Temperature, humidity, and latitude analysis to predict potential spread and seasonality for COVID-19

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Abstract

Background:
A significant number of infectious diseases display seasonal patterns in their incidence, including human coronaviruses. Betacoronaviruses such as MERS-CoV and SARS-CoV are not thought to be seasonal.

Methods: We examined climate data from cities with significant community spread of COVID-19 using ERA-5 reanalysis, and compared to areas that are either not affected, or do not have significant community spread.

Findings:
To date, Coronavirus Disease 2019 (COVID-19), caused by SARS-CoV-2, has established significant community spread in cities and regions along a narrow east west distribution roughly along the 30-50^{o} N' corridor at consistently similar weather patterns consisting of average temperatures of 5-11^{o}C, combined with low specific (3-6 g/kg) and absolute humidity (4-7 g/m^3). There has been a lack of significant community establishment in expected locations that are based only on population proximity and extensive population interaction through travel.

Interpretation:
The distribution of significant community outbreaks along restricted latitude, temperature, and humidity are consistent with the behavior of a seasonal respiratory virus. Additionally, we have proposed a simplified model that shows a zone at increased risk for COVID-19 spread. Using weather modeling, it may be possible to predict the regions most likely to be at higher risk of significant community spread of COVID-19 in the upcoming weeks, allowing for concentration of public health efforts on surveillance and containment.

Funding:
M.M.S supported by NIH grant 1R01AI147870-01A1.

Background:

Many infectious diseases show a seasonal pattern in their incidence. An onerous burden for health care systems around the globe, influenza is the characteristic example.[1] The influenza virus shows significant seasonal fluctuation in temperate regions of the world but nevertheless displays less seasonality in tropical areas.[2-4] Despite the multitude of possible mechanisms proposed to explain this variation, our current understanding of this phenomenon is still incomplete.[5]

Coronavirus Disease 2019 (COVID-19), caused by SARS-CoV-2, initially came to attention in a series of patients with pneumonia of unknown etiology in the Hubei province of China, and subsequently spread to many other regions in the world through global travel.[6] Because of geographical proximity and significant travel connections, epidemiological modeling of the epicenter predicted that regions in Southeast Asia, and specifically Bangkok would follow Wuhan, and China in the epidemic.[7,8] More recently, the World Health Organization has declared this as a pandemic. For many the biggest concern is not only the swift spread of the pandemic, but also how it will behave in the coming months, and which areas and populations are most at risk.

A number of studies, both laboratory,[9] epidemiological studies,[10,11] and mathematical modelling,[12] point to role of ambient temperature and humidity on the survival and transmission of viruses. The tremendous level of research supporting both ambient temperature and humidity in its role in transmission and infection motivated this study to examine the influence of environmental factors on COVID-19. We sought to determine whether climate could be a factor in the spread of this disease.

Methods:

2-meter (2m) temperatures, relative humidity (RH), specific humidity (Q), and absolute humidity (AH) were based on data from the ECMWF ERA-5 reanalysis. Climatologic (1979-2020) and persistence forecasting (2019 data) was used to analyze latitude and temperature trends globally and for affected areas using ERA-5. ERA-5 reanalysis data for 2019 obtained from Climate Reanalyzer (https://ClimateReanalyzer.org), Climate Change Institute, University of Maine, USA. ERA-Interim reanalysis data (https://doi.org/10.1002/qj.828). ERA-5 reanalysis was also carried out for January-February 2020 and displayed using Copernicus Climate Change Service Information 2020. The analysis of 2-meter temperature is performed in separate analysis following the upper air 4D-Var analysis. ERA-5 reanalysis data (C3S, 2017) covers the earth with a resolution of 30 km x 30 km. Preliminary daily updates are available 5 days of real time though quality-assured monthly updates are published within 3 months of real time. 2m temperature was calculated by interpolating between the lowest model level and the Earth's surface, taking into account the atmospheric conditions.

2-meter Temperature (2m) is temperature at the height of 2 meters above earth's surface. Relative humidity (RH) is the percentage of the maximum amount of water vapor that the atmosphere can hold at a given temperature (saturation). Specific humidity (Q) is defined as the mass of water vapour in a unit mass of moist air (g/kg). Absolute humidity (AH) is defined as the total mass of water vapor present in a given volume or mass of air (g/m^3). COVID-19 country-wide data was obtained from Johns Hopkins CSSE.[8]

Significant community transmission is defined as $\geq$ 10 reported death in a country as of March 10, 2020. Temperature analysis was undertaken in time period of -30 to -20 days prior to the the 1st community death, to capture a range of days when cases likely transmitted based on reported incubation period of ~ 5 days and RO of ~ 2.[13,14] For comparison we studied cities with and without COVID-19 cases, representing all regions of the globe. For each of these countries, at most one representative city was chosen (for those with COVID-19 cases, locations with community death, and if not available then community cases; for non-COVID-19 countries, capitals or largest cities). Statistical analysis was performed with Graph Pad Prism (San Francisco, CA) for the Mann-Whitney and linear regression. P values <.05 were considered statistically significant.

Results:

Through March 10, 2020, significant community transmission has occurred in a consistent east and west pattern. Initially, the new epicenters of disease were all roughly along the 30-50° N' zone; to South Korea, Japan, Iran, and Northern Italy (Figure 1).[8] After the unexpected emergence of a large outbreak in Iran, we first made this map in late February. Since then new areas with significant community transmission include the Northwestern United States, Spain, and France (Figure 1). Notably, during the same time, COVID-19 failed to spread significantly to countries immediately north (such as Russia and Mongolia) and south of China. The number of patients and reported deaths in Southeast Asia is much less when compared to more temperate regions noted above.[8]

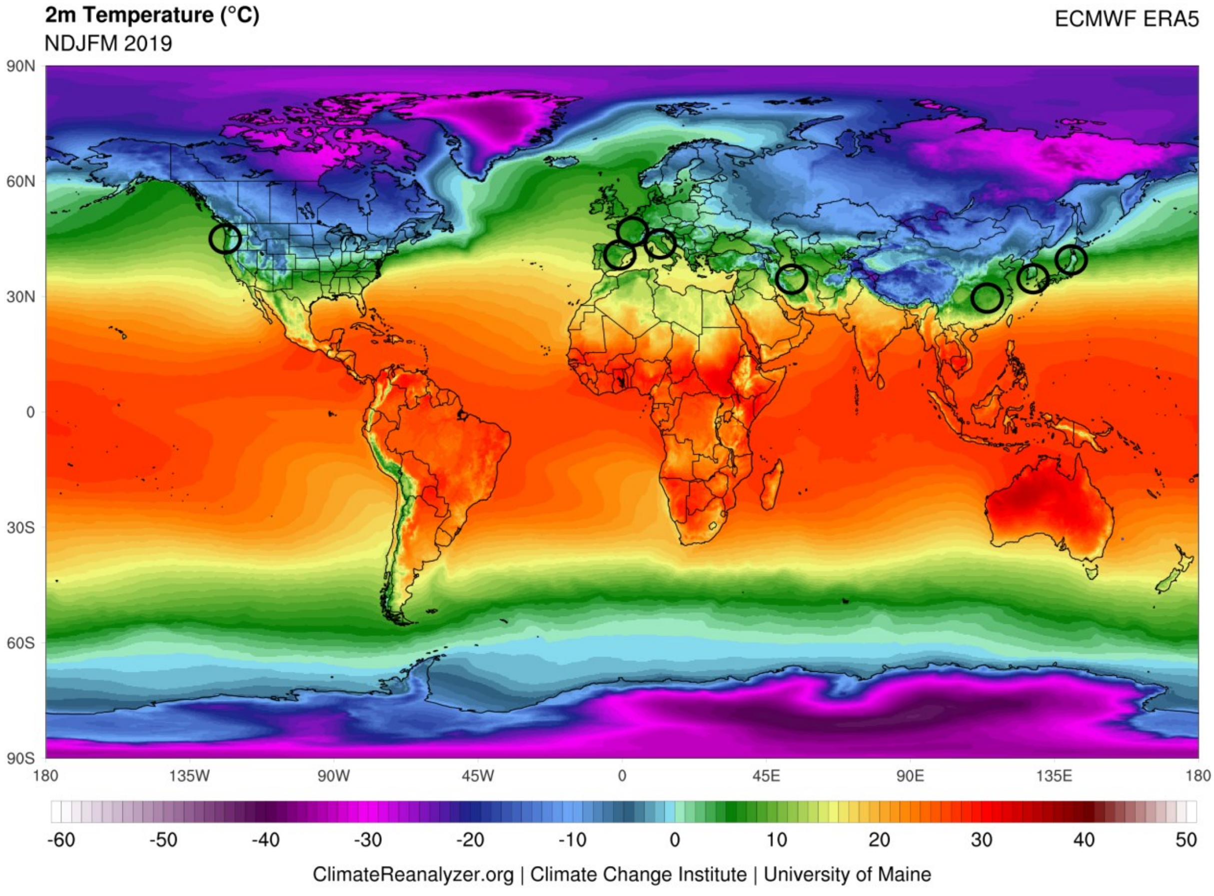


Figure 1. World temperature map November 2018-March 2019. Color gradient indicates 2-meter temperatures in degrees Celsius. Black circles represent countries with significant community transmission (≥ 10 deaths as of March 10, 2020). Image from Climate Reanalyzer (https://ClimateReanalyzer.org), Climate Change Institute, University of Maine, USA.

Further analysis using 2-meter (2m) temperatures from 2020 yielded similar results (Figure 2). In the months of January 2020 in Wuhan and February 2020 in the other affected cities, there was a striking similarity in the measures of average temperature (4-9 ºC at the airport weather stations). Average temperatures from a period of 20-30 days prior to the first community spread death in the area showed similar temperatures (3-9 ºC at the airport weather stations) (Supplementary Table 1, Supplementary Figure 1), and as city temperatures are slightly higher than airports due to urban effect,[15] they are within an estimated range of 5-11ºC. In addition to having similar average temperature, these locations also exhibit a commonality in that the timing of the outbreak coincides with a nadir in the yearly temperature cycle with relatively stable temperatures over a one month period or more (Table 1 and Supplementary Figure 1). These cities had varying relative humidity (44-84%), but consistently low specific (3-6 g/kg) and absolute humidity (4-7 g/m^3) (Table 1). The combined profile of having low average temperatures and specific humidity tightly clusters all the cities with significant outbreaks as of March 10, 2020 compared to other cities that with and without COVID-19 cases (Figure 3). The association between temperature and specific humidity was also statistically significant when comparing cities with and without significant community spread (Figures 4A and 4B), and when comparing to the total cases in their countries to other cities around the world with and without cases (Figure 4D and 4E).

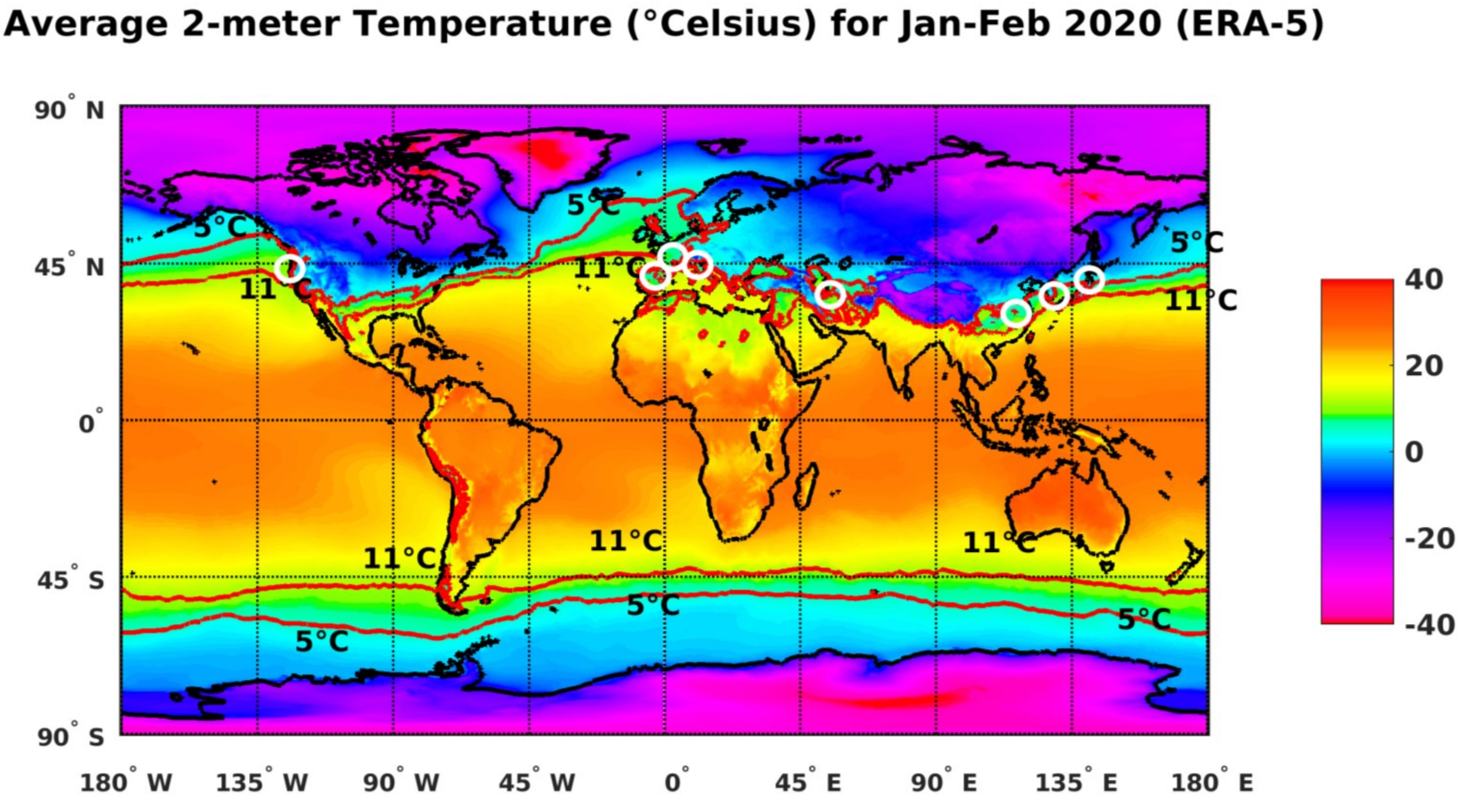


Figure 2. World temperature map January 2020-February 2020. Color gradient indicates 2-meter temperatures in degrees Celsius based on data from the ECMWF ERA-5 reanalysis. White circles represent countries with significant community transmission (≥10 deaths as of March 10, 2020), and red isolines areas with temperature between 5-11ºC. Generated using Copernicus Climate Change Service Information 2020.

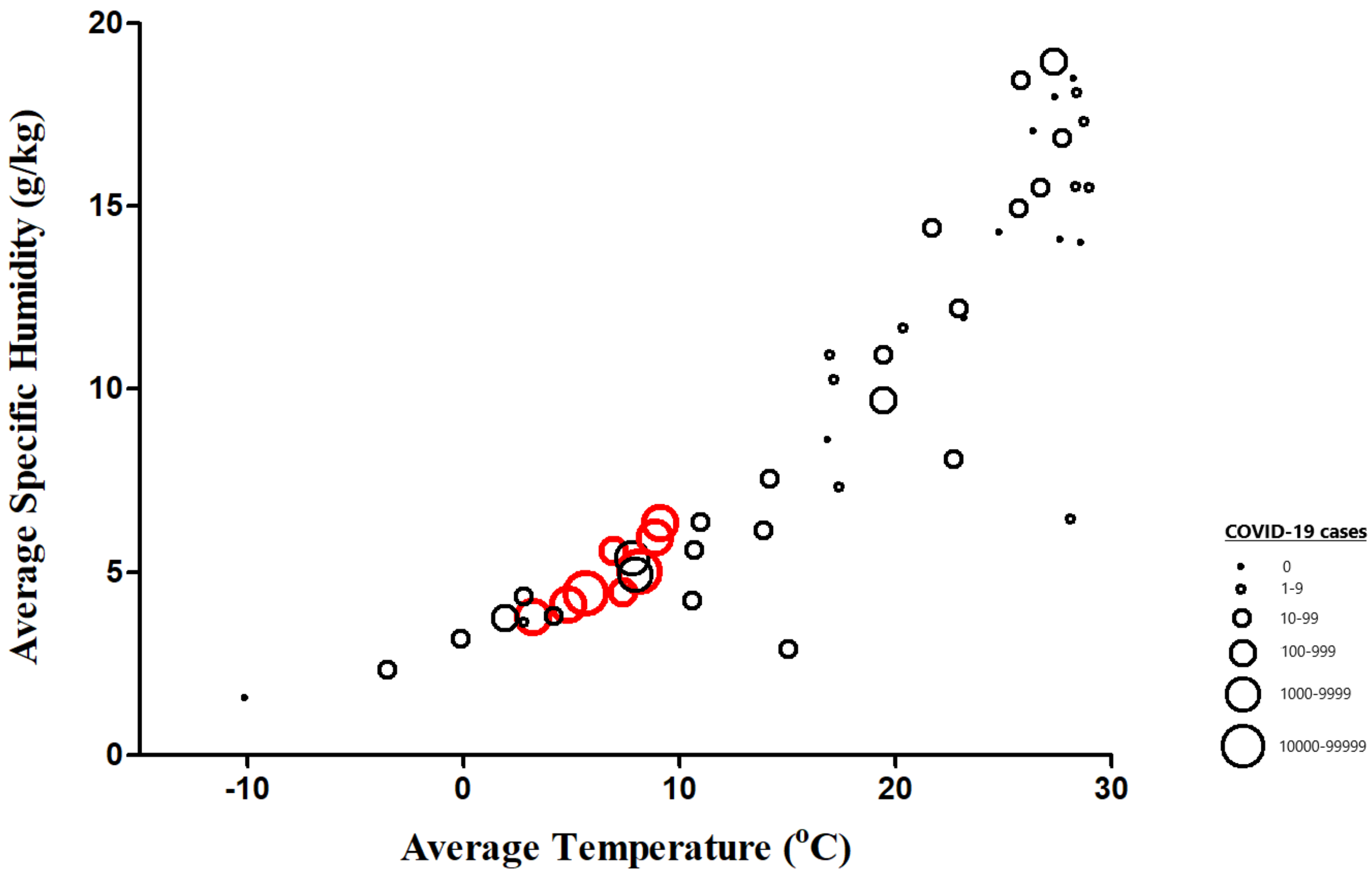


Figure 3. Temperature versus humidity plot for 50 cities with and without COVID-19. Temperatures and specific humidity are average values obtained from cities between 20 and 30 days prior of 1st community spread related death for cities with significant community outbreaks of COVID-19. Other cities with and without COVID-19 outbreaks were similarly analyzed, with benchmarks being 1st community spread related death (when available), or last day of data collection (3/10/20). Red color represent countries with significant community transmission (≥10 deaths as of March 10, 2020), and circle size represents total cases in each country. Supplementary Table 2 has characteristics of the 50 cities included.

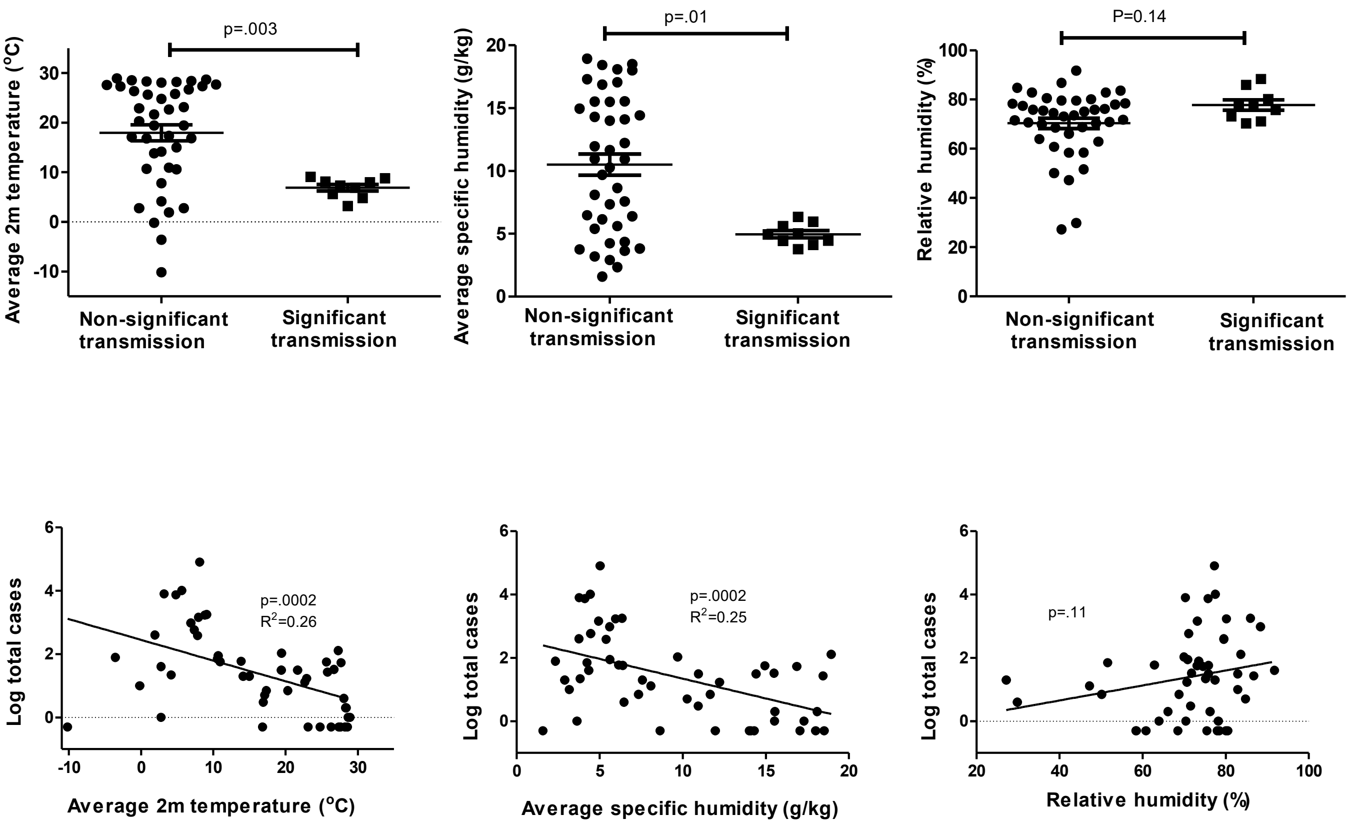


Figure 4. Comparison of average temperature and humidity between cities and countries with COVID-19. In Figures A-C, average temperature, average humidity, and average relative humidity were compared by the Mann Whitney test between cities with and without significant community transmission. In Figures D-F, average temperature, average humidity, and average relative humidity in representative cities were analyzed by linear regression against log of total cases in 50 different countries with and without COVID-19 (Supplementary Table 2 has characteristics of the 50 cities). Countries with 0 cases were assigned as 0.5 cases. Significant community transmission is defined as ≥ 10 reported death in a country as of March 10, 2020.

Given the temporal spread among areas with similar temperature and latitude, some predictions can tentatively be made about the potential community spread of COVID-19 in the coming weeks. Using 2019 temperature and humidity data for March and April, risk of community spread could be predicted to affect areas just north of the current areas at risk (Figure 5). These could include (from east to west) Manchuria, Central Asia, the Caucuses, Eastern Europe, Central Europe, the British Isles, the Northeastern and Midwestern United States, and British Columbia.

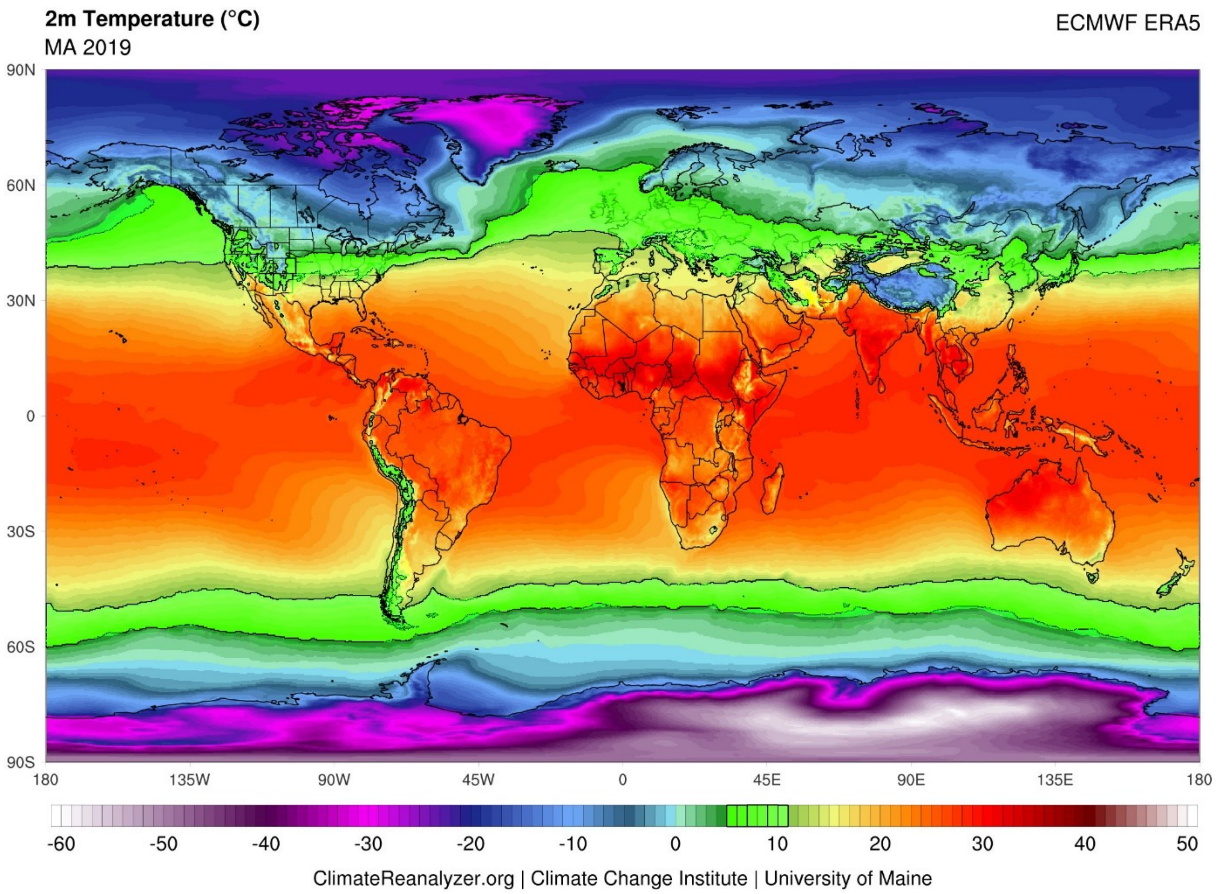


Figure 5. World 2 meter average temperature map March 2019-April 2019 predicting at risk zone for March-April 2020. Color gradient indicates average 2M temperatures in degrees Celsius, except neon green band which shows a zone with both 5-11°C and specific humidity between 3-6 g/kg. Tentative zone at risk for significant community spread in the near-term include land areas within the neon green bands, and will change based on actual average temperatures during this time period and other potential factors. Image from Climate Reanalyzer (https://ClimateReanalyzer.org), Climate Change Institute, University of Maine, USA. Digital manipulation by Cameron Gutierrez and Glenn Jameson.

Table 1. November 2019 to February 2020 monthly climate data

City	Nov 2019				Dec 2019				Jan 2020				Feb 2020			
	2m (ºC)	Rh (%)	Q (g/kg)	AH (g/m^3)	2m (ºC)	Rh (%)	Q (g/kg)	AH (g/m^3)	2m (ºC)	Rh (%)	Q (g/kg)	AH (g/m^3)	2m (ºC)	Rh (%)	Q (g/kg)	AH (g/m^3)
Cities with significant community transmission of COVID-19																
Wuhan	14	66	6	8	8	74	5	6	5	84	4	6	10	77	6	7
Tokyo	14	72	7	9	10	73	5	7	8	72	5	6	9	66	5	6
Daegu	9	68	5	6	2	62	3	4	3	67	3	4	4	62	3	4
Qom	9	61	5	5	7	72	5	6	4	69	4	4	8	44	4	4
Milan	9	85	6	8	7	80	5	6	5	77	4	5	8	60	4	5
Seattle	7	84	5	7	7	88	5	7	7	85	5	7	6	82	5	6
Paris	8	89	6	7	6	87	5	7	6	88	5	7	8	81	6	7
Madrid	9	74	6	7	8	77	5	6	6	77	5	5	9	71	5	6
Cities tentatively predicted to be at risk for COVID-19 in the coming weeks																
London	7	90	6	7	7	89	5	7	7	89	6	7	7	81	5	6
Manchester	6	92	5	7	5	91	5	6	6	90	5	7	6	84	5	6
Berlin	6	88	5	7	4	84	4	6	4	84	4	5	6	77	5	6
Prague	6	86	5	6	3	82	4	5	2	84	4	5	5	72	4	5
Hamburg	6	91	5	7	5	87	5	6	5	89	5	6	6	82	5	6
Vancouver	8	81	5	7	6	85	5	6	5	82	5	6	5	81	4	6
New York	7	65	4	5	3	74	4	5	3	69	4	4	4	69	4	5
Warsaw	6	88	5	7	3	86	4	5	2	87	4	5	4	79	4	5
Glasgow	5	88	5	6	6	89	5	7	7	86	5	7	5	85	5	6
Kiev	5	84	5	6	3	87	4	5	1	86	3	4	2	77	4	4
St. Louis	5	71	4	5	3	75	4	5	2	78	4	4	2	72	3	4
Beijing	5	53	3	4	-3	54	2	2	-3	58	2	2	1	62	2	3
Previously predicted city where COVID-19 failed to take hold																
Bangkok	28	70	16	19	26	70	15	17	28	74	17	20	28	70	16	19

Average 2m temperature (ºC), relative humidity (RH, %), specific humidity (Q, g/kg), and absolute humidity (AH, g/m^3) data from cities with community spreading of COVID-19 (as of 3/10/20). Temperature and humidity based on data from the ECMWF ERA-5 reanalysis. Temperatures not adjusted for urban effect.

Discussion: The distribution of the significant community outbreaks along restricted latitude, temperature, and humidity are consistent with behavior of a seasonal respiratory virus. The association between temperature and humidity in the cities affected with COVID-19 deserves special attention. There is a similarity in the measures of average temperature (5-11ºC) and RH (44-84%) in the affected cities and known laboratory conditions that are conducive to coronavirus survival (4ºC and 20-80% RH).[16] In the time we have written up these results, new centers of significant community outbreaks include parts of Germany and England, all of which had seen average temperatures between 5-11ºC in January and February 2020, and included in either the Jan-Feb 2020 map (Figure 2), or Mar-Apr risk map (Figure 4).

Temperature and humidity are known factors in SARS-CoV, MERS-CoV and influenza survival.[17-20] Furthermore, new outbreaks occurred during periods of prolonged time at these temperatures, perhaps pointing to increased risk of outbreaks with prolonged conditions in this range. Besides potentially prolonging half-life and viability of the virus, other potential mechanisms associated with cold temperature and low humidity include stabilization of the droplet and enhanced propagation in nasal mucosa, as has been demonstrated with other respiratory viruses.[9,21] It is important to note that even colder areas in the more northern latitudes have been relatively free of COVID-19 pointing to a potential minimum range for the temperature, which could be due to avoidance of freeze-thaw cycles that could affect virus viability or other factors (as at least one human coronaviruses tested is freeze-thaw resistant).[22] Although most studies have focused on relative humidity, this can be affected by temperature, and thus specific humidity (a measure of absolute humidity) is used to control for this variable. Researchers have found that low specific humidity is a key factor in laboratory transmission of influenza,[9] as well as the onset of seasonal influenza in the United

States.[11] All of the above points to a potential direct relation between temperature and SARS-CoV-2 environmental survival and spreading. This hypothesis can be tested in experimental conditions similar to work that has been done before,[16] environmental sample testing from areas of ongoing infection, and close epidemiologic and climate studies.

In the coming two months, temperatures will rise dramatically across many areas in the Northern Hemisphere, which potentially place many areas at risk, according to our simplified model. However, the current model does not take into account the effect of forecast temperatures or specific humidity, which will be included in future models. The areas to the north which develop temperature profiles that overlap current areas at risk, may only do so transiently as they rapidly warm (with possible exception of areas such as the Northwest United States and British Columbia, which can stay at yearly nadirs for prolonged periods of time). Furthermore, as the virus moves further north it will encounter sequentially less human population densities. The above factors, climate variables not considered or analyzed (cloud cover, maximum temperature, etc.), human factors not considered or analyzed (impact of public health interventions, concentrated outbreaks like cruise ships, travel, etc.), viral factors not considered or analyzed (mutation rate, pathogenesis, etc.), mean that although the current correlations with latitude, temperature, and humidity seem strong, a direct causation has not been proven and predictions in the near term have to be considered with extreme caution.

Human coronaviruses (HCoV-229E, HCoV-HKU1, HCoV-NL63, and HCoV-OC43), which usually cause common cold symptoms, have been shown to display strong winter seasonality between December and April, and are undetectable in summer months in temperate regions.[23] Some studies have shown that the alphacorona virus HCoV-229E peaks in the fall, while HCoV-OC43 (a betacoronavirus in the same genera as SARS-CoV-2) has a winter predominance.[24,25] Although it would be even more difficult to make a long-term prediction at this stage, it is tempting to expect COVID-19 to diminish considerably in affected areas (above the 30º N') in the coming months and into the summer. However, as SARS-CoV-2 is only recently introduced into humans, there is presumably there is no pre-existing immunity. In such cases, whether the 2009 H1N1 influenza pandemic or the first Whooping Cough pandemics documented in Persia and France in the 1400's and 1500's, the initial epidemic acted unpredictably, so in addition to their recognizable seasonal peak, they had additional peaks outside their later seasonal patterns.[14,26]

It could perhaps prevail at low levels or cause several seasonal peaks in tropical regions similar to influenza, cause outbreaks in the Southern Hemisphere at the same time, and begin to rise again in late fall and winter in temperate regions in the upcoming year. One other possibility is that, combined with intensive public health efforts, it will not be able to sustain itself in the summer in the tropics and Southern Hemisphere and disappear, just as SARS-CoV did so in 2003; however, the ever-increasing number of cases worldwide make this increasingly less likely. MERS has pointed to as a case of a betacoronavirus that is able to spread in all seasons. However, it should be remembered that the vast majority of cases were in the Arabian Peninsula and that influenza infection there does not follow the same pattern as more temperate climates.[27] In the upcoming summer months in the Northern Hemisphere, surveillance efforts for SARS-CoV-2 in currently affected areas will be important to determine if there is a viral reservoir (such as prolonged stool shedding). Similarly, surveillance efforts in the tropics, as well as New Zealand, Australia, South Africa, Argentina, and Chile between the months of June through September may be of value in determining establishment in the human population.

An avenue for further research involves the use of integrated or coupled epidemiological-earth-human systems models, which can incorporate climate and weather processes and variables (e.g., dynamics of temperature, humidity) and their spatiotemporal changes, as well as simulate scenarios of human interactions (e.g., travel, transmission due to population density). Such models can assimilate data currently being collected to accelerate the improvements of model predictions on short time scales (i.e., daily to seasonal). This type of predictive approach would allow to explore questions such as what are population centers most at risk and for how long; where to intensify large scale surveillance and tighten control measures to prevent spreading; better understanding of limiting factors for virus spreading in the Southern Hemisphere; and making predictions for a 2021-2022 virus season. A better understanding of the cause of seasonality for coronaviruses and other respiratory viruses would undoubtedly aid in better treatments and/or prevention, and be useful in determining which areas need heightened surveillance.

Conflict of interest: None to declare.

M.M.S supported by NIH grant 1R01AI147870-01A1.

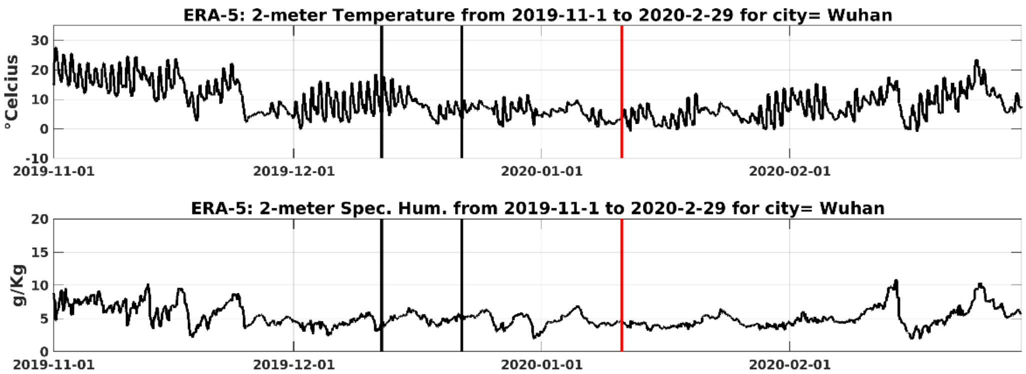
Acknowledgements: Digital manipulation of Figure 3 courtesy of Cameron Gutierrez and Glenn Jameson. The authors would also like to thank Betsy Weatherhead (Senior Scientist - retired, U. Colorado at Boulder) for analytical assistance on examining global COVID-19 and putting data in the context of environmental factors.

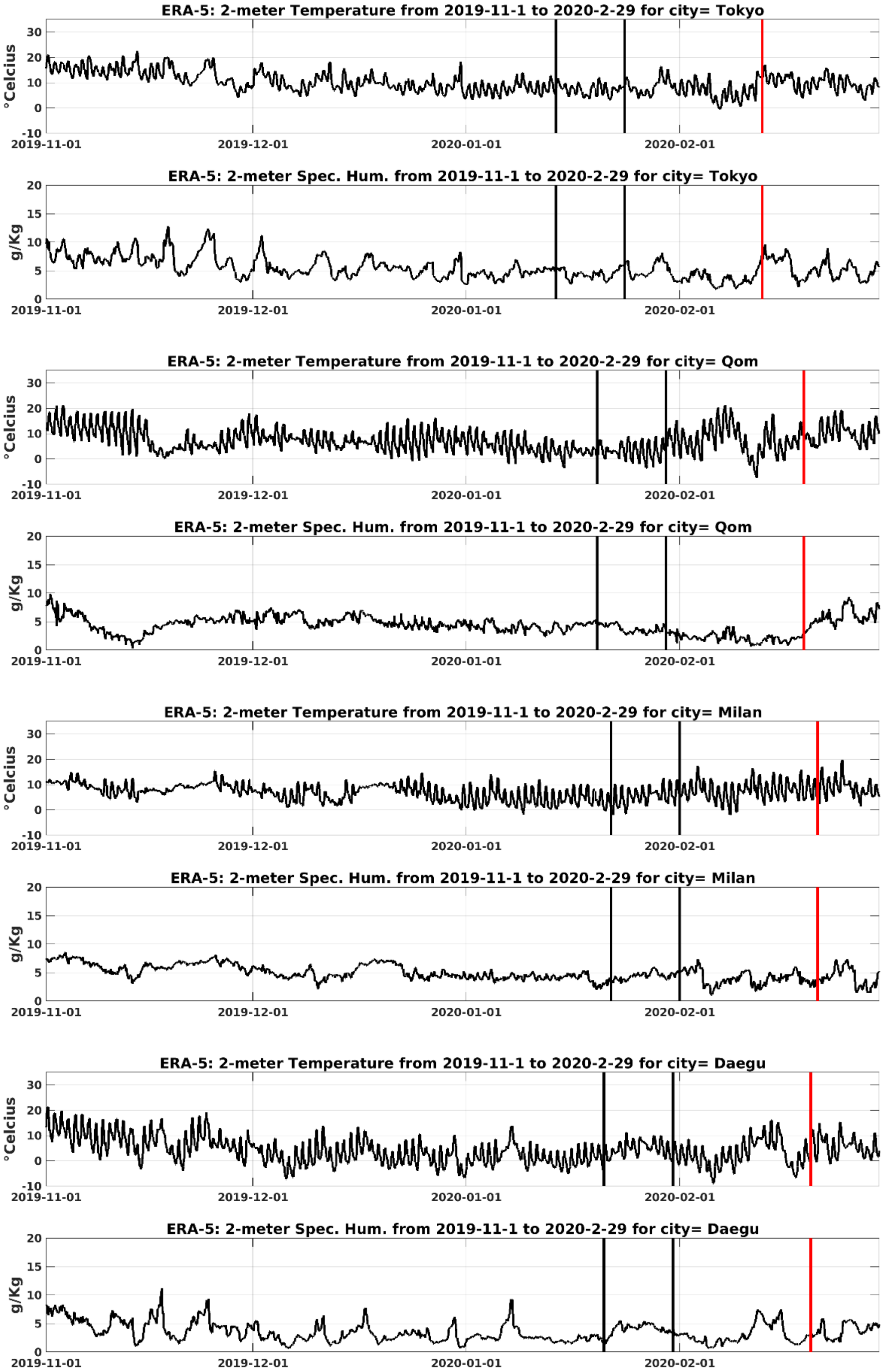
References

1. Collaborators GBDI. Mortality, morbidity, and hospitalisations due to influenza lower respiratory tract infections, 2017: an analysis for the Global Burden of Disease Study 2017. *Lancet Respir Med* 2019; **7**(1): 69-89.
2. Viboud C, Alonso WJ, Simonsen L. Influenza in tropical regions. *PLoS Med* 2006; **3**(4): e89.
3. Bloom-Feshbach K, Alonso WJ, Charu V, et al. Latitudinal variations in seasonal activity of influenza and respiratory syncytial virus (RSV): a global comparative review. *PLoS One* 2013; **8**(2): e54445.
4. Li Y, Reeves RM, Wang X, et al. Global patterns in monthly activity of influenza virus, respiratory syncytial virus, parainfluenza virus, and metapneumovirus: a systematic analysis. *Lancet Glob Health* 2019; **7**(8): e1031-e45.
5. Tamerius J, Nelson MI, Zhou SZ, Viboud C, Miller MA, Alonso WJ. Global influenza seasonality: reconciling patterns across temperate and tropical regions. *Environ Health Perspect* 2011; **119**(4): 439-45.
6. Huang C, Wang Y, Li X, et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *Lancet* 2020; **395**(10223): 497-506.
7. Bogoch, II, Watts A, Thomas-Bachli A, Huber C, Kraemer MUG, Khan K. Potential for global spread of a novel coronavirus from China. *J Travel Med* 2020.
8. Coronavirus COVID-19 Global Cases by Johns Hopkins CSSE. 2020. https://gisanddata.maps.arcgis.com/apps/opsdashboard/index.html#/bda7594740fd40299423467b48e9ecf6 (accessed 3/3/2020.
9. Lowen AC, Mubareka S, Steel J, Palese P. Influenza virus transmission is dependent on relative humidity and temperature. *PLoS Pathog* 2007; **3**(10): 1470-6.
10. Barreca AI, Shimshack JP. Absolute humidity, temperature, and influenza mortality: 30 years of county-level evidence from the United States. *Am J Epidemiol* 2012; **176 Suppl 7**: S114-22.
11. Shaman J, Pitzer V, Viboud C, Lipsitch M, Grenfell B. Absolute Humidity and the Seasonal Onset of Influenza in the Continental US. *PLoS Curr* 2009; **2**: RRN1138.
12. Zuk T, Rakowski F, Radomski JP. Probabilistic model of influenza virus transmissibility at various temperature and humidity conditions. *Comput Biol Chem* 2009; **33**(4): 339-43.
13. Liu Y, Gayle AA, Wilder-Smith A, Rocklov J. The reproductive number of COVID-19 is higher compared to SARS coronavirus. *J Travel Med* 2020; **27**(2).

14. Guan WJ, Ni ZY, Hu Y, et al. Clinical Characteristics of Coronavirus Disease 2019 in China. *N Engl J Med* 2020.
15. Aude Lemonsu MD, Deque M, Somot S, Alias A, Masson V. Benefits of explicit urban parameterization in regional climate modeling to study climate and city interactions. *Climate Dynamics* 2018; **52**: 2745-64.
16. Casanova LM, Jeon S, Rutala WA, Weber DJ, Sobsey MD. Effects of air temperature and relative humidity on coronavirus survival on surfaces. *Appl Environ Microbiol* 2010; **76**(9): 2712-7.
17. Otter JA, Donskey C, Yezli S, Douthwaite S, Goldenberg SD, Weber DJ. Transmission of SARS and MERS coronaviruses and influenza virus in healthcare settings: the possible role of dry surface contamination. *J Hosp Infect* 2016; **92**(3): 235-50.
18. Chan KH, Peiris JS, Lam SY, Poon LL, Yuen KY, Seto WH. The Effects of Temperature and Relative Humidity on the Viability of the SARS Coronavirus. *Adv Virol* 2011; **2011**: 734690.
19. van Doremalen N, Bushmaker T, Munster VJ. Stability of Middle East respiratory syndrome coronavirus (MERS-CoV) under different environmental conditions. *Euro Surveill* 2013; **18**(38).
20. Tan J, Mu L, Huang J, Yu S, Chen B, Yin J. An initial investigation of the association between the SARS outbreak and weather: with the view of the environmental temperature and its variation. *J Epidemiol Community Health* 2005; **59**(3): 186-92.
21. Schaffer FL, Soergel ME, Straube DC. Survival of airborne influenza virus: effects of propagating host, relative humidity, and composition of spray fluids. *Arch Virol* 1976; **51**(4): 263-73.
22. Lamarre A, Talbot PJ. Effect of pH and temperature on the infectivity of human coronavirus 229E. *Can J Microbiol* 1989; **35**(10): 972-4.
23. Gaunt ER, Hardie A, Claas EC, Simmonds P, Templeton KE. Epidemiology and clinical presentations of the four human coronaviruses 229E, HKU1, NL63, and OC43 detected over 3 years using a novel multiplex real-time PCR method. *J Clin Microbiol* 2010; **48**(8): 2940-7.
24. Vabret A, Mourez T, Gouarin S, Petitjean J, Freymuth F. An outbreak of coronavirus OC43 respiratory infection in Normandy, France. *Clin Infect Dis* 2003; **36**(8): 985-9.
25. Cabeca TK, Granato C, Bellei N. Epidemiological and clinical features of human coronavirus infections among different subsets of patients. *Influenza Other Respir Viruses* 2013; **7**(6): 1040-7.
26. Aslanabadi A, Ghabili K, Shad K, Khalili M, Sajadi MM. Emergence of whooping cough: notes from three early epidemics in Persia. *Lancet Infect Dis* 2015; **15**(12): 1480-4.
27. Caini S, El-Guerche Seblain C, Ciblak MA, Paget J. Epidemiology of seasonal influenza in the Middle East and North Africa regions, 2010-2016: Circulating influenza A and B viruses and spatial timing of epidemics. *Influenza Other Respir Viruses* 2018; **12**(3): 344-52.

Supplementary Figure and Table

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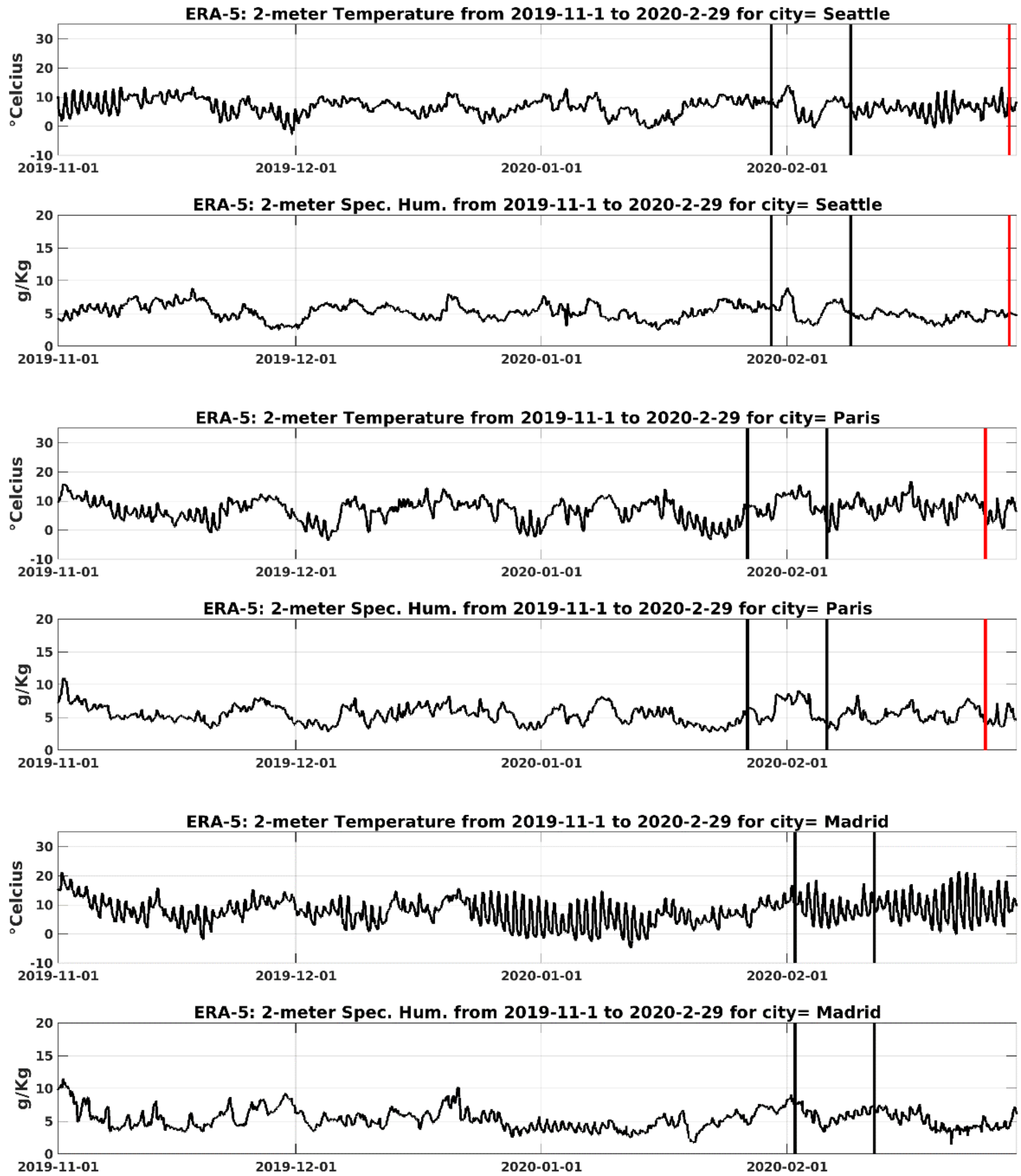
2020-01-01
2020-02-01
ERA-5: 2-meter Spec. Hum. from 2019-11-1 to 2020-2-29 for city= Daegu
g/Kg
20
15
10
5
0
2019-11-01
2019-12-01
2020-01-01
2020-02-01



Supplementary Figure 1. Average 2-meter average temperature and specific humidity charts for cities with significant COVID-19 outbreaks. Traces contain data from November 1, 2019 to the February 29, 2020 obtained from ERA-5 reanalysis. Red line indicates 1st community acquired COVID-19 case that led to death. Two black lines show the window between 20-30 days prior to the first death, presumably when community spread first occurred (assuming a doubling of cases every 5 days, and mortality rate between 2-3%).

Supplementary Table 1. City data related to significant COVID-19 outbreaks

Country (representative city)	Date of 1st reported community death	Date 1st reported case in country	Latitude (° N')	Koppen Climate Classification
China (Wuhan)	January 11, 2020	December 31, 2019	30·7766	Humid Subtropical Climate (Cfa)
Japan (Tokyo)	February 13, 2020	January 16, 2020	35·5494	Humid Subtropical Climate (Cfa)
S. Korea (Daegu)	February 20, 2020	January 31, 2020	35·8995	Dry-winter humid subtropical climate (Cwa)
Iran (Qom)	February 19, 2020	February 19, 2020	34·5756	Hot desert climate (Bwh)/ Hot semi-arid climates (Bsh)
Italy (Milan)	February 21, 2020	January 31, 2020	45·6301	Humid Subtropical Climate (Cfa)
France (Paris)	February 26, 2020	January 25, 2020	48·7262	Marine west coast climate (Cfb)
USA (Seattle	February 29, 2020	January 20, 2020	47·4502	Mediterranean warm/cool summer climates (Csb)
Spain (Madrid)	March 3, 2020	February 1, 2020	40·4983	Mediterranean hot summer climate (Csa)

Supplementary Table 2. City with and without COVID-19 outbreaks

City	Country	Time first community death or last day of data collection	Latitude	mean temp	mean specific humid	mean relative humidity	Total country death by 3/10	Total country cases by 3/10
Wuhan	China	1/11/2020	30.7766	4.83	4.11	75.76	3136	80757
Tokyo	Japan	2/13/2020	35.5494	6.91	5.60	88.39	10	581
Qom	Iran	2/19/2020	34.5756	7.82	5.39	79.59	291	8042
Milan	Italy	2/22/2020	45.6301	7.96	4.94	73.19	631	10149
Daegu	S. korea	2/20/2020	35.8995	8.83	5.96	80.22	54	7513
Seattle	USA	2/29/2020	47.4502	1.93	3.76	79.57	28	959
London	UK	3/9/2020	51.5048	13.86	6.15	62.87	6	382
Heinsberg	Germany	3/9/2020	51.0505556	27.68	16.87	74.56	2	1457
Madrid	Spain	3/3/2020	40.4983	19.44	9.69	69.98	35	1695
Oslo	Norway	3/10/2020	60.1976	26.71	15.50	71.82	0	400
Cairo	Egypt	3/10/2020	30.1128	25.80	18.45	86.79	1	59
Bangkok	Thailand	3/1/2020	13.69	9.10	6.35	85.98	1	53
Melbourne	Australia	3/1/2020	-37.669	-3.56	2.34	73.54	3	107
Manilla	Phillipines	3/5/2020	14.5123	-0.17	3.18	82.89	1	33
Solo	Indonesia	3/10/2020	-7.5155	16.91	10.94	71.58	0	27
Paris	France	2/26/2020	48.7262	21.66	14.42	82.90	33	1784
Toronto	Canada	3/10/2020	43.6777	2.77	4.35	91.77	1	79
Moscow	Russia	3/10/2020	55.9736	10.59	4.24	51.61	0	10
Bogota	Columbia	3/10/2020	4.6972	17.36	7.34	50.13	0	3
Sao Paulo	Brazil	3/10/2020	-23.4306	24.79	14.30	75.48	0	31
Helsinki	Finland	3/10/2020	60.321	28.54	14.01	58.49	0	40
Baghdad	Iraq	3/10/2020	33.267	27.61	14.10	60.82	7	71
Mexico City	Mexico	3/10/2020	19.4361	22.92	12.22	70.68	0	7
Havana	Cuba	3/10/2020	23.1136	22.66	8.09	47.22	0	0
Managua	Nicaragua	3/10/2020	12.1447	28.68	17.31	70.40	0	0
San salvador	El Salvador	3/10/2020	13.4448	23.14	11.96	68.53	0	0
Buenos Aires	Argentina	3/10/2020	-34.82	15.01	2.91	27.17	1	17
Santiago	Chile	3/10/2020	-33.3969	28.08	6.47	29.83	0	13
Asunción	Paraguay	3/10/2020	-25.2415	28.39	18.10	76.25	0	1

Montevideo	Uruguay	3/10/2020	-34.7326	28.24	18.51	77.96	0	0
Riyadh	Saudi Arabia	3/10/2020	24.958202	16.83	8.64	58.40	0	20
Dakar	Senegal	3/10/2020	14.6709	26.33	17.07	80.51	0	4
Lagos	Nigeria	3/10/2020	6.465422	20.32	11.67	68.76	0	2
Luanda	Angola	3/10/2020	-8.8481	10.67	5.61	70.87	0	0
Addis Ababa	Ethipia	3/10/2020	8.9834	4.16	3.82	75.16	0	0
Maputo	Mozambique	3/10/2020	-25.9237	14.14	7.57	77.44	0	0
Johannesburg	South Africa	3/10/2020	-26.1367	2.76	3.64	78.26	0	7
Athens	Greece	3/10/2020	37.9356	10.93	6.39	75.87	0	89
Warsaw	Poland	3/10/2020	52.4493	-10.16	1.60	80.09	0	22
Algiers	Algeria	3/10/2020	36.6975	25.66	14.95	73.13	0	20
Kiev	Ukraine	3/10/2020	50.3382	19.43	10.95	75.86	0	1
Jerusalem	Israel	3/10/2020	31.8631	28.33	15.55	66.13	0	58
Nur-sultan	Kazakstan	3/10/2020	51.0281	27.30	18.94	83.65	0	0
Mumbai	India	3/10/2020	19.0896	28.94	15.53	63.98	0	56
Hanoi	Vietnam	3/10/2020	21.2187	17.11	10.27	84.77	0	31
Phnom Penh	Cambodia	3/10/2020	11.5527	27.37	18.00	78.48	0	2
Kuala Lampur	Malaysia	3/10/2020	2.7456	4.83	4.11	75.76	0	129
Colombo	Sri Lanka	3/10/2020	7.1802	6.91	5.60	88.39	0	1
Wellington	New Zealand	3/10/2020	-41.3276	7.82	5.39	79.59	0	5
Port Moresby	Papua New Guinea	3/10/2020	-9.441	7.96	4.94	73.19	0	0