Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Global COVID-19 pandemic trends and their relationship with meteorological variables, air pollutants and socioeconomic aspects

Yi Han a,b, Wenwu Zhao a,b,*, Paulo Pereira c

a State Key Laboratory of Earth Surface Processes and Resource Ecology, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China
b Institute of Land Surface System and Sustainable Development, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China
c Environmental Management Center, Mykolas Romeris University, Ateities g. 20, LT-08303, Vilnius, Lithuania

ARTICLE INFO

**ABSTRACT**

Meteorological variables, air pollutants, and socioeconomic factors are associated with COVID-19 transmission. However, it is unclear what impact their interactions have on COVID-19 transmission, whether their impact on COVID-19 transmission is linear or non-linear, and where the inflexion points are. This study examined 1) the spatial and temporal trends in COVID-19 monthly infection rate of new confirmed cases per 100,000 people (Rn) in 188 countries/regions worldwide from March to November 2020; 2) the linear correlation between meteorological variables (temperature (T), rainfall (R), wind speed (WS), relative humidity (RH), air pressure (AP)), air pollutants (nitrogen dioxide (NO2), sulfur dioxide (SO2), carbon monoxide (CO), ozone (O3)) and socioeconomic aspects (population density (PD), gross domestic product per capita (GDP), domestic general government health expenditure per capita (GHE)) and Rn, and 3) the interaction and non-linear effects of the different variables on Rn based on GeoDetector and Boosted regression tree. The results showed that the global Rn had been spatially clustered, and the average Rn increased from March to November 2020. Global Rn was negatively correlated with meteorological variables (T, R, WS, AP) and positively correlated with air pollutants (NO2, SO2, O3) and socioeconomic aspects (GDP, GHE). The interaction of SO2 and O3, SO2 and RH, and O3 and T strongly affected Rn. The variables effect on COVID-19 transmission was non-linear, with one or more inflexion points. The findings of this work can provide a basis for developing a global response to COVID-19 for global sustainable development.

1. Introduction

COVID-19 pandemic has become an important challenge to global sustainable development (Naidoo and Fisher, 2020; Yin et al., 2021). On January 27, 2021, the global number of confirmed COVID-19 cases had surpassed 100 million (https://coronavirus.jhu.edu/map.html), representing more than 1/70th of the global population. COVID-19 pandemic created an adverse effect on human life, economy, environment, energy, and transportation (Nundy et al., 2021; Yao et al., 2020), which made sustainable development goals are being derailed (SDGs) (Nundy et al., 2021; Yao et al., 2020), which made sustainable development goals (SDGs) (Nundy et al., 2021; Yao et al., 2020) a reality (Zhao et al., 2020; Li et al., 2020). Establishing a non-drug prevention and control strategy relies on identifying variables that may affect the spatial and temporal distribution of COVID-19 transmission, especially identifying the effect of natural conditions and socioeconomic aspects on COVID-19 transmission (Han et al., 2021).

Meteorological variables, air pollutants, and socioeconomic aspects are critical links affecting COVID-19 transmission (Bolano-Ortiz et al., 2020; Bontempi et al., 2020; Copiello and Grillenzoni, 2020; Fu et al., 2021; Van Doremalen et al., 2020). Temperature (T), rainfall (R), relative humidity (RH), wind speed (WS), and air pressure (AP) affect the virus activity in the air and objects surface (Chin et al., 2020), and affect human activities (Van Doremalen et al., 2020). Air pollution increases human vulnerability (e.g., respiratory problems) to the virus effects and affects their transmissibility (Andrée, 2020; Brandt et al., 2020; Conticini et al., 2020). Socioeconomic aspects have also been identified as linked to the COVID-19 pandemic (Copiello and Grillenzoni, 2020). In addition, the interaction between meteorological variables, air pollutants and socioeconomic aspects further complicates the transmission of COVID-19.
mechanism of COVID-19 (Coccia, 2020; Lin et al., 2020a; Srivastava, 2021). For example, among meteorological factors, wind speed may affect air humidity, further restricting SARS-CoV-2 virus activity (Chin et al., 2020; Lin et al., 2020a), affecting the stagnation and diffusion of particulate matters mixed with the SARS-CoV-2 virus (Rendana, 2020). The temperature may interact with air pollutants to affect human susceptibility to the virus (Sillman and Samson, 1995; Domingo and Rovira, 2020). Air pollutants affect not only human susceptibility to the SARS-CoV-2 virus (Brandt et al., 2020; Conticini et al., 2020; Frontera et al., 2020a; Marqués and Domingo, 2022), but also affects regional meteorological conditions and human activity intensity (Fenger, 2009). Moreover, socioeconomic factors are closely related to regional environmental conditions and medical levels (Copiello and Grillenzi, 2020). The complex interaction of variables makes slowing COVID-19 transmission be a challenge.

Therefore, to establish a non-drug prevention and control strategy, it is necessary first to identify the linkages between the COVID-19 transmission and meteorological variables, air pollutants and socioeconomic aspects (Qu et al., 2020; Zhao et al., 2020). Determine whether the linkage between them is linear or non-linear, and whether there is an inflexion point at which the impact of variables on COVID-19 transmission shifts rapidly (Chien and Chen, 2020; Xie and Zhu, 2020). More importantly, the impact of interactions between variables on COVID-19 transmission needs to be analyzed to clarify the transmission path of COVID-19 and develop countermeasures (Lin et al., 2020a; Srivastava, 2021). Scholars need to pay more attention to these two aspects. This study aims to understand the evolution of global COVID-19 transmission from March to November 2020 and to analyze the interaction and non-linear effects of variables that can affect it - meteorological variables (T, R, WS, RH, AP), air pollutants (nitrogen dioxide (NO₂), sulfur dioxide (SO₂), carbon monoxide (CO), ozone (O₃)) and socioeconomic aspects (population density (PD), gross domestic product per capita (GDP), domestic general government health expenditure per capita (GHE)).

2. Materials and methods

2.1. Data acquisition and processing

In order to eliminate the effect of vaccination campaigns on identifying COVID-19 transmission mechanisms, which began in many countries in December 2020 (https://covid19.who.int/), this study focused on the period from March (COVID-19 be declared a pandemic) to November 2021. The data of COVID-19 cases, basic data, meteorological variables, air pollutants, and socioeconomic used in this study are described in Table 1. The number of newly confirmed cases in a given period only reflects the absolute number of newly confirmed cases. It does not strip the effect of the total population on newly confirmed cases (Jahangir et al., 2020). Therefore, this study used the rate of new confirmed cases per 100,000 people (R₀) to reflect the COVID-19 transmission status. R₀ was obtained by dividing the number of new confirmed cases per month by the country’s total population and multiplying by 100,000 (Cipollia et al. 2020). Meteorological and air pollutants data were monthly averaged (March to November 2020) at the country level using the zonal statistics tool in ArcGIS 10.5. In order to reflect the socioeconomic situation of each country, the 5-year average (2015–2019) was used for GDP per capita. The same process was applied concerning domestic general government health expenditure per capita (2015–2017).

| Dimension       | Variable                          | Units             | Period             | Data type | Resolution | Source                                      |
|-----------------|-----------------------------------|-------------------|--------------------|-----------|------------|---------------------------------------------|
| COVID-19 cases  | Newly confirmed cases             | Number            | March 2020–November 2020 | –         | Country    | World Health Organization (https://covid19.who.int/) |
| Basic data      | Administrative boundaries         | –                 | 2020               | Vector    | Country    | Resources and Environmental Science and Data Center of Chinese Academy of Sciences (http://www.resdc.cn/) |
| Meteorological variables | Temperature | °C         | March 2020–November 2020 | Raster    | 0.1×1   | ERA5-Land monthly average data (https://cds.climate.copernicus.eu/) |
|                 | Rainfall                           | mm                |                    |           |           |                                             |
|                 | Wind speed                         | m/s               |                    |           |           |                                             |
|                 | Relative humidity                  | %                 |                    |           |           |                                             |
|                 | Air pressure                       | Pa                 |                    |           |           |                                             |
| Air pollutants  | Nitrogen dioxide                   | mol/m²           | March 2020–November 2020 | Raster    | 7 km × 3.5 km | Sentinel-SP image in the Google Earth Engine platform |
|                 | Sulfur dioxide                     |                   |                    |           |           |                                             |
|                 | Carbon monoxide                    |                   |                    |           |           |                                             |
| Socioeconomic aspects | Population | Number       | 2019               | –         | Country    | World Bank public database (https://data.worldbank.org/) |
|                 | GDP per capita                     | US$/capita        | 2015–2019           | –         | Country    |                                             |
|                 | Domestic general government        | US$/capita        | 2013–2017           | –         | Country    |                                             |
|                 | health expenditure per capita      |                   |                    |           |           |                                             |
|                 | Population density                 | Persons/km²       | 2020               | Raster    | Year, 1 km | Gridded Population of the World (GPW) v4 (http://sedac.ciesin.columbia.edu/data/collection/gpw-v4) |

2.2. Analysis methods

2.2.1. Spatial autocorrelation analysis

Spatial autocorrelation analysis can reveal the R₀ pattern and COVID-19 transmission (Han et al., 2021), which can be applied globally and locally. Global spatial autocorrelation assessed the R₀ spatial pattern in all the studied areas. Global Moran’s I is one of the most commonly used indices for global spatial autocorrelation analysis (Cliff and Ord, 1981). It is calculated according to the following formula:

\[
\text{Global Moran's } I = \frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^{n} \sum_{j=1}^{n} (X_i - \bar{X})^2}
\]

where \(W_{ij}\) represents the weight of the spatial relationship between \(i\) and \(j\), \((X_i - \bar{X})\) represents the deviation of the attribute value of element \(i\) from its mean, and \(n\) is the total number of elements. The value of Global Moran’s I ranges from \([-1,1]\). If the index is close to 0, it indicates that the distribution of \(R_0\) has a random pattern. If the index is close to 1, the \(R_0\) distribution is dispersed. If the index is close to 1, the pattern of \(R_0\) is clustered.
Global spatial autocorrelation analysis can reveal the degree of spatial dependence in the distribution of $R_n$ but cannot identify the local differences. Therefore, we applied Local Moran’s $I$ (Anselin, 1995), which measure the Local Indicators of Spatial Association (LISA) to explore the correlation of $R_n$ between the different countries. Local Moran’s $I$ was calculated according to the formula (2):

$$I_n = \frac{1}{n-1} \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (X_i - \bar{X})(X_j - \bar{X})$$

(2)

where $W_{ij}$ represents the weight of the spatial relationship between $i$ and $j$, $(X_i - \bar{X})$ represents the deviation of the attribute value of element $i$ from its mean, and $n$ is the total number of elements. Based on Local Moran’s $I$ calculations, the LISA aggregation can classify $I_n$ into two types of positive correlations: High-High and Low-Low; two types of negative correlations: High-Low and Low-High; and non-significant correlations. Positive correlations indicate that $R_n$ is in line with the surrounding region’s trend observed. High-High type indicates high in the middle high periphery, and the Low-Low type indicates low in the middle low periphery. Negative correlations indicate that $R_n$ is opposite to the trend of the surrounding region. High-Low type indicates low in the middle high periphery, and low-high type indicates high in the middle low periphery. Non-significant correlations represent that $R_n$ has a random pattern. Significant correlations were considered at $P < 0.05$.

Both Global and Local Moran’s $I$ was computed using ArcGIS 10.5.

2.2.2. Statistical analysis

The Spearman correlation was applied to identify the linear correlation between variables and $R_n$. $P < 0.01$ and $P < 0.05$ indicated a significant correlation at 99% and 95% confidence levels. The multicollinearity test was applied to eliminate the effect of redundant variables on $R_n$. The variables were eliminated if the variance inflation factor (VIF) was greater than 10. Both Spearman correlation analysis and multicollinearity test were implemented in SPSS 24.0.

2.2.3. GeoDetector

GeoDetector (http://www.geodetector.org/) is a statistical method used to detect the driving forces affecting the spatial differentiation of geographic phenomena (Wang et al., 2010). It reflects the explanatory ability of independent variables to dependent variables through the sum of variances ratio under different classifications of independent variables to the sum of variances of dependent variables. Factor detector and interaction detector is the sub-detectors of GeoDetector. Factor detector was applied to detect the explanatory ability of independent variables to the spatial differentiation of the dependent variables. Their magnitude can be measured by $q$ value (Wang et al., 2010). The calculation formula of $q$ value is as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{\sum_{h=1}^{L} N_h \sigma_h^2} = 1 - \frac{SSW}{\text{SST}}$$

(3)

$$SSW = \sum_{h=1}^{L} N_h \sigma_h^2 \text{ SST} = N \sigma^2$$

(4)

where $N_h$ represents the category of the dependent variable ($h = 1, 2, \ldots, L$); $N_h$ and $N$ are the number of units in category $h$ and the entire region, respectively; $\sigma_h^2$ and $\sigma^2$ represent the variance of the dependent variable in the category $h$ and the entire region, respectively (Eq. (3)). $SSW$ represents the sum of the category variances of the independent variables and $SST$ represents the total variance of the dependent variable in the entire region (Eq. (4)). $q$ indicates the ability of independent variables to explain dependent variables, $q \in [0, 1]$, the larger the $q$ value, the greater the explanatory ability of the independent variable. In addition, the GeoDetector can test the significance of the $q$ value.

The Interaction detector has a key advantage that can recognize the interaction between two independent variables compared to conventional statistical methods. The $q$ value reflects the ability of bivariate interactions to explain the dependent variable. The direction and mode of interaction between the two variables can be assessed by comparing the single variable $q$ value and the double variables $q$ value. Since the GeoDetector requires the input data of the independent variables to be categorical data, we used the natural breakpoint method to classify the selected independent variables into five categories for modeling (Peng et al., 2019).

2.2.4. Boosted regression tree

Boosted regression tree (BRT) (Elith et al., 2008) is a regression algorithm built on a traditional classification regression tree algorithm (CART). BRT builds multiple regression trees based on self-learning and multiple random selections. The process of multiple fitting can gradually reduce the error of model fitting and then steadily improve the simulation accuracy of regression trees. During operation, BRT will be iterated and repeated several times. Some data will be randomly selected to analyze the effect degree of independent variables on dependent variables. The remaining data will be used for cross-validation. Finally, the average value of the generated multiple regression trees will be calculated. In the study, BRT was assessed using R version 3.6.1 (R Core Team, Vienna, Austria) using the “gbm” package and BRT equation package (Elith et al., 2008). The distribution function was set as “Gaussian” in the parameter setting, and the learning rate was 0.05. 80% of the data was extracted for training and 20% for validation. A Pearson correlation between observed values and fitted ones of the training set and validation set. Also, a Root mean square error (RMSE) obtained from the cross-validation procedure was calculated to test the fitting effect of the model. The closer the Pearson correlation coefficient ($P < 0.01$) is to 1, and the closer the RMSE is to 0, the better is the model fitting.

The results of the BRT model can reflect the relative contribution of the variables to $R_n$ through response curve plots. The horizontal coordinate of the response curve plots shows the variables change, and the vertical coordinate is the marginal effect on $R_n$. The marginal effect value is less than 0, effect of increasing variable on $R_n$ is weakened. When the marginal effect value is equal to 0, the effect of the variable increasing on $R_n$ is unchanged, and when the marginal effect value is greater than 0, the effect of increasing variable on $R_n$ is enhanced.

3. Results

3.1. Spatial and temporal transmission of COVID-19

From March to November 2020, the global average $R_n$ was an increase (Table 2). The average $R_n$ was 28.62 in March and 394.59 in November. Between March and November 2020, the countries with the high level of $R_n$ were San Marino, Qatar, Bahrain, Aruba, Andorra and Luxembourg. Andorra has the highest $R_n$, which was 3498.74. The coefficient of variation of $R_n$ ranged between 155.38% and 276.62%. Before July 2020, there were large differences in $R_n$ among different countries, with the coefficient of variation of $R_n$ higher than 200%. From July to November, the difference was reduced.

As shown in Fig. 1, in March 2020, the high level of $R_n$ was mainly distributed in European countries and the United States, while in April, $R_n$ was also observed to increase in Brazil, Peru, and Chile. In May, $R_n$ increased in Central Asian countries and some African countries. There was an $R_n$ increase in South America, North America, Europe, and some African countries from June to November.

3.2. Spatial pattern of COVID-19 transmission

In all the studied months (Table 3), $R_n$ was significantly clustered.
The Global Moran’s $I$ of $R_n$ ranged from 0.12 to 0.71 ($P < 0.01$). However, there was a decrease of $R_n$ spatial aggregation between March and May and increased from June to August. High Global Moran’s $I$ were identified in October (0.50) and November (0.71), while the lowest was registered in May (0.12).

The $R_n$ spatial pattern varied with the virus transmission (Fig. 2). Local Moran’s $I$ results showed that the $R_n$ spatial distribution was mainly High-High and Low-Low clustering types. The High-High cluster types were distributed in Europe from March to April and October to November. From May to September, the High-High cluster pattern was and mostly observed in South America. Low-Low clusters types were identified between March and November in Africa and Asia. Among other clustering types with less distribution, High-Low clustering types were only observed in South Africa in May and Russia and Libya in August. Low-High clustering types were sporadically distributed in Europe, Africa and South America.

### 3.3. Correlation between variables and COVID-19 transmission

Spearman correlation (Table 4) showed that $T$ ($-0.27$), $R$ ($-0.09$), $WS$ ($-0.07$), $AP$ ($-0.07$), $NO_2$ (0.34), $SO_2$ (0.24), $O_3$ (0.29), $GDP$ (0.45) and GHE (0.43) were significantly positive correlated with $R_n$ ($P < 0.01$). $RH$, $CO$, and $PD$ were not significantly correlated with $R_n$.

Among meteorological variables, $T$, $R$, $RH$ and $AP$ were negatively correlated with air pollutants, while $T$ and $R$ were negatively correlated with $R_n$. $NO_2$, $SO_2$, $O_3$, $GDP$, and GHE were significantly positive correlated with $R_n$ ($P < 0.01$).
with socioeconomic aspects. RH and AP were positively correlated with socioeconomic aspects. NO$_2$, SO$_2$ and O$_3$ were positively correlated with socioeconomic aspects but negatively correlated with meteorological variables. CO was negatively correlated with meteorological and socioeconomic variables. The multicollinearity test (Table S1) showed that the VIF were between 1.14 and 7.61 (VIF < 10). Therefore, all the variables were considered in the subsequent analysis.

### 3.4. Single variable effects on COVID-19 transmission

Factor detector results (Table 5) showed that all variables had a significant effect on $R_n$. Nevertheless, SO$_2$, GDP, NO$_2$, and GHE had a relatively high effect. They could explain 15.70%, 9.20%, 8.90% and 8.20% of the variance, respectively.

### Table 4

Spearman correlation coefficients results.

|       | $R_n$ | T    | R    | WS   | RH   | AP   | NO$_2$ | SO$_2$ | CO   | O$_3$ | PD   | GDP   | GHE   |
|-------|-------|------|------|------|------|------|--------|--------|------|------|------|-------|-------|
| $R_n$ | 1.00  |      |      |      |      |      |        |        |      |      |      |       |       |
| T     | -0.27**| 1.00 |      |      |      |      |        |        |      |      |      |       |       |
| R     | -0.09**| 0.08**| 1.00 |      |      |      |        |        |      |      |      |       |       |
| WS    | -0.07**| 0.12**| -0.34**| 1.00 |      |      |        |        |      |      |      |       |       |
| RH    | -0.03 | -0.01 | 0.78**| -0.21**| 1.00 |      |        |        |      |      |      |       |       |
| AP    | -0.07**| 0.33**| 0.08**| 0.58**| 0.31**| 1.00 |        |        |      |      |      |       |       |
| NO$_2$| 0.34**| -0.21**| -0.36**| -0.13**| -0.36**| -0.11**| 1.00 |        |      |      |      |       |       |
| SO$_2$| 0.24**| -0.43**| -0.13**| 0.05  | -0.03| 0.04  | 0.35**| 1.00  |      |      |      |       |       |
| CO    | 0.03  | 0.04  | -0.18**| -0.06*| -0.12**| 0.08**| 0.36**| 0.19**| 1.00 |      |      |       |       |
| O$_3$ | 0.29**| -0.48**| -0.22**| 0.15**| -0.24**| -0.03 | 0.45**| 0.34**| 0.16**| 1.00 |      |       |       |
| PD    | 0.02  | 0.15**| 0.09**| 0.06**| 0.15**| 0.31**| 0.32**| 0.06**| 0.05 | 0.03 | 1.00 |       |       |
| GDP   | 0.45**| -0.42**| -0.07**| 0.27**| 0.03 | 0.20**| 0.26**| 0.40**| -0.10**| 0.48**| 0.07**| 1.00 |       |
| GHE   | 0.43**| -0.36**| 0.38**| 0.09**| 0.28**| 0.27**| 0.23**| 0.37**| -0.08**| 0.44**| 0.11**| 0.96**| 1.00 |

Note: *P < 0.05, **P < 0.01, Temperature (T), rainfall (R), wind speed (WS), relative humidity (RH), air pressure (AP), nitrogen dioxide (NO$_2$), sulfur dioxide (SO$_2$), carbon monoxide (CO), ozone (O$_3$), population density (PD), gross domestic product per capita (GDP), domestic general government health expenditure per capita (GHE).

### Table 5

$q$ value of single variable effect on $R_n$.

|       | T    | R    | WS   | RH   | AP   | NO$_2$ | SO$_2$ | CO   | O$_3$ | PD | GDP | GHE |
|-------|------|------|------|------|------|--------|--------|------|------|----|-----|-----|
| $q$ value | 0.09**| 0.01**| 0.01**| 0.02**| 0.00 | 0.09**| 0.16**| 0.02**| 0.04**| 0.01| 0.08**| 0.09**|

| $P$ value | <0.001 | 0.002 | 0.006 | <0.001 | 0.523 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |

Note: *P < 0.05, **P < 0.01, Temperature (T), rainfall (R), wind speed (WS), relative humidity (RH), air pressure (AP), nitrogen dioxide (NO$_2$), sulfur dioxide (SO$_2$), carbon monoxide (CO), ozone (O$_3$), population density (PD), gross domestic product per capita (GDP), domestic general government health expenditure per capita (GHE).
3.5. Interaction effects on COVID-19 transmission

The interaction detector can reflect the interaction of two variables on $R_n$ (Table 6). The $q$ value of interaction was higher in $O_2$-$SO_2$ (0.33), $SO_2^2$-$RH$ (0.30), $O_2^2$-$T$ (0.28), $NO_2^2$-$RH$ (0.27) and $GHE^2$-$SO_2$ (0.26).

3.6. Non-linear effects on COVID-19 transmission

Accuracy verification results of BRT (Table S2) showed that the Pearson correlation coefficient between the observed and fitted values of the training set and verification set was 0.86 and 0.71 ($P < 0.01$), respectively. The RMSE was 0.03. The correlation coefficients were close to 1, and RMSE was close to 0. The model had a good fitting effect.

Results of the BRT (Fig. 3) showed that the average explanatory power of air pollutants, meteorological variables and socioeconomic aspects were 10.23%, 9.12%, and 4.57%, respectively. The contribution of 12 selected variables to the change in $R_n$ were in the decreasing order: $SO_2$ (21.80%), RH (17.20%), WS (15.80%), $O_3$ (8.40%), $NO_2$ (8.10%), T (6.90%), $GHE$ (6.40%), PD (4.10%), R (3.40%), GDP (3.20%), CO (2.60%), AP (2.30%). The variables effect on $Y$. Han et al.

When R was higher than 100 mm, the marginal effect of R turned stable. There were multiple inflexion points for the effect of T on $Y$. When T below 6 $^\circ$C, between 9 $^\circ$C and 12 $^\circ$C, or higher than 33 $^\circ$C, T had a positive effect on $R_n$. However, when the concentration was higher than 0.034 mol/m$^2$, CO had a slightly negative effect on COVID-19 transmission.

Among meteorological variables, when the RH was lower than 80%, RH negatively affected $R_n$ and the negative effect was relatively smooth. While atmospheric RH was higher than 80%, the effect turned positive until it stabilizes higher than 90% after the RH. When WS was slower than 3.5 m/s, WS had a positive effect on $R_n$, but when the WS was faster than 3.5 m/s, WS had a negative effect on $R_n$ and turned stable. There were multiple inflexion points for the effect of T on $R_n$. When T below 6 $^\circ$C, between 9 $^\circ$C and 12 $^\circ$C, or higher than 33 $^\circ$C, T had a positive effect on $R_n$. However, when T between 6 $^\circ$C and 9 $^\circ$C, or between 12 $^\circ$C and 33 $^\circ$C, T shifted to a negative effect on $R_n$. When R was less than 100 mm, R has a negative effect on $R_n$, which gradually decreased with the increase of R. When R was higher than 100 mm, the marginal effect of R on $R_n$ was close to 0. Overall, $R_n$ was slightly affected by changes in R. When AP was less than 8300 Pa, $R_n$ was positively affected by AP, and the positive effect reached the maximum when AP was about 8200 Pa. In contrast, with an AP higher than 8300 Pa, the effect of AP on $R_n$ turned negatively.

When GHE was less than 3500 US$/capita, the effect on $R_n$ was negative, while GHE was more than 3500 US$/capita, the effect on $R_n$ was positive and stabilized when GHE was more than 4700 US$/capita. When PD was less than 700 persons/km$^2$, the negative effect of PD on $R_n$ gradually weakens, and after PD was higher than 700 persons/km$^2$, PD had a smooth, positive effect. When GDP lower than 40,000 US$/capita, GDP had a negative effect on $R_n$, while GDP higher than 40,000 US$/capita, GDP had a slightly positive effect.

4. Discussion

4.1. Spatial and temporal characteristics of the global COVID-19 pandemic

Understanding the spatial distribution and monthly characteristics of $R_n$ is one way to understand the transmission mechanism of COVID-19. Regarding spatial distribution characteristics, the countries with the highest $R_n$ between March and November 2020 were mainly San Marino, Qatar, Bahrain, Aruba, Andorra and Luxembourg (Table 2). These countries with limited resources and are more dependent on exchanges with other countries, making it challenging to adopt effective border control measures (Bontempi, 2020a). As a result, they are more vulnerable to COVID-19 transmission, resulting in a high number of new confirmed cases. Countries with low $R_n$ were mainly located in East Asia and Africa. In East Asia countries such as China, South Korea and Japan, the COVID-19 pandemic was quickly controlled due to the strict measures imposed (Shaw et al., 2020). In addition, in the East Asian culture that emphasizes collectivism, the social isolation policy implemented by the government is also easier to be implemented (An and Tang, 2020). Africa is the second most populous continent globally, but only a few countries showed high $R_n$. Limited testing, a much younger population, climatic differences may affect the trajectory of the COVID-19 pandemic in Africa (Kandel et al., 2020; Maeda and Nkengasong, 2021). The spatial distribution of the global $R_n$ varies monthly (Fig. 1). $R_n$ observed a decline in the summer months in European countries, while they increased in the winter months in South America and South Africa in the southern hemisphere. Seasonal variations in $R_n$ may be related to seasonal variations in human susceptibility to infectious diseases (Dowell, 2001).

4.2. Variables affecting global COVID-19 transmission

4.2.1. Effect of meteorological variables on COVID-19 transmission

Meteorological factors play a crucial role in the transmission and

Table 6

| T   | R   | WS  | RH  | AP  | NO$_2$ | SO$_2$ | CO   | O$_3$ | PD   | GDP  | GHE |
|-----|-----|-----|-----|-----|-------|--------|------|------|------|------|-----|
| T   | 0.09|     |     |     |       |        |      |      |      |      |     |
| R   | 0.11| 0.01|     |     |       |        |      |      |      |      |     |
| WS  | 0.14| 0.04| 0.01|     |       |        |      |      |      |      |     |
| RH  | 0.23| 0.16| 0.04| 0.02|       |        |      |      |      |      |     |
| AP  | 0.12| 0.03| 0.02| 0.04| 0.00  |        |      |      |      |      |     |
| NO$_2$ | 0.21| 0.10| 0.12| 0.27| 0.12  | 0.09   |      |      |      |      |     |
| SO$_2$ | 0.22| 0.19| 0.24| 0.30| 0.20  | 0.23   | 0.16 |      |      |      |     |
| CO  | 0.15| 0.04| 0.05| 0.05| 0.06  | 0.14   | 0.26 | 0.02 |      |      |     |
| O$_3$ | 0.28| 0.06| 0.07| 0.05| 0.17  | 0.33   | 0.06 | 0.04 | 0.06 | 0.01 |     |
| PD  | 0.13| 0.03| 0.03| 0.04| 0.02  | 0.12   | 0.17 | 0.04 | 0.06 | 0.06 | 0.01 |
| GDP | 0.17| 0.11| 0.14| 0.15| 0.16  | 0.23   | 0.10 | 0.19 | 0.11 | 0.08 |     |
| GHE | 0.18| 0.11| 0.13| 0.17| 0.14  | 0.17   | 0.26 | 0.11 | 0.22 | 0.11 | 0.10 |

Note: Temperature (T), rainfall (R), wind speed (WS), relative humidity (RH), air pressure (AP), nitrogen dioxide (NO$_2$), sulfur dioxide (SO$_2$), carbon monoxide (CO), ozone (O$_3$), population density (PD), gross domestic product per capita (GDP), domestic general government health expenditure per capita (GHE).
control of COVID-19 (Fu et al., 2021; Guo et al., 2021; Islam et al., 2021). The effects of T and RH on COVID-19 transmission are of great interest among meteorological variables (Auler et al., 2020; Ma et al., 2020). Our study showed that the effects of T and RH on COVID-19 transmission were non-linear. Below 12°C, T increased COVID-19 transmission, while T between 12°C and 33°C reduced virus transmission. The inflexion point of RH effect is 80%, RH greater than 80% promotes the transmission of COVID-19 and vice versa. Some studies observed that T and RH were negatively correlated with COVID-19 transmission (Guo et al., 2021; Sarkodie and Owusu, 2020) and suggested that low T and dry environments increased COVID-19 transmission. The reason is that low T and humidity create conditions for the virus survival (Chin et al., 2020). Reduced T also inhibits the phagocytic function of human alveolar macrophages (Ma et al., 2020), making the human body more vulnerable to the COVID-19 virus.

WS and AP also affect COVID-19 transmission. Our results showed that when the WS was slower than 3.5 m/s, the transmission increased, while when the WS was faster than 3.5 m/s, there was a decrease in virus transmission. Wind may affect the time that virus is suspended and its dispersal distance (Bolaño-Ortiz et al., 2020). Droplets with viruses are more likely to be suspended in the air at reduced WS or settle on the surfaces that humans can contact. Contrary, high WS may blow away droplets and reduce their concentration in suspended particles (Rendana, 2020). High AP may shorten droplet suspension and reduce COVID-19 transmission (Lin et al., 2020b). When AP is lower than 8300 Pa, we found that AP may favour the atmosphere’s droplets’ suspension, increasing the likelihood of humans being infected. The reverse situation is observed if after AP is higher than 8300 Pa.

Our results showed that when monthly R was lower than 100 mm, there was a reduction in COVID-19 transmission. R may lead to a decrease in T, which in turn reduces the body blood supply, slowing the body to supply immune cells to the nasal mucosa (Shahzad et al., 2020; Wu et al., 2020). At the same time, R may also reduce the ability of solar radiation to kill the COVID-19 virus affecting the regional humidity, aggravating the virus transmission (Biasin et al., 2021).

4.2.2. Effect of air pollutants on COVID-19 transmission

Air pollution is a consequence of human activities, weather and topographical conditions. Air pollution is thought to be a key factor in coronavirus transmission and infection in two ways (Zhang et al., 2020): 1) COVID-19 is a respiratory infectious disease spread through the air. After COVID-19 is adsorbed onto atmospheric particles, it can spread and contribute to the increase of infected people; and 2) Air pollution increases the population vulnerability to virus effects since it weakens human immunity. Inhabitants that live near polluted areas have an immune system weak and are more vulnerable to respiratory or cardiovascular diseases. Therefore, the population exposed to high air pollution have a high probability of contracting and be affected by the virus (Brandt et al., 2020; Conticini et al., 2020).

High concentrations of SO₂, O₃, NO₂, and CO are common in urban areas (Fenger, 2009). The correlation result of this study found a significant positive correlation between O₃, NO₂ and CO and are common in urban areas.
oxidative stress, and exposure to high concentrations reduces lung-lining fluid’s antioxidative levels (Domingo and Rovira, 2020). PM2.5 decline caused by COVID-19 lockdown (He et al., 2020) may lead to the reactive uptake of HO₂ radicals by aerosol particles, thus stimulating O₃ production (Li et al., 2019). New produced O₃ may contribute to COVID-19 transmission. Exposure to NO₂ may induce airway epithelial cells to synthesize pro-inflammatory cytokines, leading to respiratory tract inflammation and reducing viruses’ immunity (Persinger et al., 2002). High ambient NO₂ may also be responsible for the extensive lung injury and acute effects of COVID-19 (Frontera et al., 2020a). The effects of CO on the human body stem from its ability to bind haemoglobin. High CO concentrations reduce the reactive oxygen species production and impair myoglobin function (Burnett et al., 1998), resulting in asphyxia-related death or hypoxic tissue damage (Zhao et al., 2019) and high human susceptibility COVID-19 virus.

However, unlike the research of Bashir et al. (2020) and Zhu et al. (2020), we found that SO₂ is positively correlated with RH. The SO₂ pollution effect on COVID-19 transmission may have been overlooked. Long-term exposure to SO₂ leads to cardiovascular and respiratory disease (Cole et al., 2020). The response of COVID-19 transmission to SO₂ is critical since it has a high concentration in the atmosphere (Fenger, 2009).

4.2.3. Effect of socioeconomic on COVID-19 transmission
Demographic and socioeconomic factors may also affect COVID-19 transmission (Boloaño-Ortiz et al., 2020; Bontempi et al., 2020). COVID-19 pandemic has challenged the disaster response capabilities of governments (Shaw et al., 2020). It is widely accepted that good socioeconomic and health conditions increase infectious diseases prevention (Fu et al., 2021). Coccia (2021) found that high health expenditures can effectively reduce the fatality rate of the COVID-19 pandemic. Nevertheless, this study found that GDP and GHE can reduce the infection rate of COVID-19 when they are at a low level, but a high level not (Fig. 3). It indicated that better medical facilities could avoid worsening symptoms in people after infection but cannot contain the virus from spread effectively. Individual and social behavioural sciences, which can be very heterogeneous in different countries, may have affected this phenomenon (Bavel et al., 2020). Mendenhall (2020) argued that, compared with simple socioeconomic conditions, other factors such as hypertension, diabetes, respiratory diseases, systemic racism, distrust of science and leadership, and decentralized health care system in some countries could be behind the high COVID-19 transmission.

Previous works found a positive correlation between population density and the number of COVID-19 infections in Beijing, China (Han et al., 2021). High population density will increase the possibility of person-to-person contact, thereby aggravating the transmission of COVID-19. However, here we found no significant correlation between RH and population density at a global scale, although the interaction of population density with T and SO₂ significantly affected COVID-19. The effects of population density on the COVID-19 transmission is not consistent over different geographical areas, which are likely affected by local environmental, cultural, and policy factors (Bavel et al., 2020).

4.3. Non-linear relationship between environmental variables and COVID-19 transmission
Linear correlations analysis may be limited to identify correctly the variables that affect COVID-19 transmission. For example, a negative correlation between T and humidity and COVID-19 has been observed in previous works (Guo et al., 2021; Sarkodie and Owusu, 2020), while others reported the opposite trend (Dogan et al., 2020; Islam et al., 2020). In this context, the relations between COVID-19 and meteorological variables, air pollutants and socioeconomic aspects in different regions may be affected by the non-linear effect.

Unlike linear correlation analysis, GeoDetector has no linear assumptions (Wang et al., 2010). Our result of the factor detector was different from the correlation analysis. For instance, SO₂ had the strongest explanatory power but had a low correlation coefficient (Table 4 and Fig. 3). This show that SO₂ had a non-linear effect on COVID-19 transmissibility. Previous works based on linear correlations may have overlooked the SO₂ effect. In addition, although PD and RH not significantly correlated Rₚ, they significantly correlated most meteorological and socioeconomic variables. Therefore, PD and RH may indirectly affect the transmission of COVID-19 by affecting the likelihood of human exposure to the virus and its activity (Han et al., 2021; Lin et al., 2020a).

The effect of interactions between variables on COVID-19 transmission cannot be ignored. Effects of bivariate interactions on COVID-19 transmission increased compared to single variables, with SO₂ and O₃, SO₂ and RH, O₃ and T being the most critical influences (Table 6). As atmospheric oxidants, O₃ can efficiently promote SO₂ oxidation in aerosol media and result in a high level of particulate sulfate formation particle contaminant in the air (Wang et al., 2016). Particle contaminants can promote the spread of the SARS-CoV-2 virus and reducing human immunity (Bontempi, 2020b; Marqués and Domingo, 2022). The interaction between SO₂ and RH also significantly affected COVID-19 transmission. RH affected heterogeneous reactions of SO₂ with soot particles. The reaction process generated by the ketone and sulfate species can lead to inflammation and cellular damage (He et al., 2017) and thus increased human susceptibility to COVID-19 (Cole et al., 2020; Marqués and Domingo, 2022). The interaction of O₃ and T also affect COVID-19 transmission. O₃ is produced in the troposphere by photochemical oxidation of CO, methane, and non-methane volatile organic compounds by the hydroxyl radical in the presence of reactive nitrogen oxides (Park, 2019). High T promotes the production of O₃ (Sillman and Samson, 1995), which in turn forms O₃ pollution and affects human health (Domingo and Rovira, 2020). In addition, Rendana (2020) indicated that low WS promote stagnation of particles, thus facilitating COVID-19 transmission. This study also confirmed that the interaction between WS and air pollutants strongly affects COVID-19 transmission (Table 6).

The effects of meteorological variables, air pollution, and socioeconomic aspects on COVID-19 transmission have an inflexion point. Some scholars tried to identify the T threshold effect on COVID-19 transmission. Chien and Chen (2020) found that the effect of T on COVID-19 transmission has a peak at 20–25°C. Xie and Zhu (2020) observed that when the T is below 3°C, the number of confirmed cases increased by 4.86% for every 1°C decrease. Hoang and Tran (2021) identified a 9% increase in confirmed cases of COVID-19 when the T was below 8°C. BRT results showed that all variables, not only T, have a non-linear effect on Rₚ, with positive and negative effects, and their effects have one or more inflexion points (Fig. 3). Identifying the inflexion points of variables effect on COVID-19 created the possibility of a more targeted response to COVID-19.

4.4. Potential pathways of variables effect on global COVID-19 transmission
Meteorological factors, air pollutants and socioeconomic factors affect COVID-19 transmission in three aspects: virus activity, virus transmission and human susceptibility.

COVID-19 virus activity is sensitive to changes in T and humidity. A laboratory study published by Chin et al. (2020) has reported that the virus is very stable at 4°C but is sensitive to heat. The virus survival time decreases with increasing T. High T destroys the lipid layer of the virus, reducing its activity, stability and infection potential, and therefore, the transmission. Chan et al. (2011) reported that SARS-CoV could survive for more than 5 days on smooth surfaces at T between 22 and 25°C and 40%–50% RH. However, when the T or RH increased, the viability of SARS-CoV rapidly decreased. Therefore, SARS-CoV-2 may be unstable in a high T and humidity environment and affect the human infection rate.
The main routes of COVID-19 transmission are 1) direct or indirect contact with infected subjects, (2) large droplets dispersed by coughing or sneezing, and (3) inhalation of small airborne particles remaining in the air (Domingo et al., 2020; Qu et al., 2020).

The likelihood of becoming infected after exposure to the virus may be affected by T and air pollutants. Human immunity decreases at reduced T (Ma et al., 2020). In addition, exposure to respiratory inflammation and cardiovascular disease caused by air pollutants may increase the probability of COVID-19 infection and the virus effects on human health (Brandt et al., 2020; Conticini et al., 2020).

4.5. Gaps in research, limitations, and uncertainties

Although our study provides some evidence for the relationship between the non-linear and interactive effects of meteorological variables, air pollutants, and socioeconomic effects on global COVID-19 transmission, there are important limitations (e.g., data availability, resolution, and quality). This represents an impediment to conducting conclusive studies on factors affecting COVID-19 transmission (Sarkodie and Owusu, 2021; Zhou et al., 2020). Currently, publicly available COVID-19 case data are only region-level counts. The COVID-19 case data we used is the national scale and cannot accurately reflect the spatial distribution characteristics of COVID-19 cases, and some information might have been lost. This occurred as well in meteorological, air pollutants and socioeconomic data. For socioeconomic aspects, we only selected PD, GDP and GHE, and there was a lack of consideration of national policies regarding the lockdown measures, cultural background, and personal background of the case (presence of historical illness, activity status, and smoking and alcohol use) (Hu et al., 2021). Second, to better understand COVID-19 dispersion patterns, an interdisciplinary, multidimensional approach should be encouraged to draw more definitive conclusions (Bontempi et al., 2020). Our study analyzed the effects of meteorological, air pollutants, and socioeconomic variables on COVID-19 using only geographic and statistical methods. Behavioural and social sciences that consider social context, scientific communication, and ethical norms are also important to assess COVID-19 transmission (Bavel et al., 2020). Third, as the COVID-19 vaccine becomes widespread worldwide, virus transmission becomes more complex (Wouters et al., 2021). We did not consider vaccination data, which may pose some restrictions to our analysis. Nevertheless, although our study has some limitations, it contributes to understanding the effects of environmental and socioeconomic variables on COVID-19 transmission and can inform decision-making on COVID-19 prevention and control at a global scale.

5. Conclusion

During the study period, global $R_0$ increased, and COVID-19 was spreading around the world. High $R_0$ is mainly distributed in North America, Europe, and South America. Global $R_0$ is spatially correlated, and the correlation increased with the COVID-19 pandemic intensification. Global $R_0$ was negatively correlated with meteorological variables (T, Rs, WS, AP) and positively correlated with air pollutants (NO$_2$, SO$_2$, O$_3$) and socioeconomic aspects (GDP, GHE). However, the linear correlation method cannot fully reveal the relationship between variables and COVID-19 transmission. Interactions between variables play a key role in affecting COVID-19 transmission. The interaction of SO$_2$ and O$_3$ and RH, and O$_3$ and T strongly affected $R_0$ more than each variable individually. Consider the non-linear effect, the average explanatory power of meteorological variables, air pollutants, and socioeconomic aspects for COVID-19 transmission in BRT were 9.12%, 10.23%, and 4.57%, respectively. Despite limitations in data availability, behavioural and social science analysis, and vaccination data prevented us from drawing more definitive conclusions, the variables interaction and non-linear effect on COVID-19 transmission we studied to some extent shed light on the complex mechanisms of COVID-19 transmission and provide some basis for developing a global policy response. Based on the potential transmission routes of COVID-19, social distancing and environmental disfigurement are currently effective means to slow COVID-19 transmission, and controlling environmental pollution can improve people’s overall ability to resist respiratory infections.

Author contributions section

Yi Han: Methodology, Data Formal analysis, Visualization, Writing – original draft. Wenwu Zhao: Conceptualization, Formal analysis, Writing – review & editing. Supervision. Paulo Pereira: Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the National Key Research and Development Program of China (2020YFC0849100), the Science-based Advisory Program of the Alliance of International Science Organizations (No. ANSO-SBA-2020-01), and the Fundamental Research Funds for the Central Universities of China.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envrres.2021.112249.

References

An, B.Y., Tang, S.-Y., 2020. Lessons from COVID-19 responses in East Asia: institutional infrastructure and enduring policy instruments. Am. Rev. Publ. Adm. 50, 790-800. https://doi.org/10.1177/0275800120943797.

Andrée, B.P.J., 2020. Incidence of COVID-19 and connections with air pollution exposure: evidence from the Netherlands. Policy Research Working Paper 9221. Anselin, L., 1995. Local indicators of spatial association—LISA. Geogr. Anal. 27, 93-115.

Auer, A.C., Cassaro, F.A.M., Da Silva, V.O., Pires, I.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. Sci. Total Environ. 729, 139090. https://doi.org/10.1016/j.scitotenv.2020.139090.

Bashir, M.F., Ma, B.J., Bilal Komal, B., Bashir, M.A., Farooq, T.H., Iqbal, N., Bashir, M., 2020. Correlation between environmental pollution indicators and COVID-19 pandemic: a brief study in Californian context. Environ. Res. 187, 109652. https://doi.org/10.1016/j.envres.2020.109652.

Bavel, J.J.V., Baicker, K., Boggio, P.S., Caprao, V., Cichocka, A., Ciikara, M., Crockett, M. J., Crum, A.J., Douglas, K.M., Druckman, J.N., Drury, J., Dube, O., Ellemers, N., Finkel, E.J., Fowler, J.H., Gelfand, M., Han, S., Haslam, S.A., Jetten, J., Kitayama, S., Molibs, D., Napper, L.E., Packer, D.J., Pennycook, G., Peters, E., Petty, R.E., Rand, D.G., Reicher, S.D., Schnall, S., Shariff, A., Skitka, L.J., Smith, S.S., Sunstein, C.R., Tabri, N., Tucker, J.A., Linden, S.V.D., Lange, P.V., Weeden, K.A., Will, M.J., 2020. Using and behavioral science to support COVID-19 pandemic response. Nat. Hum. Behav. 4, 460–471. https://doi.org/10.1038/s41562-020-0884-z.

Blazon, M., Bianco, A., Parreschi, G., Cavalleri, A., Cavatorta, C., Fenzia, C., Galli, P., Lestio, L., Lauoli, M., Trimbetti, E., Ambrosi, A., Redaelli, E.M.A., Saule, I., Trabattoni, D., Zanatta, A., Clerici, M., 2021. UVC irradiation is highly effective in inactivating SARS-CoV-2 replication. Sci. Rep. 11 https://doi.org/10.1038/s41598-021-85425-w.

Bolanzo-Ortiz, T.R., Camargo-Caicedo, Y., Puliafito, S.E., Ruggeri, M.F., Bolinzo-Diaz, S., Pascual-Flores, R., Saturno, J., Ibarra-Espinosa, S., Mayol-Bracero, O.L., Torres-Delgado, E., Cereceda-Balic, F., 2020. Spread of SARS-CoV-2 through Latin America and the Caribbean region: a look from its economic conditions, climate and air pollution indicators. Environ. Res. 191, 109938. https://doi.org/10.1016/j.envres.2020.109938.

Bontempi, E., 2020a. Commercial exchanges instead of air pollution as possible origin of COVID-19 initial diffusion phase in Italy: more efforts are necessary to address interdisciplinary research. Environ. Res. 187, 109652.

Bontempi, E., 2020b. First data analysis about possible COVID-19 virus airborne diffusion due to air particulate matter (PM): the case of Lombardy (Italy). Environ. Res. 186, 109629. https://doi.org/10.1016/j.envres.2020.109639.
Wang, G., Zhang, R., Gomez, M.E., Yang, L., Levy Zamora, M., Hu, M., Lin, Y., Peng, J., Guo, S., Meng, J., Li, J., Cheng, C., Hu, T., Ren, Y., Wang, Y., Gao, J., Cao, J., An, Z., Zhou, W., Li, G., Wang, J., Tian, P., Marrero-Ortiz, W., Secret, J., Du, Z., Zheng, J., Shang, D., Zeng, L., Shao, M., Wang, W., Huang, Y., Wang, Y., Zhu, Y., Li, Y., Hu, J., Pan, B., Cai, L., Cheng, Y., Ji, Y., Zhang, F., Rosenfeld, D., Liss, P.S., Duce, R.A., Kolb, C.E., Molina, M.J., 2016. Persistent sulfate formation from London Fog to Chinese haze. Proc. Natl. Acad. Sci. Unit. States Am. 113, 13630–13635. https://doi.org/10.1073/pnas.1616540113.

Wang, J.F., Li, X.H., Christakos, G., Liao, Y.L., Zhang, T., Gu, X., Zhang, X.Y., 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun Region, China. Int. J. Geogr. Inf. Sci. 24, 107–127. https://doi.org/10.1080/13658810802443457.

Wouters, O.J., Shadlen, K.C., Salcher-Konrad, M., Pollard, A.J., Larson, H.J., Teerawattananon, Y., Jit, M., 2021. Challenges in ensuring global access to COVID-19 vaccines: production, affordability, allocation, and deployment. Lancet 397, 1023-1034. https://doi.org/10.1016/s0140-6736(21)00306-8.

Wu, Y., Jing, W., Liu, J., Ma, Q., Yuan, J., Wang, Y., Du, M., Liu, M., 2020. Effects of temperature and humidity on the daily new cases and new deaths of COVID-19 in 166 countries. Sci. Total Environ. 729, 139051. https://doi.org/10.1016/j.scitotenv.2020.139051.

Xie, J., Zhu, Y., 2020. Association between ambient temperature and COVID-19 infection in 122 cities from China. Sci. Total Environ. 724, 138201. https://doi.org/10.1016/j.scitotenv.2020.138201.

Yin, C., Zhao, W., Cherbini, F., Pereira, P., 2021. Integrate ecosystem services into socioeconomic development to enhance achievement of sustainable development goals in the post-pandemic era. Geogr. Sustain. 2, 68–73. https://doi.org/10.1016/j.geosus.2021.03.002.

Zhang, Z., Xue, T., Jin, X., 2020. Effects of meteorological conditions and air pollution on COVID-19 transmission: evidence from 219 Chinese cities. Sci. Total Environ. 741, 140244. https://doi.org/10.1016/j.scitotenv.2020.140244.

Zhao, W., Zhang, J., Meadows, M., Liu, Y., Hua, T., Fu, B., 2020. A systematic approach is needed to contain COVID-19 globally. Sci. Bull. 65 (11), 876–878. https://doi.org/10.1016/j.scib.2020.03.02.

Zhao, Y., Hu, J., Tan, Z., Liu, T., Zeng, W., Li, X., Huang, C., Wang, S., Huang, Z., Ma, W., 2019. Ambient carbon monoxide and increased risk of daily hospital outpatient visits for respiratory diseases in Dongguan, China. Sci. Total Environ. 668, 254-260. https://doi.org/10.1016/j.scitotenv.2019.02.333.

Zhou, C., Su, F., Pei, T., Zhang, A., Du, Y., Luo, B., Cao, Z., Wang, J., Yuan, W., Zhu, Y., Song, C., Chen, J., Xu, J., Li, F., Ma, T., Jiang, L., Yan, F., Yi, J., Hu, Y., Liao, Y., Xiao, H., 2020. COVID-19: challenges to GIS with big data. Geogr. Sustain. 1, 77–87. https://doi.org/10.1016/j.geosus.2020.03.005.