**Climatic influence on the magnitude of COVID-19 outbreak: a stochastic model-based global analysis**

**Highlights:**

1. Analyzed the influence of climatic and bioclimatic factors on the spread of COVID-19
2. First study to analyze COVID-19 cases in 228 cities globally across three climatic zones
3. Established association between temperature and humidity, and COVID-19 transmission in cities located in temperate and sub-tropical zones
4. Mean diurnal temperature and temperature seasonality associated with COVID-19 transmission in cities within the tropic zone

**Graphical abstract:**

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**Abstract:**

We investigate the climatic influence on COVID-19 transmission risks in 228 cities globally across three climatic zones. . The results, based on the application of a Boosted Regression Tree algorithm method, show that average temperature and average relative humidity explain significant variations in COVID-19 transmission across temperate and subtropical regions, whereas in the tropical region, the average diurnal temperature range and temperature seasonality significantly predict the infection outbreak. The number of positive cases showed a decrease sharply above an average temperature of 10oC in the cities of France, Turkey, the US, the UK, and Germany. Among the tropical countries, COVID-19 in Indian cities is most affected by mean diurnal temperature, and those in Brazil by temperature seasonality. The findings have implications on public health interventions, and contribute to the ongoing scientific and policy discourse on the complex interplay of climatic factors determining the risks of COVID-19 transmission.

**Keywords:** Boosted Regression Tree; climatic association; COVID-19 transmission; SARS-CoV-2; stochastic model.

1. **Introduction**

The global surge of Severe Acute Respiratory Syndrome (SARS) coronavirus disease (COVID-19) pandemic[[1]](#footnote-1) has been unprecedented in the 21st century. The virus has spread rapidly across international borders (Cai et al. 2020) through global travel from its primary infection epicenter in Wuhan[[2]](#footnote-2) (China) to new epicenters in Europe (Italy, Spain, France, Germany, the UK) and North America (the US and Canada). The economic impact of the disease spread has potential to worsen food insecurity among marginalized communities in resource poor and low-income countries (Udmale et al. 2020). COVID-19 is highly contagious. The risk of human-to-human transmission is very high and the disease spreads mainly through close human contact and respiratory droplets (WHO 2020; CDCP 2020a). The common symptoms of COVID-19 are high fever, contagious cough, choking, severe pneumonia, and acute respiratory distress conditions (CDCP 2020a). The case fatality rate (CFR) is estimated at 3.4% globally, while it varies by countries and population groups (WHO 2020). The CFR of the current SARS-COV-2 is lower than its predecessor SARS-COV-1, but its reproduction rate is much higher.

SARS-CoV-1 outbreak in 2003 infected more than 8000 individuals from 29 countries, and 774 died within a period of eight months, whereas, COVID-19 has infected more than four million people across 212 countries with a death toll of close to 280,000 within four months (Ying et al. 2020; Sandoiu 2020; Dong et al. 2020). As on 25 September 2020, the number of COVID-19 cases exceeded 32 million and close to a million succumbed to the infection. The high infection susceptibility or high reproduction rate4 of this virus makes it particularly dangerous to older people, especially in the absence of a vaccine and appropriate drugs for treatment (Newton and Bond 2020).

Historical evidence shows that meteorological conditions such as temperature and relative humidity can induce changes into the human activities that can influence emergence of a new virus and their reproduction rate (Cellers and Mellor 1993; Hammer et al. 2000; Thai et al. 2015). For instance, the higher air temperature may lead to an increase in the use of centrally air-conditioning systems, which host and spread the bacillus, causing Legionnaires’ disease (Simmering 2017). Besides, the differential climatic conditions also lead to changes in the incidences of various infectious diseases, such as malaria(Kim et al. 2019), dengue(Liu et al. 2020), influenza(Chong et al. 2020), meningococcal meningitis(Salomon et al. 2020), cryptosporidiosis(Hu et al. 2007), Rift Valley Fever(Mweya et al., 2017) Kyasanur Forest disease (KFD) (Pramanik et al. 2020b) and Lyme disease (Brownstein 2005).

There is evidence to suggest that climatic conditions including temperature and humidity had influence in spreading infectious diseases such as SARS-COV-1 (Chan et al. 2011; Yuan et al. 2006; Chong et al. 2020). The Daily Incidence Rate (DIR) of SARS-COV-1 was 18 times higher in lower temperature than in higher temperature zones (Tan et al. 2005).Moreover, high circulation of influenza viral diseases has been found in the winter season in the temperate region of the southern and northern hemispheres (Tamerius et al. 2013; Lemaitre et al. 2019).The relative humidity is also a leading cause of occurrences of the influenza epidemic in the US and Vietnam (Dalziel et al. 2018; Thai et al. 2015).

Evidence from a few recent studies highlight the influencing role of temperature and humidity associated with COVID-19 (Wang et al. 2020a; Shi et al. 2020; Pramanik et al. 2020a; Oliveiros et al. 2020), and local climatic conditions may contribute to COVID-19 growth rate (Ficetola and Rubolini 2020).However, most of these studies are based on limited climatic variables, restricted to country or regional level data. There is little scientific understanding of the potential association between climatic factors and COVID-19 spread at the global level. Luo et al. (2020) examined the relationship between province-level climatic variability and increase of COVID-19 reported cases, and suggested that without extensive public health interventions, increase in temperature and humidity may not lead to a decline in COVID-19 cases. Oliveiros et al. (2020)argued p that temperature and humidity contributed to only 18% of variation in the rate of progression of COVID-19 cases, and remaining 82% was attributed to other factors, such as public health, population, and infrastructure.

As the virus spreads rapidly across the globe, the number of international travellers was deemed the primary predictor of COVID-19 outbreak (Luo et al. 2020) at national, regional, and local/city level. Due to high community transmission risks, the global cases are increasing on a daily basis (Ying et al. 2020).However, there is a significant variation in the number of COVID-19 cases in terms of the onset of disease spread and growth rate. Seoul (South Korea), Tokyo (Japan), and Bangkok (Thailand) appear to have "flattened the curve" by April 2020. At the same time, countries in the tropical region including Brazil and India recorded significant increase in the number of COVID-19 cases. Considering the transmission risks at the community level, more systematic research is needed, taking into consideration of climatic and bioclimatic predictors. The present study investigates the climatic influence on the scale of COVID-19 outbreak in 228 cities globally across three main climatic zones.

1. **Methods:**
	1. **Selection of study sites**

The present study focuses on cities across the world. International travel facilitates the spread of the COVID-19 and especially cities and urban centers are more susceptible to disease transmission due to substantial human mobility, service sector engagement, and tourism activities.

We collected data for the countries where more than five cities were found to be significantly affected by COVID-19 cases with a higher infection rate as of 25 May 2020. We have considered regions as well as larger spillover countries across the world. In the case of the countries with the largest spillover, including the US, Spain, Italy, France, Germany, the UK, Turkey, Russia, Brazil, and India, the study selected at least ten cities for the analysis from each country. Further, out of ten cities, we have chosen five cities with the highest number of cases, whereas the remaining five cities were selected randomly to reduce the biases in the representation of a particular country. For the rest of the countries where the reported cases were medium or less, we have considered one to three most affected cities based on the geographical region. For smaller countries, one city, and for medium or larger countries, we have considered 1-3 cities for better representation.

A total of 230 cities were selected for the present study. To understand the regional differences of COVID-19 outbreak, the cities were divided into tropical (0-23°26′11.9″ N/S), subtropical (23°26′11.9″ N/S- 40° N/S), and temperate (40° N/S - 60°N/S) zones based on latitudes. In the present study, 72, 63, and 93 cities were located in tropical, subtropical, and temperate regions, respectively **(Figure 1).** Two cities with polar climate conditions were excluded from the study. We used Boosted Regression Tree (BRT) method to model the disease risks by climatic regions and larger spillover countries.

 **2.2 Descriptions and measurement of predictors**

The present study compiled the number of COVID-19 cases data at the city level from the WHO situation reports, health websites of different countries, and cross-reference updates from national news bulletins. Air temperature and absolute humidity are two critical variables that may contribute to higher community transmission (Sajadi et al. 2020). In the context of COVID-19, the survival and transmission rates of viruses are mostly higher in the regions with low humidity and cold temperature (Ficetola and Rubolini 2020). Hence, it is hypothesized that the higher the relative humidity and temperature, the lower the number of coronaviruses cases. Therefore, for the present analysis, we used temperature and temperature-dependent bioclimatic variables (e.g., average diurnal temperature range, minimum temperature of the coldest month, average temperature of the coldest quarter, and temperature seasonality) and relative humidity as predictors. For each city, we extracted the average monthly temperature and the average relative humidity data from the ECMWF ERA-5 reanalysis for January to April 2020 (Hersbach and Dee 2016).We tabulated the month with the maximum number of recorded cases by temperature and relative humidity data for the respective countries. The bioclimatic data of all selected countries were extracted from the worldclim historical dataset with a 1 km resolution. To control for over-dispersion, we choose the maximum reported cases based on climate for the month, for example January for China and March for Italy.

 **2.3** **Modelling approach**

We analyzed the cases using a BRT model across the climatic regions and the countries with a large number of cases. The BRT model was constructed by multiple regression models, and the best iteration of the model was performed by optimizing prediction performance (Yahaya et al. 2018). We used the module of a stochastic gradient boosting tree proposed by Friedman (2002). The motivation for boosting regression was to improve various weak learners by combining two powerful procedures: regression tree and boosting (Elith et al. 2008; Hastie et al. 2011; Hair et al. 1995). More specifically, in BRT model ensemble predictions generated by the feed of base learner predictions into the meta learner (Hastie et al. 2011). A stochastic gradient boosting approach improves and extends the regression tree (Hastie et al. 2011). Gradient Boosting comes from its connection to the Gradient Descent in numerical optimization to optimize a function (Hastie et al. 2011). The main advantages of using BRT model that it has the advantages of both boosting and regression tree enabling computational efficiency, high interpretability and conceptual simplicity.

Besides, BRT is an additive stochastic model that integrates regression trees by including an outcome to their predictors by recursive binary splits and combining multiple models to a single model, optimizing the predictive performance (Elith et al. 2008). The model can describe non-linear changes, accommodate missing data, and overcome the problems of outlier data (Breiman et al. 1984). BRT models are found to be robust for a small number of data with missing data (Dedman et al. 2017). BRT model can describe multiple interaction, partial dependency (non-monotonous and non-linear) of predictors, with sufficient flexibility and very high predictive accuracy. As our data are nonlinear and interdependent, therefore keeping in mind of a world level analysis with different cities and countries to make the analysis more easy and accurate, we have used BRT to capture the influences of climatic factors on the number of COVID-19 cases. For the analysis, we also considered partial dependence plot to show the marginal effect between the variables and COVID-19 cases. The plot can capture the linear, monotonic or complex relationship between the number of COVID-19 cases and selected variables. Details of the BRT model are available elsewhere, see Friedman (2001), Hastie et al. (2011), Scikit-learn (2015), Ridgeway (2007) and Persson et al. (2017). The BRT model description is included separately **(see supplementary section 1).**

To run the BRT model, we first evaluated the multicollinearity using Pearson correlation coefficient (r) and r ≥ 0.75 was selected as a cut-off threshold **(Figure 2)** to remove the less important variables (Pramanik et al. 2020b, 2020c). The variables were cross-validated using the Variance Inflation Factor (VIF). We found that the VIF value is more than ten and insignificant for two variables, average temperature of the coldest month, and average temperature of the coldest quarter **(see Table S1),** and hence these two variables were dropped from the analysis (Pramanik et al. 2018). COVID-19 cases were selected as outcome variable along with a set of four independent variables or predictors**:** average temperature, diurnal temperature change, temperature seasonality, and relative humidity**.**

 **2.3.1 Model calibration**

This method has been simulated 1,000 times to generate statistical inference by using ten times the loss function by cross-validation. In each BRT model, the subsampling procedure requires a parameter called the ‘bag fraction’ which was set at 0.75 (Fang et al. 2013) and at least 1,000 nodes/trees were used (Elith et al. 2008). In addition, a sensitivity analysis was conducted by setting a bag fraction of 0.5. All results presented in the following sections were calculated by averaging the predicted values of 50 bootstrap replicates. The analyses were conducted using DISMO package version Rv3.4.0. Moreover, the marginal association was assessed for all independent variables across climatic regions and the countries with major COVID-19 cases spillover. The relative contribution of response variables was also assessed, where a larger value indicated higher importance (Friedman 2001).

 **2.3.2 Model validation**

We considered a 70% sample for training, and 30% sample distributed for testing. The model results were checked using the area in the Receiver Operating Characteristic (ROC) curve. Area under the ROC Curve (AUC) values differ between 0 and 1. The value of 0.5 suggests that the model results were less than random, and the value of 1.0 implies absolute discrimination (Pramanik et al., 2018; Thuiller et al., 2005).

1. **Results:**
	1. **Model validation and bag fraction analysis**

The area under the curve in ROC for the tested data was 0.8675, which confirms a high level of accuracy and forecasting ability of the model (Dedman et al. 2017). A comparison between two bag fractions (0.5 and 0.75) was carried out in BRT models **(Table S2).** In general, only small variations within 2% were observed in relative contributions (RCs) of variables. The highest difference between RCs in temperature was about 1.87% in Russia **(Table S2).**

* 1. **Descriptive statistics:**

As of 7July 2020, a total of 11.9 million people were affected, and 0.545 million deaths were reported worldwide (WHO 2020b). The virus has affected 210 territories and countries, wherein most of the cases were reported in developed countries. The climatic conditions may contribute to explaining the variation in the number of COVID-19 cases. **Table 1** shows the median, 10th percentile and 90th percentile of the average temperature, average relative humidity, diurnal temperature change, temperature seasonality in selected countries and regions across the globe**.** In the temperate zone, median average temperature, average relative humidity, diurnal temperature change, and temperature seasonality were found to be 9°C, 67%, 7°C, and 70%, respectively, and 25°C, 65%, 7°C, and 27%, respectively, in the tropical zone **(Table 1).** It indicates that there is a significant variation in temperature and temperature seasonality within these climatic regions. The number of COVID-19 cases are negatively associated with average temperature, diurnal temperature change, and relative humidity, and positively associated with temperature seasonality **(Figure 2).**

 **3.3. Relative effects of predictors**

**Table 2** presents the region and country wise association between climatic parameters and the number of COVID-19 cases. The results show that average temperature (42.9%) and average relative humidity (25.9%) were the major contributors in explaining the differentials of COVID-19 transmission in the temperate zone. At the same time, the mean diurnal range (52.2%) and temperature seasonality (30.8%) were the most significant determinants of this viral community transmission in the tropical zone. In the sub-tropical zone, the role of average temperature (61.7%) and relative humidity (17.5%) were the highest among the selected predictors.

The results show that in countries within temperate zones, the average temperature was a major contributor to the number of cases, for example, France (58.7%), Turkey (58.4%), the US (56.3%), the UK (34.6%), and Germany (35.4%). Similarly, the average relative humidity contributed more in Spain (51.0%), the UK (51.6%), and Italy (32.2%), and relative humidity for the spread was found in the range of 60-70% in countries within the temperate zone. The Russian cases were mostly affected by the temperature seasonality contributing 56.5% to the spread. The mean diurnal temperature range was contributing 49.2% of the cases in Germany **(Table 2).**

The cities located in the tropical zone, for example in countries such as India and Brazil, were mostly influenced by the diurnal temperature range. In India, 58.7% of the cases were explained by the mean diurnal temperature, followed by the average temperature (16.3%) and temperature seasonality (10.7%). The maximum number of cases in India was explained in the range of temperature seasonality varying from 22% to 38%. The community transmission in Brazil was mostly influenced by temperature seasonality (38.4%), followed by the mean diurnal range of temperature (27.1%), average temperature (11.7%), and relative humidity (12.8%) **(Table 2).**

 **3.4** **COVID-19 response to the predictors in different climatic regions**

The marginal effect was assessed by using partial dependence plot to represent the predicted association between climatic indicators and COVID-19 risks of BRT model, as illustrated in **Figure 3**. A non-linear complex association is observed in the temperate and sub-tropical zones with more than 10oC average temperature and average humidity with less than 60%. A monotonic trend is found in the tropical regions for the mean diurnal temperature ranging between 8 and 12oC, and temperature seasonality with more than 80%. The results show that average temperature was negatively associated with COVID-19 transmission risks, which tend to reduce significantly when the average temperature varied from 5oC to 12oC in the sub-tropical zone and 5oC to 11oC in the temperate zone. With increasing average temperature, community transmission is reduced significantly. A more complex association is found between the number of COVID-19 cases and relative humidity, although it was a less influencing factor in the temperate and sub-tropical zones. The probability of disease transmission increased after the threshold of about 60% relative humidity in these two regions **(Figure 3).**

On the contrary, these two meteorological parameters did not have a significant association with the disease transmission in the tropical region. The significant community transmission occurred with the changes in mean diurnal temperature, which was ranged from 4 to 8oC. After this, there was a significant decline in the number of COVID-19 cases in community transmission, which had little variations with average temperature. The temperature seasonality was also significant showing positive association for the community transmission in the tropical countries.

 **3.5 COVID-19 response to the predictors in different countries:**

**Figure 4** represents the country-wise association between the climatic predictors and the COVID-19 cases. The results show a monotonic trend with less than 10°C temperature explaining the COVID-19 cases in France, Turkey, the US, the UK, and Germany. A spurious and more complex association was found between more than 10°C and the COVID-19 cases in these countries. Therefore, maximum cases were found during the temperature varying from 5 to 10°C, and the infections declined when the temperature increased beyond 10°C.

Similarly, the average relative humidity was a contributing factor in Spain, the UK, and Italy, and favorable relative humidity for the disease transmission was found to be 60 to 70% in temperate countries. Interestingly, in the case of Turkey, the cases were increasing after crossing the 73% threshold of relative humidity. The temperature seasonality mostly influenced the number of cases in Russia. About 56.3% of the cases in Russia were influenced by temperature seasonality, followed by Italy (46.3%), and the US (20.5%). More than 70% variation of temperature (temperature seasonality) may trigger a significant increase in COVID-19 community transmission. However, with the 80% of temperature seasonality, a declining trend was noted in the US, whereas the number of infections in Russia declined after a temperature threshold of 110%. This could be attributed to the location, as Russia extends more northwards towards extreme seasonality when compared to the US. Another important variable, mean diurnal range of temperature contributes about 60% to the community transmission in Germany **(Figure 4).**

COVID-19 community transmission in the tropical zone was not strongly associated with the temperature. Maximum cases are explained by 30-40% of seasonal variation in temperature, and the cases tend to decline when the seasonal variation in temperature crosses a 40% threshold. The number of infections in India was mostly associated with the diurnal range of temperature (58.7%), whereas those in Brazil were mostly influenced by the temperature seasonality (38.4%). In Brazil, the maximum number of cases was found in the range between 5° and 8°C of the mean diurnal temperature. In Brazil, the cases increased sharply with an increase in the average temperature. The results further confirmed that the average temperature ranging from 25 to 30 oC was the most influential factor behind the number of cases in tropical zones **(Figure 4).**

1. **Discussion:**

Research studies have attempted to establish the relationship between meteorological parameters and transmission of influenza epidemic (Thai et al. 2015; Chong et al. 2020). Studies conducted more recently have also evaluated the association between climatic predictors and COVID-19 transmission (Wang et al. 2020a; Shi et al. 2020; Oliveiros et al. 2020; Ficetola and Rubolini 2020). These studies have mainly focused on regional perspectives of COVID-19 transmission and its association with climatic conditions. However, a global analysis covering different climatic regions has not been systematically undertaken. The present paper addresses this gap by providing an empirical analysis to investigate the influence of climatic, bioclimatic factors on COVID-19 community transmission across three climatic regions in countries with the most number of COVID-19 cases. The analysis considered climatic and bioclimatic data from 72 cities from the tropical, 63 cities from the sub-tropical and 93 cities from the temperate zones.

A country-level analysis in Indonesia showed that only average temperature is associated with the COVID-19 transmission (Tosepu et al. 2020). Our results demonstrate evidence that increasing temperature and decreasing average relative humidity were associated with the slowdown the community transmission of COVID-19. At the same time, Wang et al. (2020a) showed that higher average temperature and higher relative humidity considerably decreased COVID-19 transmission. About 1°C rise in average temperature is related to a reduction of reproduction rate of transmission by 0.0225 in China (Wang et al. 2020a) and a 1% rise in relative humidity lowers the reproduction rate by 0.0158. Another study by Bu et al. (2000) concluded that in China, the average temperature ranges between 13°C and 19°C and average relative humidity ranges between 50% - 80% constituted an appropriate condition for the community transmission of this virus.

Our results confirm a significant association between COVID-19 transmission risks and temperature in the temperate region, while there was no significant association between these two in the tropical region. A study from China showed that the COVID-19 transmission rate decreased with an increase in temperature in the temperate part of China (Shi et al. 2020). Shi et al. (2020) also found that the cases of COVID-19 were higher within the 10°C temperature, and considerably lower in regions with more than 10°C. It might therefore appear that COVID-19 needs a minimum temperature of 4°C for smooth transmission. Also, in the temperate and subtropical regions, COVID-19 transmission was lower when the temperature remained below 10°C. It is likely that the unfavorable temperature in these regions kept people inside their homes, maintaining ‘social distancing’. Therefore, temperature might have played a significant role in the dispersion of the virus in the temperate and subtropical regions (Lowen et al. 2007). While the average temperature was not associated with COVID-19 transmission in the tropical region, the temperature seasonality and mean diurnal temperature become important for disease transmission in the region. Other than these climatic parameters, socio-demographic and health measures play a role, for example, an overcrowded population, dwelling in slum areas, inadequate hygiene and sanitation, in accelerating the rate of COVID-19 spread in the tropical countries such as India and Brazil (Rukmini 2020; Kirby 2020). Moreover, the disease control measures fail because of chronically under-funded and patchy public health systems (Rukmini 2020).

COVID-19 outbreak varies across different climatic regions such as the temperate and tropical zones, but it may also vary by region or country due to topographical and ecological changes. Moreover, this discrepancy might be due to the differences of environmental characteristics among cities and our climate-zone level results are averaged estimates of each location within certain region (Lin et al. 2014). The extent of heterogeneity in disease transmission across climate zones is evident. However, a generalization of this result warrants caution. Thus, the regional level analysis of heterogeneous climatic associations with the transmission is equally necessary along with global assessments.

The present study found that the role of average relative humidity on COVID-19 transmission was weaker and inconsistent compared to the temperature variable. COVID-19 community transmission in temperate zones seem plausible in conditions of high relative humidity but not exceedingly wet environments (>90%). Moreover, in the tropical zone, high relative humidity is also linked with the transmission rate of COVID-19 cases, but not strongly associated, as in the temperate zone. The results of the present study are consistent with the previous studies, showing the inconsistent effects of relative humidity on COVID-19 cases in the regional case of China (Shi et al. 2020). The Shi et al study also found a similar relationship for Hemorrhagic Fever with Renal Syndrome in China, which was positively associated with the season of cold days (Cao et al. 2020). The relationship between relative humidity and COVID-19 cases can be complicated in a country-level analysis as wet conditions may block the viral replication (Chong et al. 2020; Lowen et al. 2007). Deyle et al., (2016), signified that the effect of relative humidity on influenza disease depends on the temperature. This could explicate our findings that the impact of humidity on COVID-19 transmission could be stronger in a temperate zone and weaker in a tropical zone.

More detailed country-specific findings revealed similar results to those of the regional level, albeit with slight variations. In most of the temperate countries such as France, the USA, Turkey, the UK, and Germany, the cities having an average temperature in the range 5-10°C experienced a higher level of COVID-19 transmission rate than their counterparts **(Figure 4).** Besides, other climatic parameters such as average relative humidity played an important role in some of the countries such as Italy, Spain, the UK, and Russia. In zones with a humidity around 60-70%, when infected people sneezes and coughs, the droplets can spread rapidly into the air and surrounding environment. The droplets carrying the virus may stay longer in the atmosphere and infect new cases (Ong et al. 2020). In summary, we conclude that temperature and humidity are associated with COVID-19 transmission.

Other strains of coronavirus such as HCoV-HKU1, HCoV-229E, HCoV-OC43, and HCoV-NL63 generally show common cold like symptoms. While the seasonality effect is confirmed for the months from December to April, data for other months are not yet available for making any meaningful conclusions. The transmission of the virus lessens during the summer season (Gaunt et al. 2010). In the coming months, in general, the temperature will be increasing in countries within the northern hemisphere. At the same time, the temperature will decrease in the countries of the southern hemisphere. Hence, we believe the findings from this study would have important implications in formulating strategies to deal with COVID-19 outbreak in the near future.

It is worth noting the limitations in the present research. First, in addition to climatic and bioclimatic factors, other socioeconomic, demographic and bio-behavioral factors may also influence the intensity of COVID-19 transmission. However, due to lack of data, we could not consider factors such as population mobility, stringent quarantines, public health interventions, and the human physiological response to the virus. These factors may underestimate the marginal association between COVID-19 and climatic factors. Second, COVID-19 data are gathered from a passive surveillance system could suffer from reporting bias (Ulrich et al. 2020). For example, the patients with asymptomatic and mild symptomatic may treat themselves at home rather than seeking any test and medical facilities. The underreporting bias may also underestimate the results. Third, the present study focused mainly on average monthly climatic and bioclimatic conditions considering larger spillover countries and climatic regions using city level data. Future studies may consider using weekly or daily climatic data to improve the prediction of disease transmission outcomes.

1. **Conclusions:**

We conclude that climatic and bioclimatic factors across cities in three climatic zones significantly predict the spread of the number of COVID-19. The findings of the present study contribute to a better understanding of the relationships between the climatic variables and COVID-19 transmission risks. It underlines the importance of meteorology-based early warning systems to facilitate timely response to COVID-19 community transmission. The findings from the present study also contribute to ongoing debates on the influence of climatic factors on the intensity of COVID-19 spread, and offer directions for policymakers and decision-makers to make appropriate decisions for preventing the disease transmission.

*Conflict of Interest:*

We have no conflict of interest of any matter regarding manuscript, figures and tables that submitted in your journal, all of submitted files are prepared by the authors.

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1. On 30 January 2020, the COVID-19 was declared a pandemic of global concern, requiring public health emergency. [↑](#footnote-ref-1)
2. Originated from the Wuhan wet market in December, 2019. [↑](#footnote-ref-2)