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ARTICLE

Climatic factors influence the spread of COVID-19 in Russia

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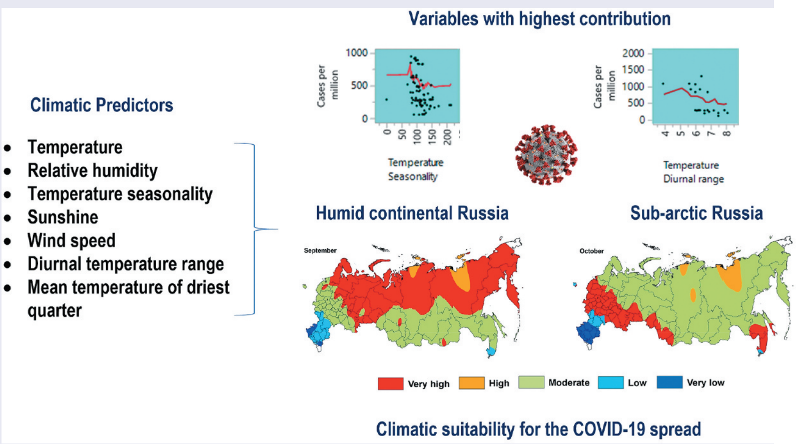
ABSTRACT

The study is the first attempt to assess the role of climatic predictors in the rise of COVID-19 intensity in the Russian climatic region. The study used the Random Forest algorithm to understand the underlying associations and monthly scenarios. The results show that temperature seasonality (29.2 ± 0.9%) has the highest contribution for COVID-19 transmission in the humid continental region. In comparison, the diurnal temperature range (26.8 ± 0.4%) and temperature seasonality (14.6 ± 0.8%) had the highest impacts in the sub-arctic region. Our results also show that September and October have favorable climatic conditions for the COVID-19 spread in the sub-arctic and humid continental regions, respectively. From June to August, the high favorable zone for the spread of the disease will shift towards the sub-arctic region from the humid continental region. The study suggests that the government should implement strict measures for these months to prevent the second wave of COVID-19 outbreak in Russia.



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Introduction

The COVID-19 is a highly transferable viral disease brought about by severe acute respiratory condition coronavirus 2 (SARS-CoV-2), which was first reported in Wuhan, China (Huang et al. 2020). The infection has spread to more than 212 nations and regions around the world, with a total number of affirmed cases being 7.11 million (including 0.406 million deaths) as on 8 June 2020.[1] On 31 January 2020, the World Health Organization (WHO) (WHO 2020) has proclaimed COVID-19, a general public health emergency of worldwide concern – just the 6th time the organization has recognized a crisis of this scale.[2] It denotes the seriousness and potency of the COVID-19 pandemic. The sudden onset of this disease has raised many questions, in particular about its rapid spread across the globe (Zheng et al. 2020). The COVID-19 has spread across international borders reaching North America (the United States of America, Canada) and Europe (Italy, Spain, France, Germany, Russia, the United Kingdom) with a significant number of cases and deaths (Cai et al. 2020).

Weather patterns and human behavior (such as human-to-human contact and population mobility) can be used to foresee the spread of the COVID-19 (Chen et al. 2020). The climatic predictors such as humidity, sunlight, temperature, and wind speed can influence the stability of a droplet in the environment, or influence endurance of infections as temperature, and thus influence COVID-19 transmission (Chen et al. 2020). A significant number of studies on the impacts of climatic predictors on COVID-19 transmission have been conducted in China (Liu et al. 2020), the United States, and Europe (Bukhari and Jameel 2020). Recent studies have shown that the weather factors, for example, humidity and air temperature, may drive the pace of the COVID-19 infections (Shi et al. 2020; Ficetola and Rubolini 2020). A recent study by Asyary and Veruswati (2020) has shown that sunlight helps recovery of coronavirus. The conclusions concerning the relationship between weather and COVID −19 are still not conclusive. Some of the studies (Shi et al. 2020; Cai et al. 2020) did not show any evidence that COVID-19 case counts could decline as the weather warms up.

From the first week of April (2020) Russian cases have been increasing dramatically (MoH 2020). Russia has reported a total of 0.477 million cases and about 5.97 thousand deaths as of 9 June 2020 (MOH 2020). As of the time of writing this paper, Russia has the third highest number of confirmed cases after the United States and Brazil, with a daily growth of about ten thousand cases from 3 May 2020 (MOH 2020). Nearly half of the Russian cases are reported in the city of Moscow. Russia is facing a severe and relatively delayed outbreak, due to a swiftly warming seasonal weather. The humid continental climate dominates the country with an exception of northern Russia and Siberia, which have the sub-arctic environment. As humid continental climate conditions dominate over the majority of Russia, exploring the relationship between weather and the spread of COVID −19 can bring essential recommendations for disease control measures. Yet, to date, no studies have been undertaken to understand the climatic role in the intensity of COVID-19 transmission in Russia. Our study aims to fill this gap by providing statistical evidence on the influence of climatic variables on the intensity of COVID-19 spread in Russia.

The present study hypothesizes that there is a significant association between climatic factors and the intensity of the COVID-19. The study investigates the relationship between climatic factors such as air temperature, relative humidity, wind speed, sunshine, diurnal temperature change, and temperature seasonality and the COVID-19 spread in the geographical regions in Russia. Besides, the present study develops a scenario-based map of weather-related increase in the COVID-19 spread for June to end of the year for implementing mitigation measures. The findings of the study are expected to enrich the ongoing discussion on the effect of weather on the COVID-19 spread and translate into essential recommendations for disease control measures.

Data and methods

Study area

Russia is located in the northern hemisphere between 41° and 82° N latitude and 19° E and 169° W longitude. Russia is a transcontinental (Northern Asia and Eastern Europe) and the largest country in the world, with a geographic area of approximately 17.12 million sq. Km. The country has a significant range of climatic variations due to its vast geographic area (Figure 1). According to Köppen's climate classification, 80.2% of the Russian region comprises a humid continental climate, a 15.75% sub-arctic climate, 1.46% a cold semi-arid climate, and 2.58% a humid sub-tropical (Beck et al. 2018). It has been reported that the cities across the world are more prone to COVID-19. Russia is not an exception. Therefore, a total of 101 primarily selected cities for the analysis are classified into two climatic regions (79 cities in the humid continental and 22 cities in the sub-arctic climate).

Data source and description

The number of COVID 19 cases as the dependent variable were collected from WHO situation reports and the Ministry of Health (MoH), Russia (MoH 2020). Air temperature and absolute humidity are two critical variables that may contribute to higher community transmission (Wang 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 was hypothesized that the higher the relative humidity and temperature, the lower the number of coronaviruses cases. Therefore, for

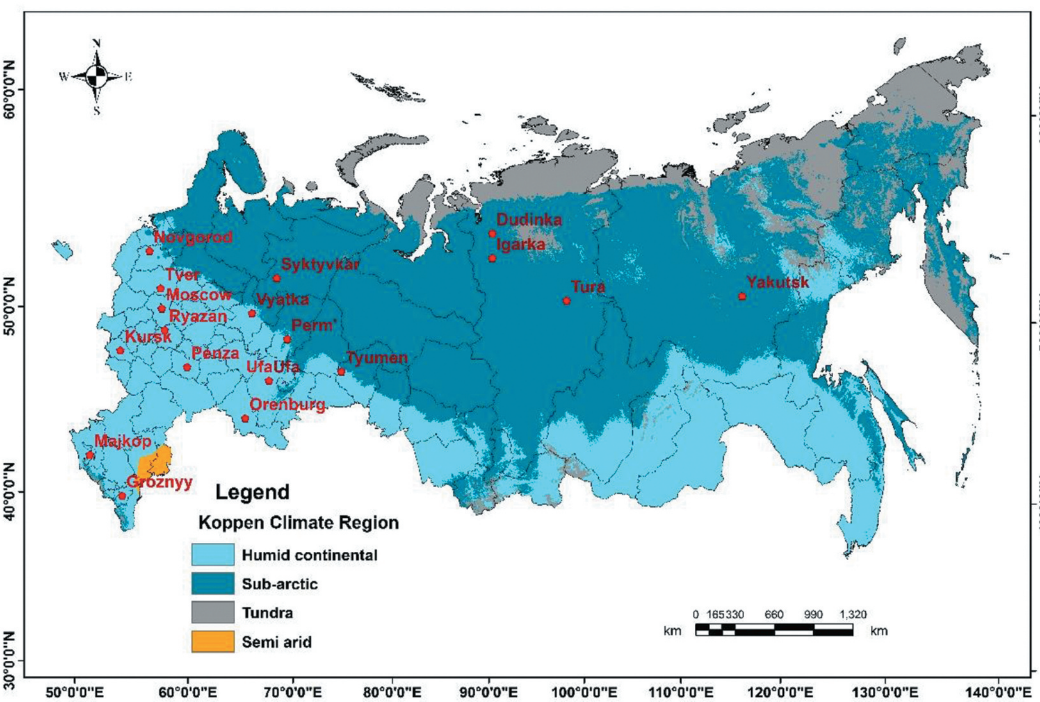

Figure 1. The Köppen Climate Classification of Russia (Source: Beck et al. 2018) shows the broad climatic region (i.e., humid continental climate, sub-arctic climate, tundra climate, and semi-arid) in Russia. Humid continental climate, the sub-arctic climate was considered for the analysis, and tundra and semi-arid region excluded from the analysis as there were very few cases were registered.

the present analysis, the study used temperature and temperature-dependent climatic variables (e.g., average diurnal temperature range, coldest month minimum temperature, the coldest quarter average temperature, temperature seasonality, isothermality, the driest quarter mean temperature) and relative humidity as predictors (independent variables). The diurnal temperature range is a constant temperature measurement and is an index of variation in temperature to determine the effects on human health. The average monthly temperature (2 m), the mean relative humidity, wind speed, and sunshine data the cities are extracted from the ECMWF ERA-5 reanalysis for April 2020 (Hersbach and Dee 2016). The climatic data of all selected countries were extracted from the 'world climate' historical dataset with a 1 km resolution. It is assumed that climatic and bioclimatic factors are responsible for the transmission of COVID-19 in a specific range (Ficetola and Rubolini 2020; Kampf et al. 2020).

Variance Inflation Factor (VIF) was used to select climatic variables for the RF model. The VIF greater than 10 shows that multicollinearity exists between the variables. Seven of the total ten climatic variables with VIF in the range of 1.34 to 5.39, which was less than ten, were selected for the model (see Supplementary file, Table S1). The three variables, the coldest month mean temperature, the coldest quarter mean temperature, and isothermality, showed multicollinearity (VIF >10) and were excluded from the analysis. The climatic variables used to set up the Random Forest (RF) model are listed in Table S1. The study used the RF as described in the following subsections.

Model description

Random forest model

As mentioned previously, the study explores the association between climate factors and the COVID-19 spread in two regions (humid continental and sub-arctic climate) in Russia. The primary objective is to identify the climatic and bioclimatic determinants of COVID-19 cases in these two regions. The RF model was used for the analysis.

The RF approach of machine learning was developed based on a small change in the bagging algorithm, where regression classification and regression tree can be united together. The model can create several decision-making trees to illustrate the spatial relations between COVID-19 cases and climatic factors. It toils by creating several decision trees during training and output classes, which are the shape of regression and classification of individual trees. The decision tree is designed to generate the classes (Breiman 2001). The estimation of the dependent variable was obtained for the regression algorithm. The RF model does not use any assumptions of the relation between explaining factors and response factors. In large data sets, this is an effective way to test hierarchical and non-linear interactions (Olden et al. 2008). A RF model can, therefore, be used to predict new cases better and its performance can be different from other traditional regression models. RF approaches can fit a complex non-linear relationship among heterogeneous predictors (independent variables) (Ye et al. 2019). The study used the RF model to estimate the relative importance of climatic factors associated with COVID-19 transmission in Russia, as the RF can avoid overfitting and can estimate the significance of each predictor.

To assist the RF model interpretation, the study used partial dependence plots. Variable importance influences the relative variations of the model. In tree-based model variable importance is averaged and measured by the improvement of square error. Partial dependence plots are used to show the marginal effects of independent variables on the visible dependent variable and to plot the selected range of the independent variable (Friedman 2001).

Gini index was applied to characterize the rank of the most important predictor (Dangeti 2017). Simultaneously, if the value of the Gini index is high in RF depicts that the significance of the influencing factors. Gini index measured in this research *i(t)* as,

$$= 1 - \sum_{j=1}^{m} f\left(a_{X(xi)}, j\right)^2 \quad (1)$$

Where $f\left(a_{X(xi)}, j\right)$ denotes the proportion of sample value, X_i fitting to leave j as node t. Splitting criteria of the decision tree are attributed to the lowest Gini index value (I_G).

A new development of decision trees of the RF was proposed by Breiman (2001). It is paired with the rule-based approach to all the single RT algorithms. It promises the highest level of accuracy than other machine study algorithms, since it assumes the prediction can be combined more accurately.

Typically, RF regression builds a K number of regression trees and average the results. After k number of trees $\{T(a)\}_1^k$ are grown, the predictor equation takes the following forms,

$$f_{rf}^{K}(a) = \frac{1}{K}\sum_{k=1}^{K} T(a) \quad (2)$$

In a typical RF regression, generalize error articulated as follows (Masetic and Subasi 2016; Chen et al. 2018),

$$= av_k I(h_k(x) = y) - max_{j \neq y} av_k I(h_k(x) = j) \quad (3)$$

Where x and y are COVID-19 conditioning predictors, mg refers to margin function, and I (*) refers to indicator function (Masetic and Subasi 2016; Chen et al. 2018). Therefore, the development of RT started with mixed samples and divided continuously in each node until it reaches on best class. During this process, the maximum value of the Gini index is selected in every stage of the tree.

Generation of the COVID-19 spread-related climatic suitability

The 'randomForest' Open source R software package for all the modeling process was used in this study, and the final map was generated by importing final R output in ArcGIS to generate a climate suitability map of COVID-19. The climatic suitability of COVID-19 for each month was classified according to the quintile classification technique as it has very high classification accuracy (Bennette and Vickers 2012). The map was categorized into five different climatic suitability classes, including very high, high, medium, low, and very low.

Model calibration and validation

In the RF model, 30% of the sample was used for training, and 70% of the sample was distributed for testing. This model has been simulated 1,000 times for statistical inference by cross-validation with ten times the loss function. The receiver operating characteristic (ROC) curve was widely used in the variety of studies to calculate the mapping efficiency (Brownstein et al. 2005; Heikkinen et al. 2006; Pramanik et al. 2020b; Pramanik et al. 2020c; Monaghan et al. 2015). The curve is a scientific method for the explanation and estimation of the performance of deterministic and probabilistic systems (Swets 1988). Furthermore, some methodological uncertainties that occur due to statistical methodologies and variations in the data sources used for modeling (Heikkinen et al. 2006). In the quantification of uncertainty in model prediction, Zipkin et al. (2012) showed that the area under the ROC Curve (AUC) is helpful. The model results were checked using the ROC curve, and the success rate and the prediction performance curve were determined to evaluate the efficiency and reliability of the RF model tests. The 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 implies absolute discrimination (Thuiller et al. 2005; Pramanik et al. 2018). In addition, all independent variables across climate regions have been tested by the marginal association. Also, the relative contribution of response variables was evaluated, where a larger value indicates higher importance (Friedman 2001).

Results

Status of COVID-19 spread and meteorological variables in Russia

The first Russian case of COVID-19 is conformed in the capital Moscow on 2 March 2020 (MOH 2020). At around mid-April, the number of COVID-19 cases started to grow exponentially. As of 26 May 2020, Russia stands third in the world, after the US and Brazil, in terms of the number of COVID-19 cases. Total 360 thousand COVID-19 cases and four thousand fatalities are reported in Russia on 26 May 2020 (Figure 2(a)). Moscow ranks first in Russia with 170 thousand COVID-19 cases followed by Moscow Oblast (35 thousand) and Saint Petersburg (14 thousand) federal subjects (Figure 2(b)). About 130 thousand reported being recovered cases in Russia as of 26 May 2020. The COVID-19 fatality rate in the country is found to be 0.9% (MOH 2020). It is feared that the COVID-19 death rate could be 70% higher than the reported death rate in Moscow and 80% higher in the country's region (Nechepurenko 2020).

The climatic and bioclimatic conditions lead to this variation of COVID-19 cases. Therefore, to understand the climatic predictor, Table 1 shows the median, 10th percentile, and 90th percentile of average temperature, average relative humidity, sunshine, wind speed, diurnal

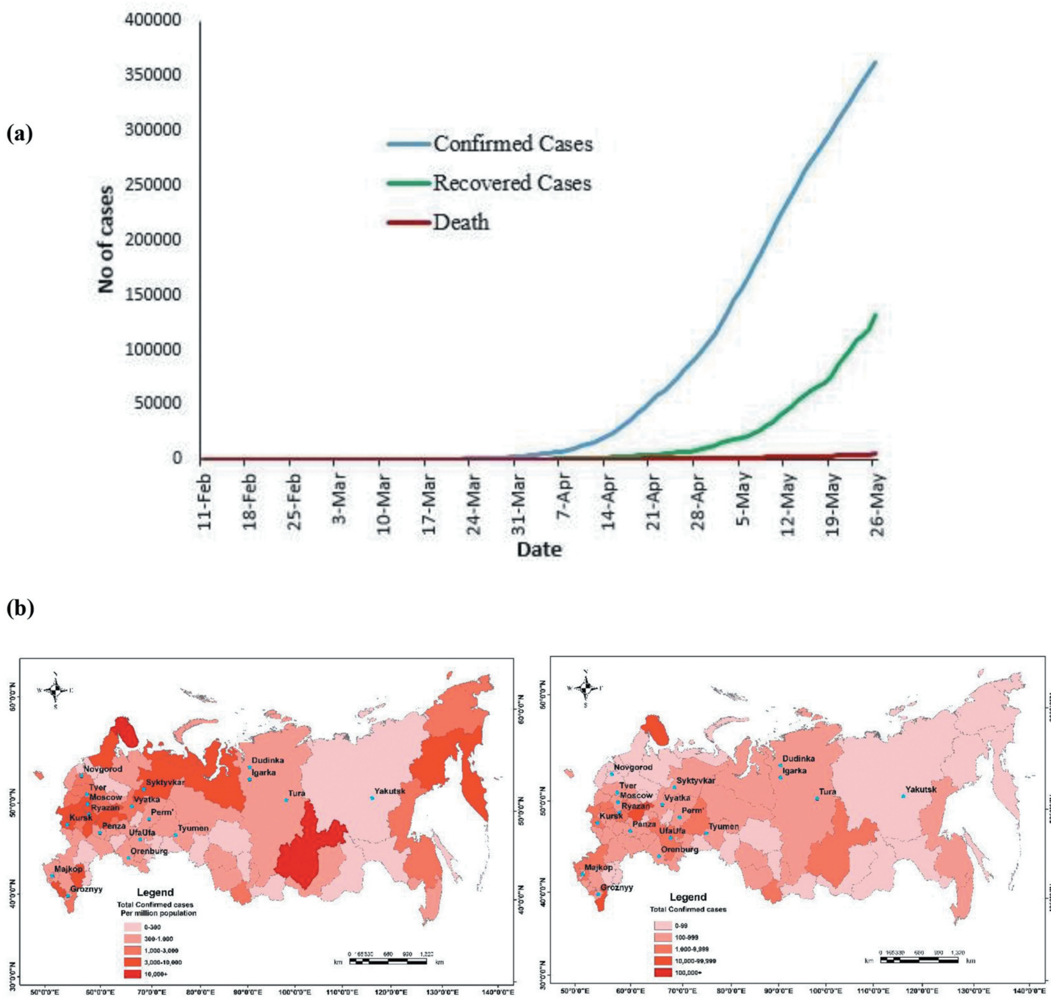

Figure 2. (a) Total COVID-19 cases and the death toll in Russia and (b) spatial distribution of the cases till date 26 May 2020.

Table 1. Meteorological quantiles (10th, 90th percentiles) of climatic, bioclimatic variables for the number of COVID-19 cases in different climate zones of Russia.

		Medians (10^{th}, 90^{th} percentiles)	
Sl. no.	Predictors	Humid continental climate	Sub-arctic climate
1.	Average temperature (°C)	8.18 (5, 12.9)	−1.14 (−10, 5)
2.	Relative humidity (%)	62.96 (49, 73)	81.82 (73.4, 91.9)
3.	Sunshine (hour)	235.42 (198.7, 272.3)	160.61 (76.1, 242.7)
4.	Wind speed (km/h)	12.52 (9.51, 15.2)	12.8 (9.21, 17.24)
5.	Temperature Diurnal range (°C)	7.76 (6.61, 9.1)	6.44 (5.61, 7.5)
6.	Temperature Seasonality (%)	110.23 (84.75, 142.38)	112.90 (87.33, 164.09)
7.	Mean Temperature of Driest Quarter	−5.96 (−17.66, 0.13)	−12.49 (−23.84, −6.9)

temperature change, temperature seasonality, and mean temperature of the driest quarter of the selected region in Russia. Concerning the unique characteristics of the humid continental and sub-arctic climate, the selected variables show a considerable difference in climate variables, mainly the average relative humidity, temperature, mean temperature of the driest quarter, and sunshine hours. The median of average relative humidity, temperature, wind speed, sunshine hours, diurnal temperature change, mean temperature of driest quarter, and temperature seasonality were 62.96 (78.82) %, 235.42 (160.61) hrs/month, 8.18 (−1.14) °C, 12.52 (12.8) km/hr, 7.76 (6.44) °C, −5.96 (−12.49) °C, and 110.23 (11,290) % in humid continental (sub-arctic) climate regions, respectively (Table 1).

The COVID-19 cases are, therefore, significantly varying between the regions due to climatic dissimilarity across Russia. The relationship between COVID-19 cases in the humid continental region in Russia are significantly correlated with climatic variables i.e. average temperature ($r = 0.21$, $p = 0.001$), sunshine ($r = 0.20$, $p = 0.002$), wind speed ($r = 0.26$, $p = 0.01$), and temperature seasonality ($r = -0.29$, $p = 0.01$) (see supplementary Figure 3(a)). In the sub-arctic region, diurnal temperature range ($r = -0.60$, $p = 0.02$), and temperature seasonality ($r = -0.29$, $p = 0.03$) are most significantly correlated, and remaining variables in the region like relative humidity, temperature, wind speed, sunshine, and the temperature in the driest quarter are not significantly associated with COVID-19 (see supplementary Figure 3 (b)). This low relationship found due to the very less and even negative temperature experienced throughout the sub-arctic region as located in the higher latitude, and before pick season, there was too cold season in Russia. With increasing temperature, the COVID-19 cases were late but sharply increased after that.

Influence of climatic factors on the COVID-19 spread

The present study explored the influence of climatic factors on the COVID-19 cases in the sub-regions of Russia. Table 2 shows the RF model-based climatic variables importance to the COVID-19 cases in humid continental and sub-arctic region in Russia. In the humid continental climate, the temperature

Table 2. Relative importance of predictors (climatic, bioclimatic variables) in percentages (±SD) and goodness of fit of the RF model.

		Predictors importance (%) in Russia	
Sl. No.	Predictors	Humid continental climate	Sub-arctic climate
1.	Average temperature (°C)	13.7 ± 0.8	14.4 ± 1.3
2.	Relative humidity (%)	2.70 ± 0.2	10.2 ± 1.2
3.	Sunshine (hour)	14.0 ± 0.5	10.1 ± 1.0
4.	Wind speed (km/h)	9.10 ± 0.1	13.2 ± 0.5
5.	Temperature diurnal range (°C)	10.1 ± 0.3	26.8 ± 0.4
6.	Temperature seasonality (%)	29.2 ± 0.9	14.6 ± 0.8
7.	Mean temperature of the driest quarter (°C)	21.1 ± 1.1	10.7 ± 1.3
8.	R2	0.912	0.893

(a)

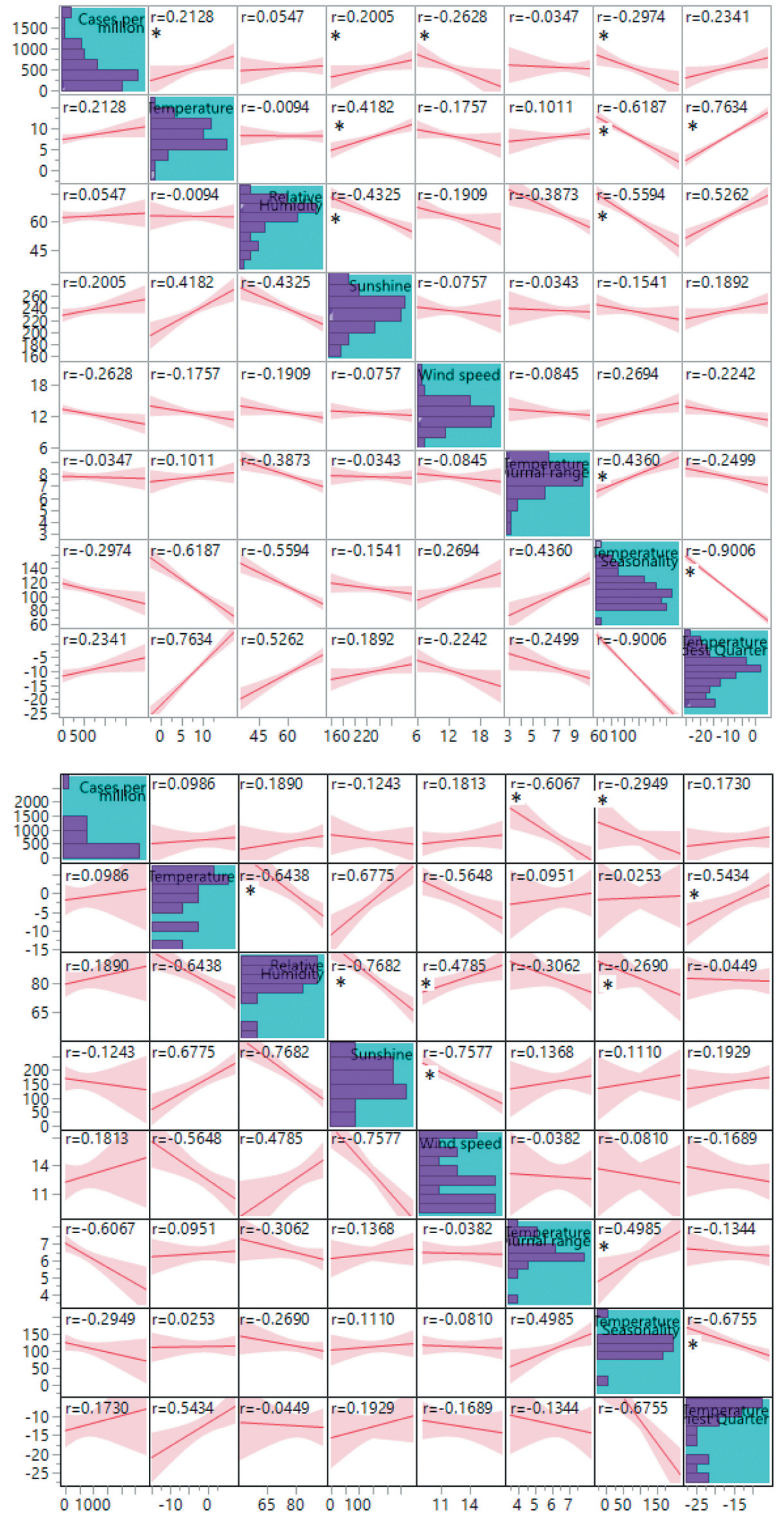

Figure 3. Scatterplot matrix showing the relationship between climatic variables and the number of COVID-19 cases in the humid continental region (a), sub-arctic region (b) in Russia. The corresponding correlation value (r) to identify significant variables for the model are shown on the plots. * significant at 1% probability level (p).

seasonality (29.2 ± 0.9%), mean temperature of the driest quarter (21.1 ± 1.1%), and average temperature (13.7 ± 0.8%) found to be explaining the differentials of COVID-19 transmission in Russia. Whereas in the sub-arctic climate region, the diurnal temperature range (26.8 ± 0.4%) and average temperature (14.5 ± 1.3%) followed by temperature seasonality (14.5 ± 0.8%) found to explaining the differentials of COVID-19 transmission as compared to other four climatic variables. It highlights that the average temperature, diurnal temperature range, temperature seasonality, and mean temperature of the driest quarter can explain the spread of the disease in both regions. It was observed that with 2.7 ± 0.2% contribution in relative humidity in the humid continental climate can explain the spread of the disease, whereas it contributes 10.2 ± 1.2% in the sub-arctic climate of Russia. Another considerable difference is observed in diurnal temperature change, explaining the number of cases. It was explaining higher importance in the sub-arctic climate (26.8 ± 0.4%) compared to humid continental (10.1 ± 0.3%). The temperature seasonality and mean temperature of the driest quarter explained the differentials of COVID-19 transmission with a higher importance in the humid continental climate as compared to the sub-arctic climate of Russia.

The marginal model output shows the relationships between selected climatic variables and the number of COVID-19 cases in Russia. The association between selected climatic predictors and the intensity of community transmission of COVID-19 in the humid continental region and sub-arctic region of Russia are displayed in Figure 4. Non-linear relationships were observed between the number of COVID-19 cases (dependent variable) and all seven selected climate variables (independent variables) included in the analysis. In the humid continental climate, the number of cases increased with the temperature seasonality ranges from 80 to 100%. More than 80% variation in temperature (temperature seasonality) might have caused a significant increase in the COVID-19 cases. The cases with the mean temperature of the driest quarter were also positively associated with COVID-19 cases in this region, where very few cases were observed in the driest quarter temperature less than 0°C. The third-most influential predictor, the average temperature in the humid continental climate, showed an increasing trend in the number of COVID-19 cases from 4 to 13°C and a declining trend observed after temperature increased beyond 13°C. These three variables explained about 64% importance in the differentials of COVID-19 transmission in the humid continental climate. The number of COVID-19 cases showed increasing, decreasing, mixed, and stable trends against the rest variables, sunshine hours, diurnal temperature range, relative humidity, and wind speed respectively.

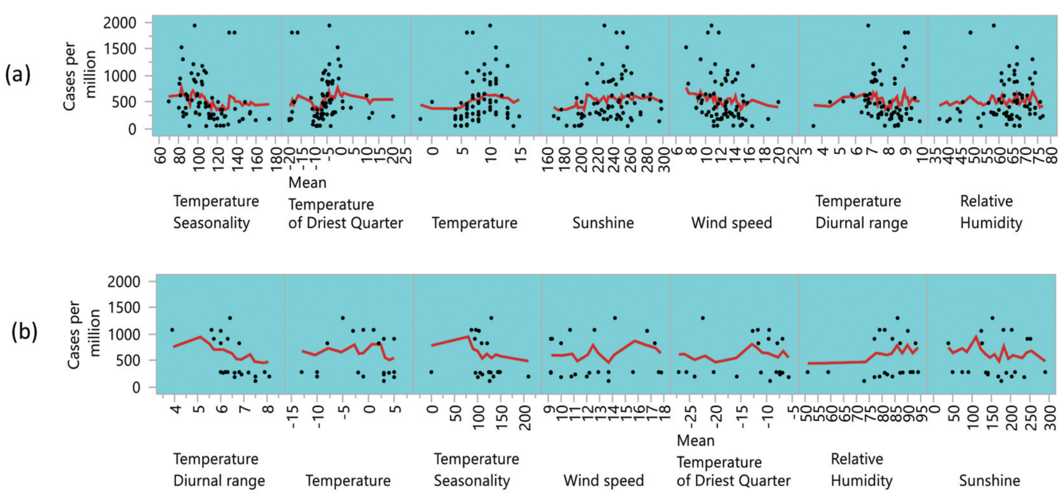

Figure 4. Marginal dependence graphs for the seven predictors in the model for COVID-19 transmission in (a) the humid continental climate (b) the sub-arctic climate regions of Russia. For explanation of predictors and their units, see Table 2. *Y*-axes represent the number of COVID-19 cases, and X-axes represent predictors.

In the sub-arctic climatic region, the diurnal temperature range, average temperature, and temperature seasonality explained about 56% of importance in the differentials of the COVID-19 transmission. In addition, the transmission of COVID-19 intensity was declined with a rise in the diurnal temperature range about 6°C and temperature seasonality at 90%. Whereas, the number of cases increased with the average temperature at 5°C. The number of cases against wind speed, mean temperature of the driest quarter, and relative humidity showed an increasing trend. The number of COVID-19 cases in this region is not strongly associated with temperature. As compared to a mixed trend observed against the increased sunshine hours showed a decreasing trend in the number of cases in the sub-arctic region of Russia.

Model performance and climatic suitability for COVID-19

Under the ROC process, the model had an excellent ability to differentiate between absence/presence: all iterations had AUC greater than 0.90 and an average of 0.944 (between 0.91 and 0.97). The AUC of the present iteration is 94.85%, which indicates that the model is highly accurate.

In this study, we prepared monthly suitability maps based on climatic variables maps for the magnitude of COVID-19 cases, as shown in Figure 5. The final eight suitability maps, derived by the model using monthly historical climatic conations (past ten years average climatic conditions of 2009–2019), revealed an interesting spatio-temporal pattern COVID-19 suitability in the month from May to December. As the analysis and writing of the draft were nearly completed in mid-May; therefore, the data for May was used for validation of the COVID-19 regional cases in Russia. The results show (Figure 5) that in May, most of the cities in the sub-arctic regions have favorable climatic conditions for the COVID-19 community transmission, whereas the cities in the humid continental region have relatively less suitable climatic conditions for the disease transmission. Thus, these unfavorable climatic conditions may act as a limiting factor and may reduce COVID-19 cases in the humid continental region.

Similarly, the suitability maps in September and October show favorable climatic conditions for the spread of the disease in sub-arctic and humid continental regions of Russia, respectively. During the month from June to August, the high suitable zones will be shifted towards the sub-arctic region from the humid continental region (Figure 5). Hence it is recommended that the government implement strict measures in the sub-arctic region in June and issue advisories to prevent the high transmission rate of the COVID-19. In the month of November, the south-western part of Russia returns to moderate to high suitable conditions, which is under the humid continental climate. Also, in December, the persistence of suitable conditions is confined to the narrower south-western belt of the humid continental region is suitable for moderate conditions. While in the humid continental climatic region, the suitable climatic condition was also found in October, therefore the government should have to implement strict measures for that time.

Discussion

The pandemic of COVID-19 has triggered significant global health and economic challenges. In this study, we evaluated the links between climate and bioclimatic variables with COVID-19 cases across the regions in Russia. The results showed that the effects on temperature, sunshine on the COVID-19 rate, and a significant negative relationship between the COVID-19 intensity, temperature seasonality, and wind speed are significantly affected in the Russian humid continental region. In the sub-arctic region, the effects of diurnal temperature range, wind speed, and relative humidity, on the intensity of the COVID-19 transmission were observed.

Our results further showed that there is a positive association between temperature seasonality and wind speed and the intensity of COVID-19 transmission in the humid continental region. On the other hand, in the sub-arctic region, diurnal temperature range, humidity, and temperature all have a positive effect on the spread of COVID-19. The results of climatic associations are consistent with the previous studies (Pramanik et al. 2020a). In addition, the number of studies showed that COVID-

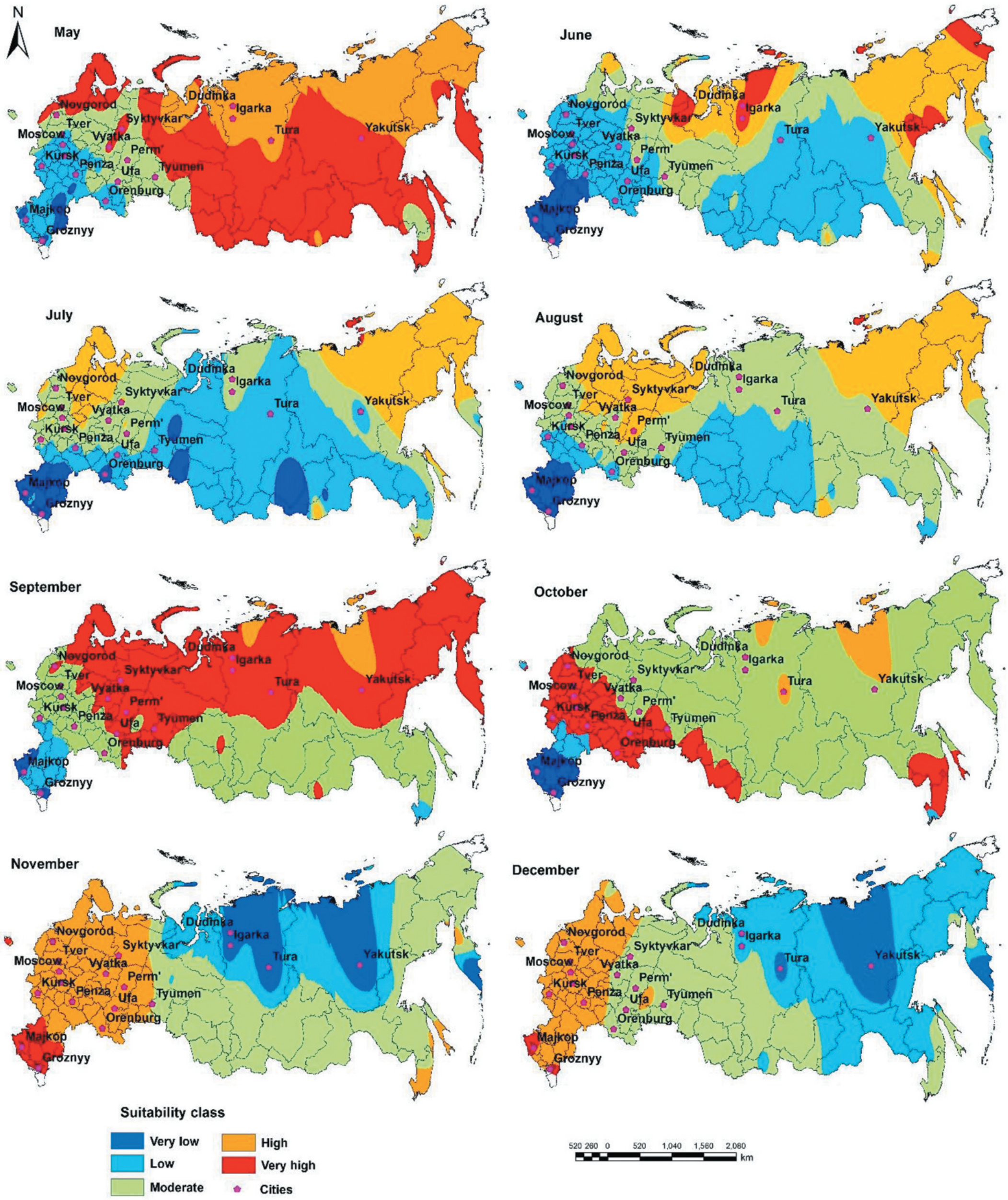

Figure 5. The climatic suitability for the COVID-19 transmission for May – December in Russia.

19 cases and deaths are influenced by temperature fluctuation (Fallah and Mayvaneh 2016), and sturdily correlated with lower temperature (Gomez-Acebo et al. 2013; Dadbakhsh et al. 2017). The results are also consistent with previous studies examining temperature influence (or temperature-related micro variables) on the number of confirmed COVID-19 cases (Liu et al. 2020; Xie and Zhu 2020). Further studies found that the effects of both heat and cold could adversely affect respiratory disease (Li et al. 2019) and that a rising diurnal temperature range risk was linked with a greater risk of cardiovascular disease in 30 eastern Asian cities (Kim et al. 2016).

The relative cumulative risk of cardiovascular, respiratory, and non-accidental, deaths, and cases in the winter season in Tabriz increased with a high diurnal temperature range (DTR) (Sharafkhani et al. 2019). In a series of times in the Shanghai region, the effect of diurnal tempering ranges on the daily mortality of obstructive pulmonary disease (COPD) was reported, showing that every 1°C rise in diurnal temperature ranges represented 1.25% of the risks for COPD cases (Song et al. 2008). A study of immune functions and cold exposure indicated that immune function could suppress by lower temperatures (Shephard and Shek 1998). In addition, sudden changes in temperature can impose additional pressures on the respiratory and cardiac system that cause cardiopulmonary problems, and high diurnal temperature range can contribute to environmental stress (Sharafkhani et al. 2019). Its increasing negative impact on human health, disease, the risk may significantly influence the intensity of COVID-19 transmission in the sub-arctic region of Russia. The transmission of influenza was also influenced by temperature seasonality (Thai et al. 2015). Moreover, in tropical regions, the transmission of the virus was found to be dependent on seasonality (Gaunt et al. 2010).

As Russia is located at a higher latitude, the temperatures in these months relatively low (less than 2°C), typically rising from April, when temperature levels appear to be favourable for the COVID-19 transmission. This situation was observed in the humid continental region, more specifically Moscow city, where a significant rising intensity of COVID −19 transmission was delayed, due to a swiftly warming seasonal weather (Figure 5).

Our study also established that the role of average relative humidity on the intensity of the COVID-19 transmission was moderately associated and consistent. According to our results, 60–65% relative humidity in the humid continental region and 75–80% in the sub-arctic region is more suitable for the virus and moderately associated. The COVID-19 transmission in a temperate zone was generally suitable in the conditions of high relative humidity but not exceedingly wet environments (>90%). Moreover, in tropical areas, high relative humidity is also linked with the transmission of COVID-19 cases but not strongly associated as a temperate region. These findings are in line with a study from China that average temperature ranges between 13°C and 19°C and average relative humidity range between 50% – 80% constitute an appropriate condition for the community transmission of this virus (Bu et al. 2020).

A new finding from our research is that the temperature seasonality and temperature diurnal range are important in the context of the intensity of COVID-19 transmission. In the humid continental region, a positive impact was found between the temperature and COVID-19 intensity (0.21, 95% CI: 0.001). Increased average temperature led to a reduced effect of average relative humidity on the intensity of COVID-19 cases in humid the continental region in Russia. Shi et al. (2020) found that the cases of COVID-19 were highest within the 10°C while it is considerably low more than 10°C temperature in China. It might, therefore, appear that COVID-19 needs a 4°C of a minimum level of temperature for smooth transmission. Also, in the temperate and subtropical regions, COVID-19 transmission was lower when the temperature remains less than 10°C (Pramanik et. al. 2020a). In Russia, before April, all places were below the required temperature, as it was a cold season. In April, the temperature of the southern part of the country increased to temperature, which accelerates the intensity of COVID-19 cases in Moscow as well as the humid continental region. The temperature of the northern region of Russia reached favourable temperature for the spread of the disease with time a lag which proved the lower number of cases in the beginning and delayed surge in spread with the limited intensity of COVID-19 cases.

One potential explanation may be that the nasal mucosa is vulnerable to minor ruptures by mixing low temperatures and humidity, increasing the risk of virus transmission (Zhou and Jiang 2004). An association between minimum humidity and influenza has been analyzed in the previous research (Firestone et al. 2012; Liu et al. 2019). However, previous studies have rarely assessed the effect of climatic variables on the intensity of COVID-19 transmission and have focused on the influence of particular predictor, i.e. moisture or temperature (Wang et al. 2020). As highlighted in the present study, the effect of climatic variables on the transmission of the disease should be integrated into disease prevention and mitigation strategies. The rise in temperature in the southern climatic region, with the advent of spring in Russia, could lead to a decline in the intensity of COVID-19 transmission from May to onwards (Figure 5). Conversely, prevention and monitoring need to be given more attention to COVID-19 because of the persisting suitable climate conditions in subarctic regions with low relative humidity and low temperature.

The COVID-19 transmission had a strong seasonality effect from December to June. The transmission of the virus lessens in the summer seasons in tropical countries and winter seasons in the temperate countries (Gaunt et al. 2010). In the coming months, in general, the temperature will be increasing in the countries of the northern hemisphere. At the same time, the temperature will be decreasing in the countries of the southern hemisphere. Hence, the findings from this research would have significant implications in formulating strategies for the coming months. This study does not predict the climatic parameter based months of higher risk of the disease spread for the cities in different regions. Future studies may also predict the monthly climatic conditions and the intensity of COVID-19 cases across regions in the world. Furthermore, due to data limitations, this study did not include other factors, such as the human physiological response of a community to the virus, and other social and economic determinants of viral transmission.

Conclusions

We investigated the regional level COVID-19 community transmission based on important climatic, bioclimatic variables using approximately 0.37 million Russian confirmed cases from January 29 to 26 May 2020. As to the best of our knowledge, it is the first attempt to examine the implications of climatic variables on the intensity of COVID-19 cases across the major climatic regions in Russia. The model (RF) provided good predictions for all the climatic regions of Russia. The study explained the number of COVID-19 cases based on temperature-related micro variables across the Russian regions. In the humid continental region, temperature seasonality is the primary influencing variable to explain the intensity of COVID-19 transmission, whereas the mean temperature diurnal range is the primary influencing factor in the sub-arctic region. A better understanding of COVID-19 transmission related climate predictor ties and climatologically suitable areas, which would help to develop climate-based early warning systems to allow rapid response to the increasing COVID-19 cases and deaths. Improved understanding of these relationships is critical for controlling fast-growing cases and deaths through better climate-responsive interventions, a fundamental element to control and prevent the COVID-19 pandemic.

Notes

1. https://www.worldometers.info/coronavirus/countries-where-coronavirus-has-spread/.
2. https://www.who.int/news-room/detail/27-04-2020-who-timeline—covid-19.

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Highlights

- First study assessing the influence of climatic variables on COVID-19 spread in Russia
- Temperature seasonality influence COVID-19 spread in humid continental Russia
- Temperature (diurnal range and seasonality) are influential in sub-arctic Russia
- Proposed maps for climate-response interventions to control the spread
- June and October climatic conditions found to be favorable for the spread of COVID-19 in Sub-arctic and humid continental Russia

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