event was defined as the week when a minimum of 50 confirmed cases were reported in a county. This allowed us to exclude the cases that did not reflect local transmission of the pathogen. Then, we applied a moving average for the time series with a 5-week interval by the function:

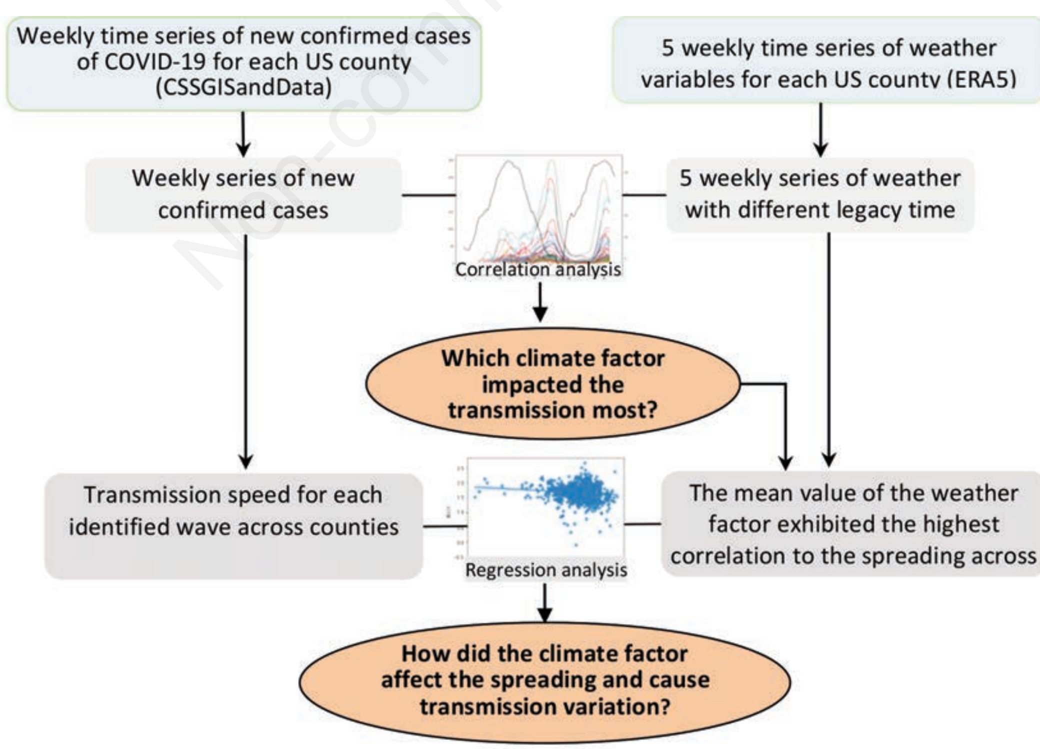

Figure 1. Dataset, data process, analysis method and workflow of the study.

week(i)=sum(week(i-2, i-1, i, i+1, i+2))/5 Eq.1

This simple smoothing technique eliminated the effects of temporal fluctuation caused by factors like changes in containment policies and testing facilities, making it easier to uncover potential underlying trends of the evolution of the COVID-19 spread. For each county, the spreading trajectory was plotted with the weekly confirmed cases against week. The waves were identified by local valleys and peaks of the curve with a publicly available R script (https://gist.github.com/sixtenbe/1178136). A full wave was defined as a period from one local valley to the following local valley. We estimated the COVID-19 transmission for each wave by considering the rate of spread from the onset of the wave to the peak of the same wave. This rate was computed by regressing the weekly case against time (slope) and then normalized and harmonized by dividing with the county population.

Environmental variables

Environmental data were downloaded from the Johns Hopkins University CSSE repository. We only considered three climatic variables for which significant impacts on the spreading dynamics have been reported (Briz-Redon & Serrano-Aroca, 2020), namely temperature (T), relative humidity (RH) and precipitation (P). The original weather data in the dataset was derived from the fifth-generation European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis of the global climate (ERA5) (Hersbach *et al.,* 2020). ERA5 provides reanalysis data of meteorological datasets at a global scale at the horizontal resolution of 0.25°x0.25° and the temporal resolution of an hour. This dataset has been extensively tested against observations and found to accurately capture the main observed weather quantities (Bell *et al.*, 2021; Herbach *et al.*, 2020). To match the COVID-19 time series, all weather variables were averaged at a weekly time-step from their initial daily temporal resolution. Prior studies reported various latency periods of the infection (Li *et al.*, 2020). We accounted for this by creating five weather series for each of the three weather variables, namely using the weather data 0~4 weeks before the onset of the COVID-19 curves and identified the weather series that exhibited the highest correlation to the weekly reported cases.

Statistical analysis

We used simple but powerful Pearson correlation analysis to investigate the importance of climate drivers on the transmission of COVID-19. The association between COVID-19 confirmed cases and climate factors allowed us to understand how climate affects the trajectory of COVID-19 in each region. This was done by correlating the weekly COVID-19 cases against specific meteorological factors for each county, with various times lags (0~4 weeks). The coefficient of determination and the significance, which used an alpha level of 0.05, were then recorded. The median latency period was derived by finding the median of the latency period for each county that produced the strongest correlation. The weather variable with the highest correlation coefficient was retained for further analysis. The importance of the meteorological driver on COVID-19 was measured by two indicators – the proportion of counties that exhibited significant correlation and the median correlation coefficient (*R*) across these counties.

To investigate the evolution of the climate driver importance, we compared the transmission-weather relationship over waves and climate zones. The pandemic in the US experienced a clear seasonal pattern (Sen *et al.*, 2021), therefore we clustered the waves into several periods according to the peak times (Figure 2). We further categorized all counties into nine climate zones (NE: Northeast, UM: Upper Midwest, OV: Ohio Valley, NR: North Rockies and Plains, NW: Northwest, SE: Southeast, ST: South, SW: Southwest, WS: West) based on the definition set by the National Oceanic and Atmospheric Administration (NOAA) as given by Karl and Koss (1984) (Figure 3). Transmission-weather responses were estimated for each combination of the time period and climate zone by regressing the rate of spread against corresponding weather variables across each county. These responses were compared between periods and climate zones to explore the changes in climate impacts on COVID-19 transmission.

Results

Temporal and spatial variations of COVID-19 transmission

At the national level, pandemic waves in the US were evident during summer (around June to August) and autumn to winter

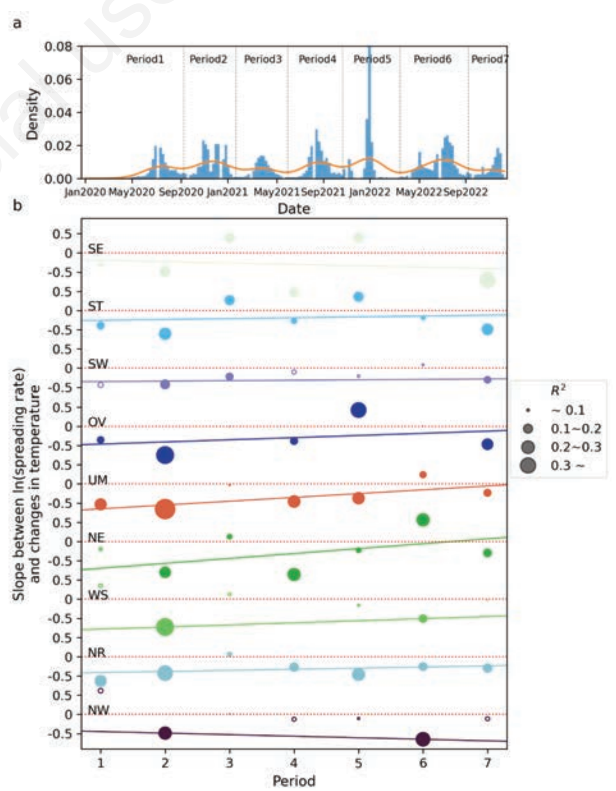

Figure 2. Changes in the relationship between the COVID-19 rate of spread and temperature. a) histogram of the wave peak times from all U.S. counties; b) changes in relationship between COVID-19 and temperature change - each dot value denotes the regressed slope between the rate of spread and temperature change - size indicates the value of the determination coefficient (R2), with the line showing the regression fit - filled dots denote significant spreading-temperature (95% CL) responses, while empty dots represent insignificant responses and were thus not included as points regressed in the trend line.

(around November to January) from 2020 to 2021 (Figure 4a). There was only one pandemic wave in 2022, likely in part due to reduced testing rates or the gradual achievement of herd immunity. The wave peaks were generally higher in winter than in spring and summer, suggesting seasonal dependence of the virus transmission. The reason for this, commonly ascribed to virus persistence on surfaces or in the air, depends on sensitivity to temperature, humidity and ultraviolet light (Chin *et al*., 2020). This fact changed susceptibility of human victims and led to changes in human social behaviour under different weather pattern (Engelbrecht & Scholes, 2021) such as a closer proximity of people in households during the cold season. The highest peak wave occurred in the autumn-winter of 2021, while the slowest occurred in the spring of 2020.

The structure of the transmission pattern differed among regions. While all nine climate zones experienced strong winter waves, NW, NR, WS, OV, ST, and SE experienced strong activities during summer. NE and UM also underwent obvious outbursts in cases during spring. In contrast with previous findings that indicated that colder weathers favoured the spread of the COVID-19 (Figure 4b), the proportion of accumulated cases to the total population was higher in the South where the mean temperature was higher (Figure 3). This can largely be attributed to the higher spreading rates in the South during the 2021 winter because of the domination of *Omicron* variant (Harris, 2022). Counties in ST exhibited the highest proportion in the population with confirmed COVID-19 positive, with a median of 30%, followed by SE of 29.8%, while counties in NW experienced the smallest positive proportion, with a median of 23.9%.

Importance of the weather driver

Prior studies have reported variable incubation periods between the infection and confirmation of the cases due to the onset of symptoms, COVID real-time tests, and publication of confirmed cases (Ficetola & Rubolini 2020, Li *et al*., 2020). We computed mean climatic variables assuming different exposure periods starting 0 ~ 4 weeks before the onset of the waves (referred to as $\Delta 0$, $\Delta 1$, $\Delta 2$, $\Delta 3$, $\Delta 4$). However, the COVID-19 data displayed very little time lag with respect to temperature as the temperature at the same period of spread exhibited the highest correlation across the US with the COVID-19 series. The COVID-19 series displayed a time lag of $\Delta 3$ and $\Delta 1$ weeks, respectively, for RH and P. A high correlation between the time series of the meteorological factors and the number of confirmed COVID-19 cases indicated the strong dependence of the pandemic on weather patterns. The number of COVID-19 cases was significantly correlated to the meteorological factors across most of the continental US. Of the three meteorological factors, temperature (T) exhibited a dominantly negative relationship to COVID-19 cases across the majority US, reflected by over 95.6% of the counties experiencing a significant correlation ($p<0.05$) between weekly cases and the climatic factors (Figure 5a, Table 1), with a median value of correlation coefficient -0.42. However, relative humidity (RH) and precipitation (P) indicated a mixed relationship to the case throughout the country. For RH, 74% of counties exhibited a significant correlation between RH and cases, with a median coefficient of 0.25. A positive correlation is dominant in the country, with a large number of counties in NR, ST, OV and SW either exhibiting an insignificant or a negative relationship between RH and the cases (Figure 5b). For pre-

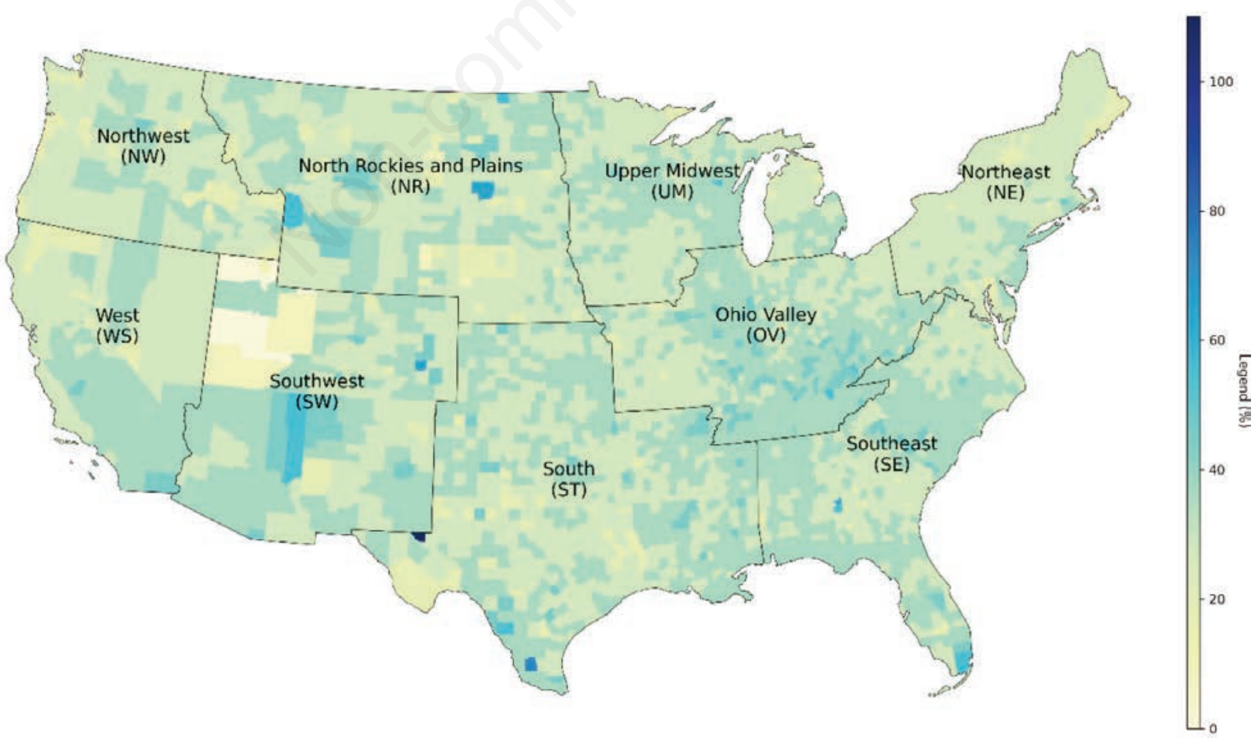

Figure 3. Climate zones and percentages of accumulated confirmed cases to the population in counties in United States.

cipitation, only 67% of mainland counties experienced a significant relationship with the weekly reported cases, with a median correlation coefficient of 0.16. Counties in the middle climate zones including NR, SW, UM, ST, and OV exhibited a negative correlation between P and the cases, with mostly positive relationships in counties across the eastern and western climate zones (Figure 5c).

Spread of COVID-19 in response to temperature

Given the significance of temperature on the spread of COVID-19 across most of mainland US, we continued to examine the impacts of T on the spatial variation of COVID-19 transmission. We estimated different temperature indicators, including mean temperature, diurnal temperature and range of the period of

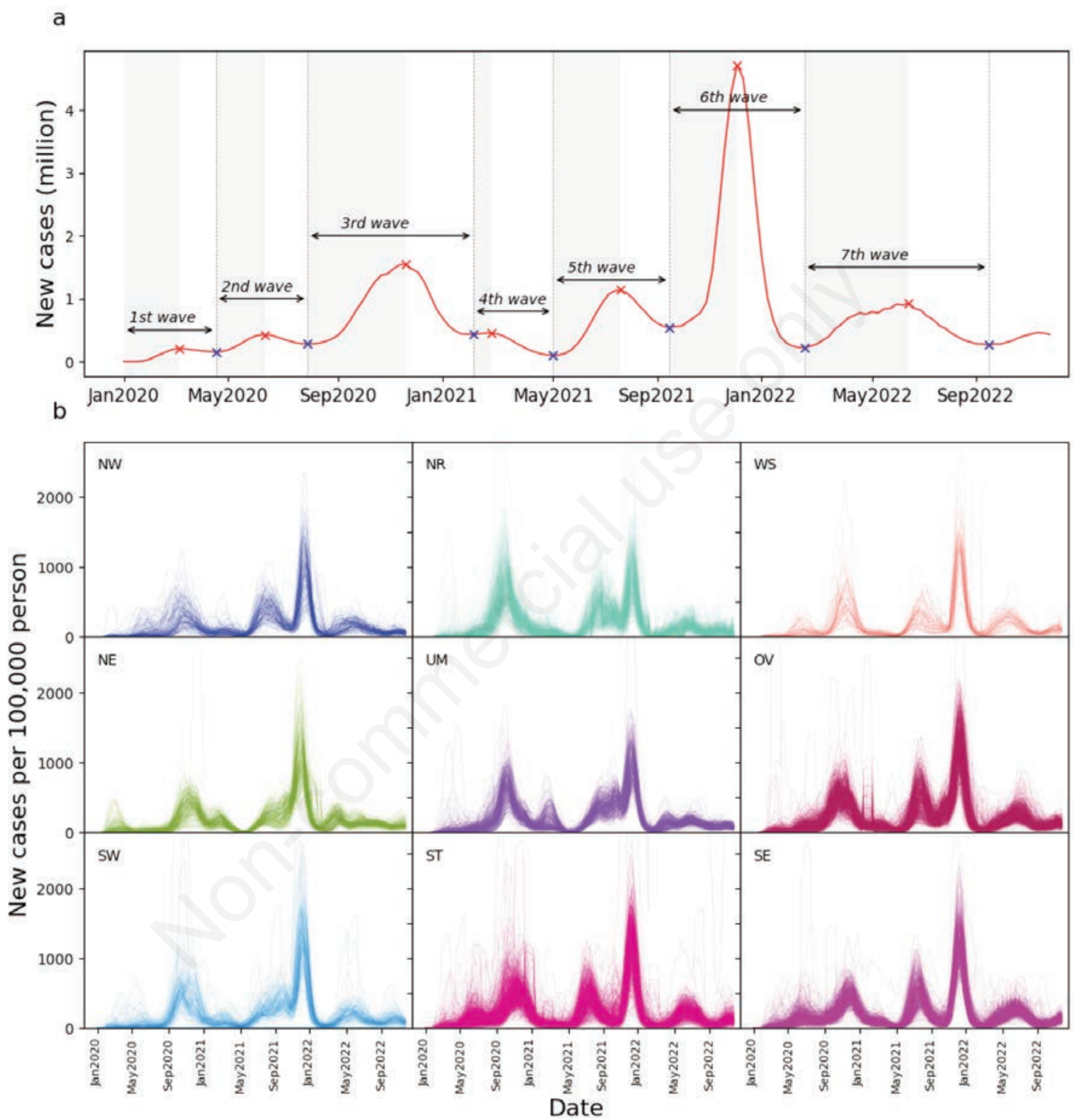

Figure 4. The COVID-19 waves and their variation over the climate zones across United States. a) continental US; b) by county in the nine climate zones.

Table 1. Summary statistics of regression between COVID-19 cases and climatic variables across United States.

	T	RH	P
Counties with a significant correlation* (%)	95.6	74.0	67.0
Median correlation coefficient (R)	-0.42	0.25	0.16
Median week latency	0	3	1

T, average near-surface air temperature; RH, relative humidity; P, precipitation; *p<0.05.

pagepress

spread, temperature variability and temperature change to examine their explanatory power on the variation of spreading rates. Although there were widespread and high correlations between the mean temperature and the weekly COVID-19 cases across the county, the rates of spread exhibited a weak and negligible response to mean temperature, with an R^2 of 0.025 and a slope of 0.02 (Figure 6a). In contrast, temperature change − a change in temperature during the period of spread, or the regressed slope of mean temperature against spreading time − exhibited a significant and exceptionally high explanatory power to the spatial and temporal variation in the rate of spread, with an R^2 of 0.201 and a slope of –0.41 between the log (rate) and the temperature change. This negative and significant relationship indicates that different temperature change rates can explain more than 20% of the variation in COVID-19 transmission, suggesting that temperature fluctuations rather than the mean temperature are responsible for the variations in the rate of spread. The negative response (slope=-0.41) suggests a faster temperature decline/rising corresponds to a faster increase/decrease in COVID-19 cases. Converting the ln(slope) to the absolute change of COVID-19 spreading resulted in *spreading rate%* = 100 ´ ($e^{slope\ (DT)}$ – 1) . In other words, with a fast rate of COVID-19 spread from autumn to winter, the temperature quickly going down (by 1ºC) can accelerate the rate of spread by 50.1%; while a slower temperature decrease (by 1ºC) leads to a 33.6% reduction in the predicted spreading rate.

The spread-temperature response

The pandemic waves across the US counties concurrently occurred in seven time windows due to specific virus variants, control measures and immunization conditions (Figure 2a). A temporal window here was defined as the time period that local waves peak simultaneously for the entire mainland US. Therefore, we conducted the spatial correlation analysis separately for waves in the combination of seven temporal windows and nine climate zones (Figure 2b). The two statistical indicators – the coefficient of determination (R^2) which reflects the dependence of the spread on the weather pattern on the one hand, and the *slope* of COVID-19 rate of spread on temperature change which represents the responding extent to a unit change in weather factors on the other – were used to depict the explanatory power of temperature on the spread of the infection and the spread-temperature response.

Not surprisingly, waves in the second and fifth periods (during autumn to winter) exhibited a significant and higher spatial correlation between the COVID-19 spread and temperature change, suggesting a larger impact of the weather on the spread of the infection in autumn to winter. For the nine climate zones, the R^2 averaged across all periods was the highest in NR (0.1) followed by UM (0.09), implying that the weather impact on the spread of COVID-19 was more obvious in the North than in the South.

However, the spread-weather response (*i.e.*, the slope) demonstrated a clear change over time in six out of nine climate zones

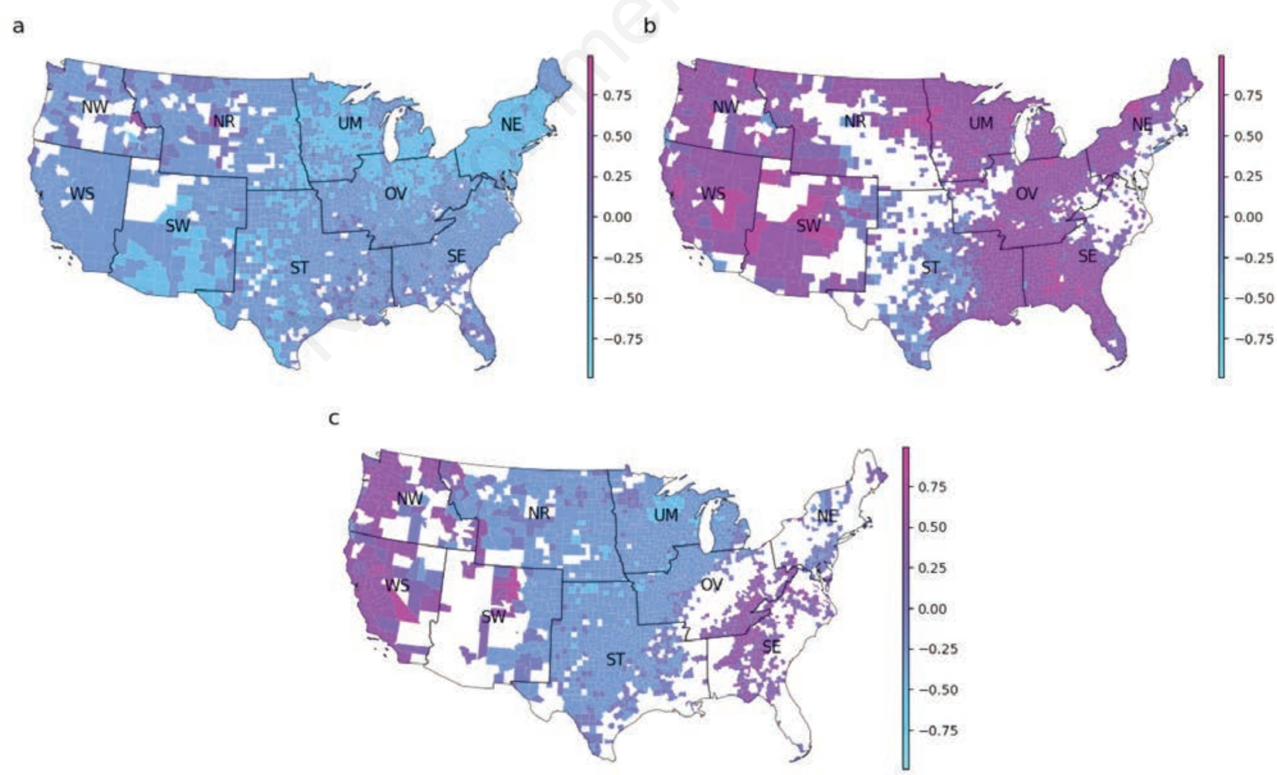

Figure 5. Spatial pattern of correlation coefficients between COVID-19 weekly confirmed cases and corresponding variables. a) temperature, b) relative humidity and c) precipitation; White area denotes an insignificant correlation at the 95% confidence level.

(NR, WS, NE, UM, OV, ST). They exhibited a decreasing temperature impact on COVID-19 between the beginning and the present of the pandemic as indicated by diminishing slope values. SW expressed small changes in weather impact, with a nearly zero trend over time, while SE and NW were the only zones that exhibited an increased climate impact as indicated by the increasing absolute value of the slope, which suggested a faster rate of spread with a unit decrease in temperature (Figure 2b).

Discussion

A growing number of studies have been assessing the relationships between the COVID-19 growth rate and multiple environmental features (Chien & Chen, 2020; Chien *et al.*, 2022; Ma *et al.*, 2021). However, the results of these studies were inconclusive and inconsistent, casting doubts on the possibility of correctly identifying environmental signals on COVID-19 spread dynamics (Carlson *et al*., 2020). Our analysis supports the belief that this virus, like other circulating human coronaviruses and influenza viruses, is influenced by the weather with respect to spreading rate and level of severity of the disease. Out of the three selected climatic variables, our results show that temperature is the one most strongly linked with COVID-19 transmission. This is reflected by a significant correlation between the weekly confirmed case and temperature across most of the US. Furthermore, the large temporal and spatial heterogeneity in the rate of spread can partly be explained by temperature. However, contributing to previous findings, we find that temperature change had the highest explanatory power of spatial and temporal rate variation. In addition, across different periods and climate zones, climate played a heterogeneous role as a driver (Xiao *et al.*, 2021). The observed changes in spread with regard to extent and direction give a reasonable explanation for the ambiguity in previous studies on whether meteorological drivers affect COVID-19 transmission (Briz-Redon & Serrano-Aroca 2020). Environmental features, containment measures and population immunity can translate to complex temporal and spatial dynamics in the course of an outbreak. Three factors likely caused the change in impact of the weather drivers: i) viral strain variation, *e.g.*, the SARS-CoV-2 *Delta* variant caused a rapid spread in the summer of 2021(Zhao *et al.*, 2021); ii) the change in population immunity induced by the US vaccination strategy (Cot *et al.*, 2021); and iii) implementation of control measures, including social distancing and reduced human mobility (Pan *et al.*, 2020). Thus, while weather drivers can create seasonal or geographic differences in the COVID-19 intensity, the impact was heavily confounded by immunity (induced or natural), interventions, human behaviour and also other details that are usually left out in the models used by prior studies. Although these factors can lead to potentially spurious conclusions, our results indicate the important mechanisms of weather variability with respect to COVID-19 spread. First, a sudden decline in temperature tends to increase human susceptibility to infection (e.g., due to weaker immunity, closer proximity and the like), resulting in a faster spread rate of COVID-19 from autumn to winter. This is indicated by the small lag between temperature and the viral waves and the strong explanatory power of temperature change on the rates of spread. Second, when the dominant virus variant shifted from *Alpha* to *Delta* and then to *Omicron* with their increasing ability to transmit, the virus had to adapt to the environment, such as warmer climates or larger temperature variability. This is indicated by the fact that the southern US has gradually exhibited a higher rate of spread and level of severity compared to the North where its environment is believed to have favoured the viral spread at the beginning.

Current analysis also suffers from several drawbacks. For example, most available contact tracing data indicates that the pro-

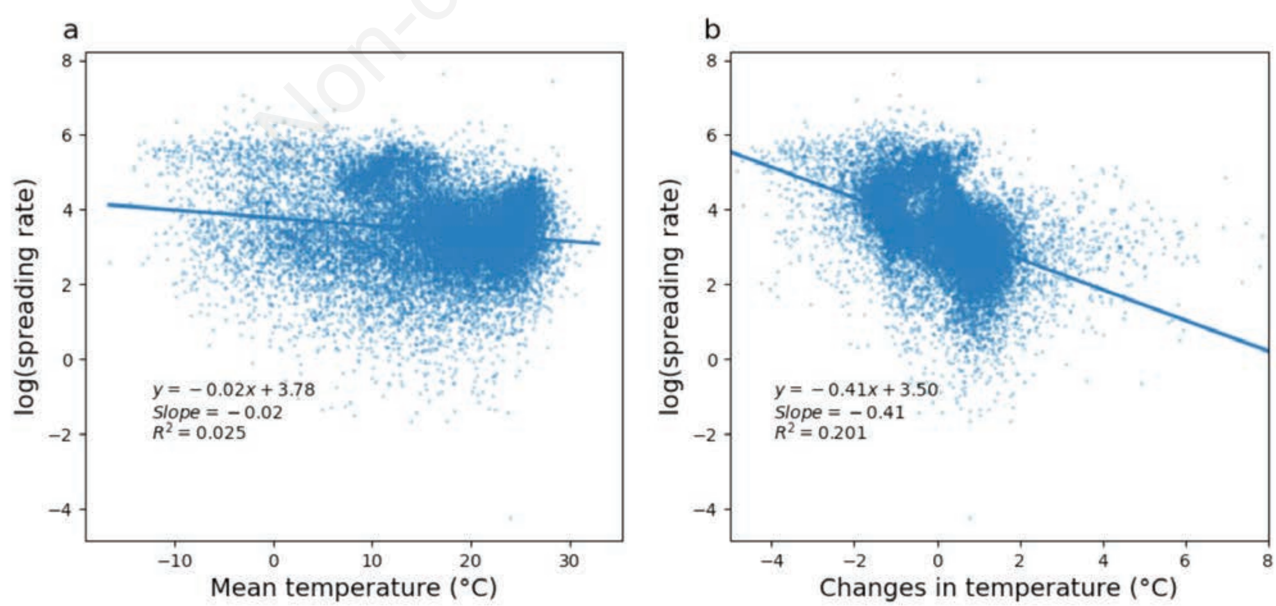

Figure 6. Regression between the rate of spread of the COVID-19 waves and temperature. a) mean temperature; b) changes in temperature.

portion of indoor transmission is high, likely caused by a combination of social contact patterns (including number, intensity and duration of contacts), air circulation, and potential weather drivers, such as sunlight or humidity. However, due to the environmental data availability, we had to use gridded climate data or local weather data that represent outdoor conditions rather than what is the case indoors, where transmission events are primarily related aerosolized viral clouds (Chen *et al.*, 2021). Social behaviour, perhaps the biggest confounder, is environmentally driven and seasonal but still rarely weighed alongside environmental and immunity drivers as hypothesis for why infectious diseases show seasonality (Fares, 2013; Martinez, 2018). For example, school terms are seasonal and have a marked influence on social mixing patterns relevant to influenza transmission, even in pandemics. Future studies in developing forecasting models should consider all these factors and their changes over time.

References

Badr HS, Zaitchik BF, Kerr GH, Nguyen NH, Chen YT, Hinson P, Colston JM, Kosek MN, Dong E, Du H, Marshall M, Nixon K, Mohegh A, Goldberg DL, Anenberg SC, Gardner LM, 2023. Unified real-time environmental-epidemiological data for multiscale modeling of the covid-19 pandemic. Sci Data 10:367.

Baker RE, Yang W, Vecchi GA, Metcalf CJE, Grenfell BT, 2020. Susceptible supply limits the role of climate in the early SARS-CoV-2 pandemic. Science 369:315-319.

Bashir MF, Ma B, Bilal Komal B, Bashir MA, Tan D, Bashir M, 2020. Correlation between climate indicators and COVID-19 pandemic in New York, USA. Sci Total Environ 728:138835.

Bell B, Hersbach H, Simmons A, Berrisford P, Dahlgren P, Horányi A, Muñoz-Sabater J, Nicolas J, Radu R, Schepers D, Soci C, Villaume S, Bidlot JR, Haimberger L, Woollen J, Buontempo C, Thépaut JN. 2021. The ERA5 global reanalysis: Preliminary extension to 1950. Q J Royal Meteorol Soc 147:4186-4227.

Briz-Redon A, Serrano-Aroca A, 2020. The effect of climate on the spread of the COVID-19 pandemic: A review of findings, and statistical and modelling techniques. Prog Phys Geogr 44:591-604.

Carlson CJ, Gomez ACR, Bansal S, Ryan SJ, 2020. Misconceptions about weather and seasonality must not misguide COVID-19 response. Nat Commun 11:4312.

Chen B, Jia P, Han J, 2021. Role of indoor aerosols for COVID-19 viral transmission: a review. Environ Chem L 19:1953-1970.

Chien L, Chen L, 2020. Meteorological impacts on the incidence of COVID-19 in the U.S. Stoch Environ Res Risk Assess 34:1675-80.

Chien L, Chen L, Lin R, 2022. Lagged meteorological impacts on COVID-19 incidence among high-risk counties in the United States – a spatiotemporal analysis. J Expo Sci Environ Epidemiol 32:774-781.

Chin AWH, Chu JTS, Perera MRA, Hui KPY, Yen H, Chan MCW, Peiris M, Poon LLM. 2020. Stability of SARS-CoV-2 in different environmental conditions. Lancet Microbe 1:e10.

Cot C, Cacciapaglia G, Islind AS, Oskarsdottir M, Sannino F. 2021. Impact of US vaccination strategy on COVID-19 wave dynamics. Sci Rep11:10960.

Davis JT, Chinazzi M, Perra N, Mu K, Piontti AP, Ajelli M, Dean NE, Gioannini C, Litvinova M, Merler S, Rossi L, Sun K, Xiong X, Longini Jr IM, Hallran ME, Viboud C, Vespignani A, 2021. Cryptic transmission of SARS-CoV-2 and the first COVID-19 wave. Nature 600:127-32.

Dong E, Du H, Gardner L, 2020. An interactive web-based dashboard to track COVID-19 in real time. Lancet Infect Dis 20:533-435

Engelbrecht F, Scholes RJ, 2021. Test for COVID-19 seasonality and the risk of second waves. One Health 12:100202.

Fares A, 2013. Factors influencing the seasonal patterns of infectious diseases. Int J Prev Mec 4:128-132.

Ficetola GF, Rubolini D, 2021. Containment measures limit environmental effects on COVID-19 early outbreak dynamics. Sci Total Environ 761:144432.

Harris JE. 2022. Mobility was a significant determinant of reported COVID-19 incidence during the Omicorn Surge in the most populous U.S. Counties. BMC Infect Dis 22:691.

Hersbach H, Bell B, Berrisford P, Hirahara S, Horányi A, Muñoz-Sabater J, Nicolas J, Peubey C, Radu R, Schepers D, Simmons A, Soci C, Abdalla S, Abellan X, Balsamo G, Bechtold P, Biavati G, Bidlot J, Bonavita M, De Chiara G, Dahlgren P, Dee D, Diamantakis M, Dragani R, Flemming J, Forbes R, Fuentes M, Geer A, Haimberger L, Healy S, Hogan RJ, Hólm E, Janisková M, Keeley S, Laloyaux P, Lopez P, Lupu C, Radnoti G, de Rosnay P, Rozum I, Vamborg F, Villaume S, Thépaut JN. 2020. The ERA5 global reanalysis. Q J R Meteorol Soc 146:1999-2049.

Karl T, Koss WJ, 1984. Regional and national monthly, seasonal, and annual temperature weighted by area, 1895-1983. Historical climatology series, 4-3. Available athttps://repository.library.noaa.gov/view/noaa/10238.

Li Q, Guan X, Wu P, Wang X, Zhou L, Tong Y, Ren R, Leung KSM, Lau EHY, Wong JY, Xing X, Xiang N, Wu Y, Li C, Chen Q, Li D, Liu T, Zhao J, Liu M, Tu W, Chen C, Jin L, Yang R, Wang Q, Zhou S, Wang R, Liu H, Luo Y, Liu Y, Shao G, Li H, Tao Z, Yang Y, Deng Z, Liu B, Ma Z, Zhang Y, Shi G, Lam TTY, Wu JT, Gao GF, Cowling BJ, Yang B, Leung GM, Feng Z. 2020. Early transmission dynamics in Wuhan, China of novel coronavirus infected pneumonia. N Engl J Med 382:1199-208.

Liu J, et al, 2020. Impact of meteorological factors on the COVID-19 transmission: A multi-city study in China. Sci Total Environ 726:138513.

Ma Y, Shaman J, Dubrow R, Chen K, 2021. Role of meteorological factors in the transmission of SARS-CoV-2 in the United States. Nat Commun 12:3602.

Martinez ME, 2018. The calendar of epidemics: Seasonal cycles of infectious diseases. PLoSPathog 14:e1007327.

Nickbakhsh S, Ho A, Marques DFP, McMenamin J, Gunson RN, Murcia PR, 2020. Epidemiology of seasonal coronaviruses: establishing the context for the emergence of coronavirus disease. J Infect Dis 222:17–25.

Pan Y, Darzi A, Kabiri A, Zhao G, Luo W, Xiong C, Zhang L. 2020. Quantifying human mobility behaviour changes during the COVID-19 outbreak in the United States. Sci Rep 10:20742.

Petrova VN, Russell CA, 2020. The evolution of seasonal influenza viruses. Nat Rev Microbiol 16:47–60.

Runkle JD, Sugg MM, Leeper RD, Rao Y, Matthews JL, Rennie JJ, 2020. Short-term effects of specific humidity and temperature on COVID-19 morbidity in select US cities. Sci Total Environ 720:140093.

Sen P, Yamana TK, Kandula S, Galanti M, Shaman J, 2021.

Burden and characteristics of COVID-19 in the United States during 2020. Science 598:338-341.
Shaman J, Pitzer VE, Viboud C, Grenfell BT, Lipsitch M, 2010. Absolute humidity and the seasonal onset of influenza in the continental United States. PLoS Biol 8:e1000316.
van Doremalen N, Bushmaker N, Morris T, Holbrook DH, Gamble MG, Williamson A, Tamin BN, Harcourt A, Thornburg JL, Gerber NJM, et al. 2020. Aerosol and surface stability of SARS-CoV-2 as compared with SARS-CoV-1. N Engl J Med 382:1564-7.
WHO Coronavirus (COVID-19) Dashboard. 2022. World Health Organizations. Accessed November 2022. Available from: https://covid19.who.int/
WHO, 2020. Clinical characteristics of covid-19 in China. N Engl J Med 382:1859-62.
Xiao S, Qi H, Ward MP, Wang W, Zhang J, Chen Y, Bergquist R, Tu W, Shi R, Hong J, Su Q, Zhao Z, Ba J, Qing Y, Zhang Z. 2021. Meteorological conditions are heterogeneous factors for COVID-19 risk in China. Environ Res 198:111182.
Zhao Y, Huang J, Zhang L, Chen S. 2021. The global transmission of new coronavirus variants. Environ Res 206:112240.