GLOBAL ACADEMIC RESEARCH INSTITUTE

PONTA DELGADA, PORTUGAL | COLOMBO, SRI LANKA

GARI International Journal of Multidisciplinary Research

ISSN 2659-2193

Volume: 11 | Issue: 01

On 31st March 2025

https://www.research.lk

Author: M Luckshan, PGRNI Pussella

Sabaragamuwa University of Sri Lanka

GARI Publisher | GIS | Volume: 11 | Issue: 01

Article ID: IN/GARI/JOU/2025/P89 | Pages: 28-36 (09)

ISSN 2659-2193 | Edit: GARI Editorial Team

Received: 19.01.2025 | Publish: 31.03.2025

ENVIRONMENTAL AND DEMOGRAPHIC DETERMINANTS OF SPREAD OF DECEASES: A GEOSPATIAL ANALYSIS OF CORONAVIRUS DISEASE (COVID -19) SPREAD IN COLOMBO DISTRICT, SRI LANKA

M Luckshan, PGRNI Pussella

Department of Remote Sensing and GIS, Faculty of Geomatics, Sabaragamuwa University of Sri Lanka

ABSTRACT

COVID-19 pandemic situation brought many risks to the public health systems globally. Environmental and demographic conditions have been impacted largely as transmission factors. This research attempted to investigate the statistical and spatial relationships between demographic and environmental parameters in transmission of COVID-19 in Colombo District, Sri Lanka during 2020. Environmental determinants such as rainfall, temperature, humidity and population density and demographic variables such as the number of schools, temples, public places, dispensaries and market places were considered in the study. Geospatial data analysis and regression modeling techniques were applied to estimate the effect of these determinants on spreading of COVID-19. COVID-19 cases were spatially joined with the environmental and demographic data using Geographic Information System (GIS) procedures in order to analyze correlations and spatial differences. Regression analysis was employed to measure the degree of influence of each factor on the transmission of COVID-19. The results show that population density, availability of public facilities, rainfall, temperature and humidity are significantly related to high infection rates. The results justified that both environmental and demographic determinants are collectively responsible for the transmission of viruses among urban communities. The study concludes that integration of spatial analysis with epidemiological data offers valuable insights for designing effective mitigation strategies that balance environmental realities with demographic pressures, while highlighting the need for interdisciplinary approaches in managing health crisis.

Keywords: COVID-19, GIS, Decease Spread

INTRODUCTION

Covid-19 can be considered as one of the most feared words because of the impact created for humans. Up to date, the global total Covid confirmed cases is approximately 778,318,500 and overall deaths are approximately 7,097,592. It spread globally during late 2019 and have gigantic effects on public health systems, economies, and daily life. COVID-19 is a sickness that spread all over the world which created a pandemic situation started in 2019. The symptoms of this virus were cough, fever and troubles in breathing (Singhal, 2020). The first case of COVID-19 in Sri Lanka was found in January 2020. More people started getting ill after that, especially in the urban areas of the country. Colombo, being the most populated city, most urbanized and busiest city in Sri Lanka, had more victims compared to other cities (Amaratunga et al., 2020). The government closed schools, offices and factories, and instructed to the general public to limit their movements in order to stop the spread of the virus. Since the public health interventions were implemented thoroughly in the country, a lesser number of incidents were recorded compared to other surrounding countries (Swenson, 2021). However, it is needed to identify the environmental, demographic, and geographical factors appeared to be the key drivers of the spread and intensity in various regions for the future management activities of diseases. It is easier for COVID-19 to be transmitted when people are closed to each other. The situation would become severe in the public areas such as offices, schools, temples and factories. It also spreads in health-related locations where victims are having more movements. Further, the virus easily transfers from one person to another specially in the public gathering places such as supermarkets, buses and trains. The situation is much severe in the congested areas.

Weather factors such as temperature, humidity and rainfall affect remarkably on the behavior and spread of the virus. Therefore, scientists need to understand how the virus spreads around in cities, towns, and villages under different weather conditions. In this, GIS based models provide a solid platform to predict the impact areas of the virus (Wang et al., 2022). A number of attempts have been taken to study these circumstances taking different weather patterns, air quality and population density (Othman et al., 2022). These models are very useful in avoiding future outbreaks. COVID-19 virus, generally, spreads based on environmental, geographic, and demographic factors. Transmission of infectious diseases is normally associated with temporal and spatial patterns that can be utilized to improve capture and response efforts via real-time analysis, as well as predictive models of overall performance (Ciotti, 2020). Whether it is hot weather or cold weather, it will influence the rate at which COVID-19 is transmitted. As per some experts, the virus does not favor very hot or very cold weather conditions. However, at normal temperature levels, it can last longer. In places with warm temperature levels, though the number of cases were less, it's not the only explanation (Wang et al., 2020). Humidity is also an influential factor for the spread of virus. With a higher value of humidity, the virus sometimes sticks to surfaces or falls to the ground quickly. Therefore, higher humidity levels decrease the transmission of the virus (Tamerius et al., 2013). Another important factor is the population density. Specially, in urban areas, the virus is transmitted faster (Chen et al., 2020).

Therefore, it is necessary to investigate the role of demographic and environmental variables on the spread of COVID-19. With this objective, this research focuses on the behavior of variables using geospatial analysis methodology and a Multiple Linear Regression (MLR) model.

METHODOLOGY

Colombo, the capital of Sri Lanka, is a densely populated urban area covering approximately 37.31 square kilometers. With a population of over 750,000 people, it is home to diverse socioeconomic groups. Its coastal location, high population density, and busy transportation networks make it a key region for studying the spread of COVID-19. The city's healthcare infrastructure and different living conditions provide unique insights into how environmental, and demographic factors influence on disease transmission.

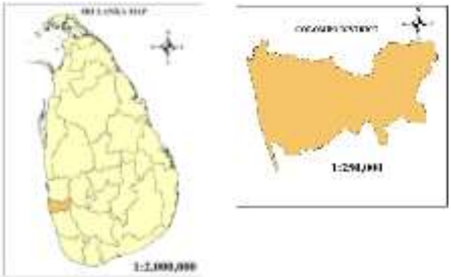

Figure 1: Study Area Maps

The most daunting work prior to conducting any analysis is identifying the variables which would have an effect on the spread of COVID-19. The variables were selected on the basis of previous studies and real-life events that dictate people's movement and gatherings. The variables used in the study were temperature, humidity, and rainfall as weather conditions. Further, population density was chosen as a variable, since highly populated areas are likely to have more physical contacts. Secondly, locations such as schools, super markets, dispensaries, hospitals, and bus stops were included since they are common points of congregation.

After identifying the necessary information for the study, the next important step was to gather related data from reliable sources. Climate related data, including rainfall, temperature, and humidity, were collected from the Meteorological Department of Sri Lanka and Population-related details were obtained from the Census and Statistics Department of Sri Lanka. Data on COVID-19 cases was collected from the Epidemiology Department of the Ministry of Health, Sri Lanka. Data on the locations of public facilities such as schools, markets, dispensaries, and other relevant places within Colombo was collected from the yearly media release published by the Ministry of Economic Policies and Plan Implementation. These combined sources helped build a complete dataset for the research

Figure 2: Flow Chart for Methodology of the Research

After the collection process of data, it had to be structured in order to identify the missing values, fixing strange numbers and arranging data in the correct format. The data was kept in CSV format which is easier to deal with various software applications such as ArcMap. In addition, values for all regions were not provided by weather stations in Colombo. Therefore, in order to fill missing weather values, IDW interpolation method in ArcMap was used. This process estimates values according to the proximity of a location using other locations with the available dataset. Places that are closed to one another tend to share the same climatic conditions, and, thus, this method estimated the missing climate values very accurately. After the missing values had been estimated, raster maps for rainfall, temperature, and humidity were created. These maps were then clipped to obtain the maps showing Colombo District. Using the Zonal Statistics tool in ArcMap software package, mean values for every climatic variable were calculated for all DS Divisions within the study area. These mean values were then propagated back to the original dataset for use in later steps.

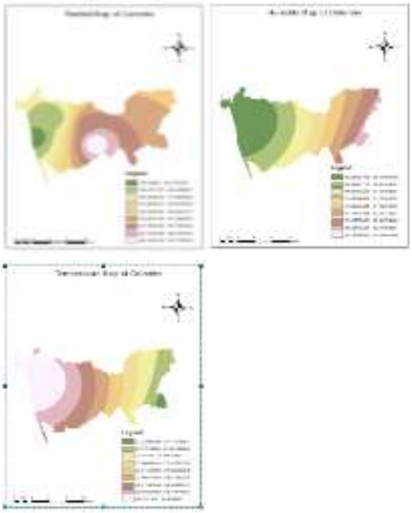

Figure 3: Interpolated maps for Environmental factors

Multiple linear regression model method was used to identify the individual influences of variables in the number of cases of COVID-19. This model works with a mathematical equation explaining how each of the factors such as population or temperature change the number of cases. It helps to decide and identify the most influential variables on the spread of COVID-19 virus. The model was developed in Google Colab, which is a free-to-use online coding platform. Libraries such as Pandas, NumPy were utilized to run the regression. The data that had been cleaned was loaded into the system, Ordinary Least Squares (OLS) method was utilized to calculate the results. To see the extent to which each factor is contributing to the spread of COVID-19, the Analytical Hierarchy Process (AHP) technique was employed. AHP is widely applied as it simplifies complex decisions into comprehensible, easy to compare components. Instead of taking an educated estimate about which factor contributes more, AHP makes it possible to conduct a simple step-by-step analysis. The process started with carefully collecting quantitative values for pairwise comparisons. The values were not randomly chosen. Instead, they were based on published results, expert consensus, and experiential knowledge of how each factor can influence disease transmission. For example, if previous research had shown that population density would have a greater impact on transmission than rainfall, this was reflected in the comparison scores. Once the entire comparison table had been built, the values were normalized and the average row values were calculated to provide the weight for each factor.

While AHP provided weights based on expert judgments, the regression model offered statistical evidence of how strongly each factor influenced COVID-19 spread. Each coefficient from the regression model showed whether a factor increased cases (positive coefficient) or reduced them (negative coefficient). To combine these findings, the absolute values of regression coefficients were normalized to the same 0–1 scale used for AHP weights. Importantly, negative coefficients were not ignored. Instead, they were treated as protective factors. This means that their weight remained positive, but their corresponding data layers were inverted in GIS. To avoid bias towards expert opinions from AHP method and statistical results obtained from the regression method, a hybrid weighting approach was adopted. In this method, AHP weights and regression-based weights were combined using the formula (Equation 01).

$Wi^{final} = 0.5 \times W_i^{AHP} + 0.5 \times W_i^{OLS}$…... Equation 01

Where W_i^{AHP} is the weight from AHP, and W_i^{OLS} is the normalized regression weight. The equal balance (0.5 each) was chosen so that both expert judgment and statistical evidence had the same influence.

Table 1: Final Weighted table

	Factor	Coefficient (β)	Normalized	Normalized Co-efficient	AHP Weights	Final Weights
2	No. of Schools	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	No. of Hospitals	-11.4159	[illegible]	[illegible]	[illegible]	[illegible]
4	Temperature	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
5	Humidity	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
6	Rainfall	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	Population	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	Market Place	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
10	Public Transport	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Each factor had a certain level of importance based on above hybrid weighting method. These weights helped to balance the influence of each factor properly. Once all the data was normalized, apply the weights that were calculated earlier using the method. Each factor had its own level of importance based on how much it could affect the spread of COVID-19. For every DS Division, the normalized value of each factor was multiplied by its weight, and then all those results were added together. These values can be identified as the final number for each area called the Vulnerability Index (Equation 2).

Vulnerability Index=$\sum(W_i^{final} \times L_i^{\prime})$ … Equation 2

Where L_i' is the normalized value (N) for factors.

Vulnerability Score = (Population × Weight) + (Temperature × Weight) + … + (Transport × Weight)

Table 2: Final Weighted table

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

After calculating the vulnerability scores for all areas, they were added into the map using ArcGIS software package. For every DS Division, the weighted values of all factors were added together to produce a single vulnerability score. These scores were linked to the spatial data in ArcGIS, where each DS Division was mapped and classified into categories such as Very Low, Low, Medium, High, and Very High Vulnerability. A clear color scale was applied to visualize the most vulnerable areas of Colombo District. This process resulted in a final vulnerability map that highlighted areas at greater risk of COVID-19 spread by integrating both expert-based and data-driven insights.

RESULTS AND DISCUSSION

The results of the study shows that DS Divisions such as Colombo, Kaduwela and Kesbewa are more dangerous, registering thousands of cases, while other divisions are with less vulnerable for the spread of COVID-19. These are not only the source of economic activities but also quickly urbanized areas where people live, study, do business, and pray within a closer proximity. The streets of these areas are always crowded with traffic, markets are full of people, and public areas are vibrant even during a restriction. Naturally, the virus had plenty of opportunities to spread itself in these environments. Further, the study identified the DS divisions such as Ratmalana, Dehiwala, and Padukka as lower vulnerable areas. These sub-divisions are situated in countryside-based with open spaces, smaller population densities, and smaller amenity locations. Humans are more spread out here, and interaction among them is less frequent compared to the closely populated areas.

This modest but perceptive observation set the scene for establishing that prior to carrying out statistical analysis, human density and activity patterns were far more important than environmental factors in the explanation of COVID-19 spread. Parallel to this, environmental factors were recorded to confirm their possible impact. The average temperature of Colombo District was ranged from 26°C to 32°C, and humidity values were in between 70% and 90% and Rainfall followed the monsoon pattern as predicted, with increased showers during April–June and October–December.

However, as Colombo District is smaller in size and relatively homogeneous in climate, such environmental factors reflected marginal differences in DS Divisions. When comparing the maps of precipitation and temperature within the study area, the trend seemed to be virtually flat in comparison to the stark differences existing in population numbers. This suggested directly that environmental factors would not be enough to explain why populations containing more infections were found in specific areas.

The regression model provided more scientific confirmation of these results. Comparing every factor to the count of COVID-19 cases, the model learned coefficients that explained how much and in which direction every factor influenced the spread. Population density emerged as the greatest predictor for COVID-19 spread. If the population density is higher and statistically significant, as more people packed into a given space, the number of COVID-19 cases is also increased vastly. Colombo city was hit hard because it was dense. The virus propagates most efficiently where people live, work, and travel together side by side. Market density and public spaces trailed as strong indicators. These spaces were open avenues to the virus where it had easy passage from one person to another. The regression found that regions with more markets continued to record infection rates. Schools are statistically significant coefficients. Dispensaries, though less powerful than schools or bazaars but still contributed in significant numbers.

Figure 4: Model Summary

The following scatter plots illustrate the individual influences of each factor on the spread of COVID-19. Each plot highlights the relationship between the number of reported cases and the respective variable, thereby providing a clearer understanding of each factor's contribution on infections across the Colombo District.

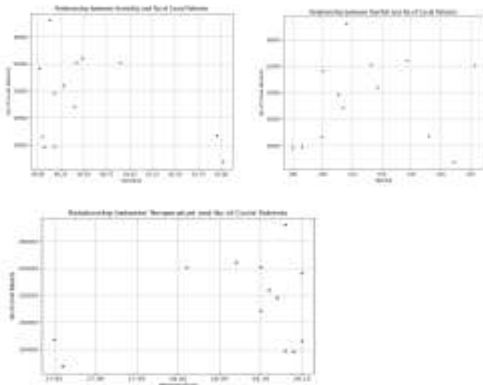

Figure 5: Environmental factors influence plots

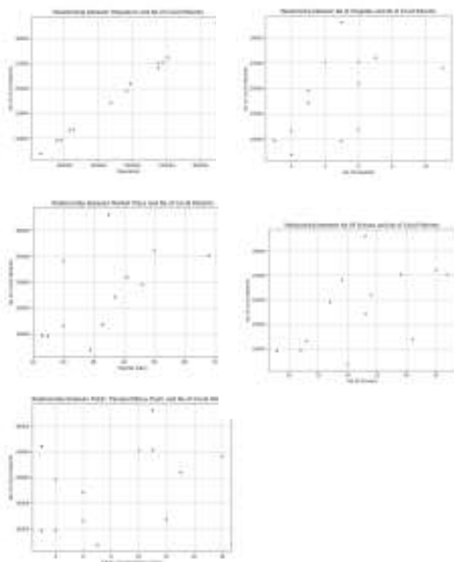

Figure 6: Demographic factors influence plots

Using the combination of weighting method that incorporated AHP values and regression coefficients, each factor received a weight relative to its importance. The weighted values were then summed and mapped to show the total vulnerability of each DS Division to COVID-19 transmission. The vulnerability map immediately exhibite a very strong trend. Homagama, Colombo, and Kaduwela were emitting as hotspots for COVID-19 virus on the map. They had all the virus needed high population, schools, markets, and public places. They weren't just moderately exposed; they were as good as it gets in terms of vulnerability. Divisions such as, Maharagama, Seethawaka and Moratuwa were included in the medium level category. The divisions had significant density and activity, though not as higher as Colombo city. Divisions such as Sri Jayawardanapura kotte, Dehiwala and Padukka were categorized as low vulnerable areas. The following figure 7 shows the level of vulnerability of different DS Divisions of Colombo District.

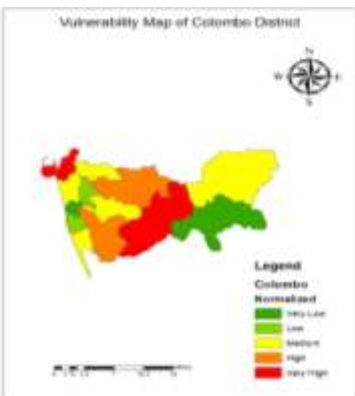

Figure 7: COVID-19 Vulnerability map

The final step of the analysis was to verify the statistical model. Validation plots were used to plot predicted values and actual cases. The validation result provides a close fit between predicted and actual data.

Figure 8: Predicted COVID-19 cases

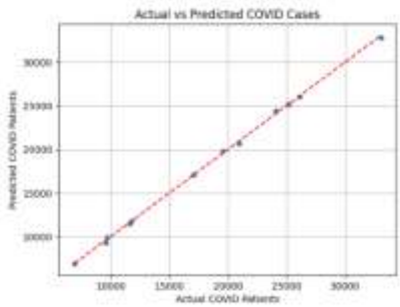

Figure 9: Actual Vs Predicted COVID cases plot

CONCLUSION AND RECOMMENDATION

The results of this study concluded that the virus spread most quickly where the density and interaction of humans were greatest, and spread slowly where humans lived further apart from each other. These results may be far differ from expected results but by proving it through statistical and geographical evidence it can be acceptable for further developments. In brief, COVID-19 cases were not uniformly distributed across Colombo District. The regression analysis justified that population, schools, markets, and dispensaries were the primary determinants of spread of COVID-19 and environmental factors such as rainfall, temperature, and humidity had practically less significant impact on the issue. The map of vulnerabilities visually confirmed these findings, presenting unique clusters of high, medium, and low vulnerability regions. The evidences are clearly determined that human factors were more important than environmental factors in the dissemination of COVID-19 in Colombo District. Even though in this research work the influence of determinants of environment and population has been established successfully. Some potential enhancements can render it more useful. Utilization of real-time movement data (mobile location, transportation utilization) may also provide a more realistic depiction of human movement and the spread of disease. Machine learning and spatial-temporal modeling are some of the new geospatial techniques that can potentially improve predictions. A further extension of the study to cover other regions of Sri Lanka would provide room for comparative analysis. Incorporating socioeconomic and behavioral information may allow variation in disease transmission at the community level to be analyzed. These extensions would allow the model to be enhanced and made more representative for planning for potential future epidemic and pandemic events.

Final results and the findings if this research provide insights for public health planning and management. By Identifying key Environmental and Demographic factors inside the study Area that can influence viruses to spread, Health authorities can design various plans to reduce the risk of spreading viruses in hazardous regions such as densely populated divisions, schools, and public places. The geospatial approach also supports resource allocation, such as distributing medical facilities, vaccination centers, and awareness programs in locations with greater vulnerability. Not only for COVID-19 can this methodology be used for spread of other infectious diseases. Also it is a useful decision-making tool for both current and future public health challenges.

REFERENCES

Abdullah, M., Husin, N. A., & Rahmat, R. A. O. K. (2021). The role of public facilities in the spread of COVID-19: A spatial analysis approach. International Journal of Environmental Research and Public Health, 18(12), 6459.

Amaratunga D, Fernando N, Haigh R, Jayasinghe N. (2020). The COVID-19 outbreak in Sri Lanka: A synoptic analysis focusing on trends, impacts, and science-policy interaction. Progress in Disaster Science, 8, 100133.

Auler, A. C., Cássaro, F. A., da Silva, V. O., & Pires, L. F. (2020). Evidence that high temperatures and intermediate relative humidity might favor the spread of COVID-19 in tropical climate: A case study for the most affected Brazilian cities. Science of the Total Environment, 729, 139090.

Briz-Redón, Á., & Serrano-Aroca, Á. (2020). A spatio-temporal analysis for exploring the effect of temperature on COVID-19 early evolution in Spain. Science of The Total Environment, 728, 138811.

Chen J, Kelley WJ, Goldstein DR. (2020). Role of aging and the immune response to respiratory viral infections: potential implications for COVID-19. Journal of Immunology, 205(2), 313–320.

Ciotti M, Ciccozzi M, Terrinoni A, Jiang WC, Wang CB, Bernardini S. The COVID-19 pandemic. Crit Rev Clin Lab Sci. 2020;57(6):365–88.

Desjardins, M. R., Hohl, A., & Delmelle, E. M. (2020). Rapid surveillance of COVID-19 in the United States using a prospective space–time scan statistic: Detecting and evaluating emerging clusters. Applied Geography, 118, 102202.

Franch-Pardo, I., Napoletano, B. M., Rosete-Verges, F., & Billa, L. (2020). Spatial analysis and GIS in the study of COVID-19. A review. Science of The Total Environment, 739, 140033.

Gentile F, Aimo A, Forfori F, Catapano G, Clemente A, Cademartiri F, Emdin M, Giannoni A. COVID-19 and risk *of pulmonary fibrosis: the importance of planning ahead. Eur J Prev Cardiol. 2020;27(13):1442–6.*

Kamel Boulos, M. N., & Geraghty, E. M. (2020). Geographical tracking and mapping of coronavirus disease COVID-19/severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) epidemic and associated events around the world: How 21st century GIS technologies are supporting the global fight against outbreaks and epidemics. International Journal of Health Geographics, 19(1), 8.

Kang, D., Choi, H., Kim, J. H., & Choi, J. (2020). Spatial epidemic dynamics of the COVID-19 outbreak in China. International Journal of Infectious Diseases, 94, 96–102.

Mollalo, A., Vahedi, B., & Rivera, K. M. (2020). GIS-based spatial modeling of COVID-19 incidence rate in the continental United States. Science of The Total Environment, 728, 138884.

Othman M, Indawati R, Suleiman AA, Qomaruddin MB, Sokkalingam R. (2022). Model forecasting development for dengue fever incidence in Surabaya City using time series analysis. Processes, 10(11), 2454.

Pal M, Berhanu G, Desalegn C, Kandi V. (2020). Severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2): an update. Cureus, 12(3):e7423.

Rocklöv, J., & Sjödin, H. (2020). High population densities catalyze the spread of COVID-19. Journal of Travel Medicine, 27(3), taaa038.

Sajadi, M. M., Habibzadeh, P., Vintzileos, A., Shokouhi, S., Miralles-Wilhelm, F., & Amoroso, A. (2020). Temperature, humidity, and latitude analysis to predict potential spread and seasonality for COVID-19. JAMA Network Open, 3(6), e2011834.

Sarkodie, S. A., & Owusu, P. A. (2020). Global assessment of environment, health and economic impact of the novel coronavirus (COVID-19). Environment, Development and Sustainability, 23, 5005–5015.

Singhal T. (2020). A review of coronavirus disease-2019 (COVID-19). Indian Journal of Pediatrics, 87(4), 281–286.

Swenson KE, Swenson ER. Pathophysiology of acute respiratory distress syndrome and COVID-19 lung injury. Crit Care Clin. 2021;37(4):749–76.

Tamerius JD, Shaman J, Alonso WJ, Bloom-Feshbach K, Uejio CK, Comrie A, Cécile V. Environmental predictors of seasonal influenza epidemics across temperate and tropical climates. PLoS Pathog. 2013;9(11).

Wang, J., Tang, K., Feng, K., Lin, X., Lv, W., Chen, K., & Wang, F. (2020). High temperature and high humidity reduce the transmission of COVID-19. Available at SSRN 3551767.

Wang Y, Yan Z, Wang D, Yang M, Li Z, Gong X, et al. (2022). Prediction and analysis of COVID-19 daily new cases: Time series forecasting and machine learning models. BMC Infectious Diseases, 22, 495.