Title: Influence of socio-ecological factors on COVID-19 risk: a cross-sectional study based on 178 countries/regions worldwide Dai Su<sup>1,2</sup>, Yingchun Chen<sup>1,2</sup>, Kevin He<sup>3</sup>, Tao Zhang<sup>4</sup>, Min Tan<sup>1,2</sup>, Yunfan Zhang<sup>1,2</sup>, Xingyu Zhang<sup>5</sup> 1 Department of Health Management, School of Medicine and Health Management, Tongji Medical College, Huazhong University of Science and Technology, Wuhan, China 2Research Center for Rural Health Services, Hubei Province Key Research Institute of Humanities and Social Sciences, Wuhan, China 3 Department of Biostatistics, University of Michigan School of Public Health, Ann Arbor, United States 4 Department of Epidemiology and Health Statistics, West China School of Public Health and West China fourth Hospital, Sichuan University, Sichuan, China 5 Department of Systems, Populations, and Leadership, University of Michigan School of Nursing, Ann Arbor, United States Corresponding to: Xingyu Zhang (zhangxyu@umich.edu) Department of Systems, Populations, and Leadership, University of Michigan School of Nursing Ann Arbor, Michigan Word counts Abstract word counts: 295 Main text word counts: 5236 

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**Abstract** Background: The initial outbreak of COVID-19 caused by SARS-CoV-2 in China in 2019 has been severely tested in other countries worldwide. We aimed to describe the spatial distribution of the COVID-19 pandemic worldwide and assess the effects of various socio-ecological factors on COVID-19 risk. Methods: We collected COVID-19 pandemic infection data and social-ecological data of 178 countries/regions worldwide from three database. We used spatial econometrics method to assess the global and local correlation of COVID-19 risk indicators for COVID-19. To estimate the adjusted incidence rate ratio (IRR), we modelled negative binomial regression analysis with spatial information and socio-ecological factors. Findings: The study indicated that 37, 29 and 39 countries/regions were strongly opposite from the IR, CMR and DCI index "spatial autocorrelation hypothesis", respectively. The IRs were significantly positively associated with GDP per capita, the use of at least basic sanitation services and social insurance program coverage, and were significantly negatively associated with the proportion of the population spending more than 25% of household consumption or income on out-of-pocket health care expenses and the poverty headcount ratio at the national poverty lines. The CMR was significantly positively associated with urban populations, GDP per capita and current health expenditure, and was significantly negatively associated with the number of hospital beds, number of nurses and midwives, and poverty headcount ratio at the national poverty lines. The DCI was significantly positively associated with urban populations, population density and researchers in R&D, and was significantly negatively associated with the number of hospital beds, number of nurses and midwives and poverty headcount ratio at the national poverty lines. We also found that climatic factors were not significantly associated with COVID-19 risk. **Conclusion:** Countries/regions should pay more attention to controlling population flow. improving diagnosis and treatment capacity, and improving public welfare policies. Keywords: socio-ecological factors; COVID-19 risk; cross-sectional study; 178 countries/regions worldwide

#### 1. Introduction

The novel coronavirus disease (COVID-19) that has spread to more than one hundred countries and killed hundreds of thousands of people has officially been categorized as a pandemic by the World Health Organization. The initial outbreak of COVID-19 caused by SARS-CoV-2 in China in 2019 has been severely tested in other countries worldwide. As of April 6, 2020, COVID-19 had infected 1,345,048 patients in 184 countries/regions and caused 74,565 deaths, as countries worldwide responded to a human-to-human respiratory disease pandemic caused by COVID-19. Emerging infectious diseases (EIDs), such as SARS and COVID-19, pose a vast economic and public health burden worldwide [1,2].

COVID-19 not only seriously endangers people's life safety and health but also greatly affects economic globalization. To address the challenges posed by COVID-19, the links among the transmission of COVID-19, socio-economic factors and climatic factors must be understood to suggest better strategies for predicting, preventing, coping with and mitigating the associated challenges. Simultaneously, given that the climate and socio-economic context are unlikely to change in the short term, it is easier to intervene accordingly [3]. The spread of many EIDs has been reported to be influenced by socio-ecological factors, including socio-economic and climate factors [1,2,4-7]. Previous studies have found that climatic conditions limit the geographical and seasonal distribution of EIDs, and weather affects the timing and intensity of outbreaks [8-12]. In addition, whereas climate patterns may control the potential global distribution of EIDs, the actual size and spatial scope of a region may be controlled by several non-climatic factors associated with transmission, including epidemiological, socio-economic and demographic factors [13-18]. However, research on the climatic and socio-economic drivers of COVID-19 transmission remains lacking, especially regarding the effects of socioeconomic factors and the total effects of socio-ecological factors. Ignoring important nonclimatic factors or other confounding factors (such as urban development, economic growth, poverty, health, infrastructure, science and technology, social security and labor) would overestimate the effects of climate change. Therefore, studying the influence of socio-ecological factors on the transmission risk of EIDs is highly important.

For most EIDs, three elements are essential: an agent (or pathogen), a host (or vector) and the environment of transmission [19]. Appropriate climatic and weather conditions are necessary for the survival, reproduction, distribution and transmission of disease pathogens, vectors and hosts. Therefore, changes in climate or weather conditions may affect EIDs by affecting pathogens, vectors, hosts and their living environments [19–21]. Although many climate variables may influence the transmission of EIDs, some studies have shown that changes in the four main variables have the greatest effects on infected diseases with strong environmental components (temperature, precipitation, relative humidity (RH) and wind) [22–26]. In recent studies, although the severity of some cases of COVID-19 has mimicked that of SARS-CoV cases [27–30], the reproductive number (average R0=3.28) of COVID-19 is higher than that of SARS-CoV; therefore, considering the climate and environment may improve understanding of the pathogen's vectorial capacity and basic reproduction number, and the risk of transmission of COVID-19 [31,32].

In recent decades, many rapid and pronounced changes in human social ecology have altered the likelihood of the emergence and spread of infectious diseases [33–35]. These changes include increases in population size and density; urbanization; persistent poverty (especially in

the expansion of urban slums); the number and movement of political, economic and

- 121 environmental refugees; differences in infrastructure and science and technology; and poor
- health awareness [36]. The socio-economic environment contributes significantly to the health
- of individuals as well as communities [37] and is the root cause of health and health equity.
- 124 These socio-economic drivers have contributed to the shifting global ecology of vector
- transmission that enabled COVID-19 to emerge worldwide, by dangerously uniting the human
- hosts, vectors and pathogen. Socioeconomic changes interact with environmental changes in
- promoting EID spread and increase the harm of EIDs to humans.
- The purpose of this study was to describe the spatial distribution of the COVID-19 pandemic
- worldwide, and assess the effects of different socio-ecological factors, including climate and
- socio-economic factors, on COVID-19 risk in 178 countries/regions worldwide, including
- incidence rate (IR), cumulative mortality rate (CMR) and daily cumulative index (DCI). In
- addition, this study analyzed intervention policies in different countries and regions to establish
- early warning and decision support systems and provide guidance for COVID-19 management
- in different countries/regions.

### 2. Methods

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# 2.1. Concept model

- According to previous research [38-41], we established the Potential Risk Assessment
- Framework for COVID-19 (Figure 1). The influence of global socio-ecological factors (climate
- and socio-economic factors) on the risk of COVID-19 can be tested by its influence on the
- 141 following three disease components: agent (or pathogen), host (or vector) and the environment
- of transmission. A combination of natural and human influences led to the COVID-19 pandemic.
- We used three main variables to assess the potential risk of COVID-19: IR, CMR and DCI.

### 2.2 Definitions of different cases for COVID-19

- A confirmed case of COVID-19 infection was defined by laboratory confirmation of the virus
- causing COVID-19 infection, regardless of clinical signs and symptoms [42–44]. However, some
- reported case numbers from China have included people with symptoms of COVID-19 without
- laboratory confirmation. The definitions of COVID-19 related deaths differ across countries. In
- 149 Italy, any death of a person with positive reverse transcriptase—polymerase chain reaction (RT-
- 150 PCR) testing for SARS-CoV-2 is considered COVID-19 related.

#### 2.3 Data collection

#### 2.3.1 Outcome variables

- 153 A dashboard published and hosted by researchers at the Center for Systems Science and
- 154 Engineering, Johns Hopkins University (JHU-CSSE) [45] shows the numbers and locations of
- 155 confirmed COVID-19 cases, deaths and recoveries in all affected countries. All collected data
- on COVID-19 from the Johns Hopkins University are made freely available by the researchers
- through a GitHub repository. All manual updates (for countries and regions outside mainland
- 158 China) are coordinated by a team at Johns Hopkins University. We extracted the global time
- series data of confirmed and recovered cases and deaths due to COVID-19 from the JHU-CSSE GitHub repository. The data were recorded from January 22, 2020 and were updated
- once daily around 23:59 (UTC). We selected the cross-sectional data from April 6, 2020. On the

basis of the availability of the data, we extracted 178 countries from the database (excluding countries/regions without COVID-19 cases and some unmatched countries/regions, such as Taiwan, China). The first-level geographical unit of the dataset is the country/region, and the second-level geographical unit is the province/state. We uniformly selected first-level geographical units (countries/regions). In addition, we further classified the countries/regions in the data set according to UN geographical divisions and divided the countries with epidemic COVID-19 into 20 regions. As previously mentioned, for outcome variables, we selected IR, CMR and DCI as indicators to measure COVID-19 risk. The specific calculation process is shown in Table 1.

IR was used to describe the distribution of COVID-19, explore the etiological factors, propose an etiological hypothesis, and evaluate the efficacy of detection and prevention measures. CMR reflects the total deaths due to COVID-19 and is an indicator of the risk of death from COVID-19. DCI mainly describes the growth rate of COVID-19 in different countries/regions and is a measure of the risk of disease transmission. The World Health Organization, on March 11, 2020, declared the COVID-19 outbreak a global pandemic, thus indicating that COVID-19 had broadly spread worldwide. Therefore, when we considered IR, CMR and DCI in different countries/regions, these measures reflected not only the rapid growth in the number of people infected with COVID-19 but also the detection level in the entire country/region, which was used to identify more people infected with COVID-19.

#### 2.3.2 Climate data

We obtained daily meteorological observation values from the Global Surface Summary of the Day (GSOD) via The Integrated Surface Hourly (ISH) dataset. The ISH dataset includes global data obtained from the USAF Climatology Center, which is located in the Federal Climate Complex with NCDC. GSOD comprises 12 daily averages computed from global hourly station data. Except in United States stations, 24-hour periods are based on UTC times. The latest daily summary data are normally available 1-2 days after the date-time of the observations used in the daily summaries. More than 9,000 stations' data worldwide are typically available. Daily weather elements include mean values of temperature, dew point temperature, sea level pressure, station pressure, visibility, wind speed, maximum and minimum temperature, maximum sustained wind speed and maximum gust, precipitation amount, snow depth and weather indicators. However, we chose the climate data from April 6, 2020 and selected four variables from the GSOD dataset that significantly affected COVID-19 risk: (1) mean temperature (.1 Fahrenheit); (2) mean dew point (.1 Fahrenheit); (3) mean wind speed (.1 knots); and (4) precipitation amount (.01 inches). The reason for extracting the average dew point variable was to calculate the RH value by using this variable and the temperature variable. The temperature and dew point in Celsius were used to calculate the RH according to the temperature and dew point at each time point [46]:

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$$C = \frac{F - 32}{1.8}$$

$$RH = e^{\frac{17.625D}{243.04+D} - \frac{17.625T}{243.04+T}}$$

where C is the temperature in Celsius, F is the temperature in Celsius, D is the mean dew

point for the day in Celsius, T is the mean temperature for the day in Celsius, and e is the

203 base of the natural log.

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### 2.3.3 Socio-economic data

Indicators of socio-economic factors affecting the spread of COVID-19 were derived from the World Development Indicators dataset, the primary World Bank collection of development indicators, which compiles relevant, high-quality and internationally comparable statistics about global development and the fight against poverty. The database contains 1,600 time series indicators for 217 economies and more than 40 country groups, and data for many indicators cover a period of more than 50 years. As shown in Table 2, we selected 32 indicators affecting COVID-19 risk in seven dimensions in 178 countries/regions. The index value for 2019 was taken as the priority for each indicator. If the index was missing in 2019, the index value of the most recent year was selected as a substitute.

### 2.4 Statistical analysis

- 2.15 2.4.1. Spatial econometrics method
- 216 First, we used Moran's I to measure the global correlation of COVID-19 risk indicators [47].
- 217 Global Moran's I is a measure of global spatial autocorrelation, and the value of Moran's I
- 218 usually ranges from -1 to +1. Values significantly below -1/(N-1) indicate negative spatial
- 219 autocorrelation, and values significantly above -1/(N-1) indicate positive spatial autocorrelation.
- 220 If significant global spatial autocorrelation was found, we then used local indicators of spatial
- autocorrelation (LISA) to evaluate the locations of COVID-19 clusters. The meaning of local
- Moran's li is similar to that of global Moran's I. A positive li indicates that the high (or low) value
- of region i is surrounded by the surrounding high (or low) value; A negative li indicates that the
- high (or low) value of region i is surrounded by the surrounding low (or high) value. The general
- 225 models are described in Eq. 1–2.

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$$Moran's I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \overline{x}) (x_j - \overline{x})}{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n} (x_i - \overline{x})^2}$$
(1)

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$$Local Moran's I = \frac{n(x_i - \overline{x}) \sum_{j} w_{ij} (x_j - \overline{x})}{\sum_{i} (x_i - \overline{x})^2}$$
 (2)

- where n is the number of spatial units indexed by i and j, x is the variable of social ecology
- factors,  $\bar{x}$  is the mean of x, and  $w_{ii}$  is a matrix of spatial weights with zeroes on a diagonal
- 230 (i.e.,  $w_{ii} = 0$ ).
- Second, to better approximate the real infectious disease spatial spread process, we fit a one-
- order spatial autoregressive regression model comprising spatial lags. Because we believed
- that COVID-19 risk transmission in a certain country/region would be different for neighboring

countries/regions, we sought to reflect this difference in the model. A one-order spatial autoregressive process takes the form (Eq. 3) [48]:

$$Y = \delta WY + \varepsilon \tag{3}$$

where  $\delta$  is the spatial autoregressive coefficient, W is the i, j-th element of the exogenous, non-negative  $N \times N$  spatial weight matrix with zero diagonal elements that describes the arrangement of the spatial units in the countries/regions, and  $\mathcal E$  is i.i.d. innovations with zero mean and finite variance  $\sigma^2$ . For simplicity, in this paper, we assumed that the spatial weight matrix W was non-standardized and also used a queen spatial weight matrix.

# 2.4.2. Processing of missing values

Before negative binominal regression, the k-nearest neighbors (k-NN) approach was used to impute missing data for some socio-ecological variables. For a given patient with missing values, the k-NN method identifies the k-nearest countries/regions on the basis of Euclidean distance. Using these countries/regions, we then replaced missing values by using a majority vote for discrete variables and weighted means for continuous features. One advantage of using this method is that missing values in all features are imputed simultaneously without the need to treat features individually.

# 250 2.4.3. Negative binomial regression

First, we established the correlation matrix of socio-economic factors to check for multicollinearity. If there was a strong correlation (> 0.8) among socio-economic factors, then we removed the factor with strong correlation with other variables. Then, the incidence rate ratio (IRR) of each socio-ecological factor was calculated with single factor negative binomial regression analysis, that is, the effect of each socio-ecological factor on COVID-19 risk by changing the average COVID-19 risk value by a specific unit quantity. The spatial autoregressive models comprising spatial lags, which were a weighted average of observations on the diseases over neighboring units, were input into the model to adjust for spatial variation in COVID-19 risk. Modeled values of climate factors were centered on the mean values for each station in every country/region [49]. The factors with P < 0.05 were included in the multi-factor negative binomial regression analysis with spatial information to calculate the adjusted IRR (aIRR). The general model is described in Eq. 4.

$$y_i = \alpha + \delta WY + \beta_1 T_i + \beta_2 H_i + \beta_3 M_i + \beta_4 P_i + \sum_n S_n + \varepsilon_i$$
 (4)

where  $y_i$  denotes the daily counts of COVID-19 risk indicators in county/region i; WY represents spatial lags, and W is the spatial weight;  $S_n$  represents socio-economic factors (all variables are in Table 2);  $T_t$  is the mean temperature in county/region i;  $H_t$  is the RH in county/region i;  $M_t$  is the wind speed in county/region i;  $P_t$  is the precipitation amount in county/region i; and  $\mathcal{E}_i$  is a random intercept.

Sensitivity analyses with maximum and minimum temperatures instead of average temperatures were also conducted with the same procedures, in which we used the same non-informative priors for the minimum and maximum temperatures [49, 50]. All statistical analyses were

- 272 performed in Stata statistical software Version 15, and p-values were two-tailed, with statistical
- significance set at.05. ArcMap 10.7 and Geoda software were used to process basic geographic
- information. Data visualization mainly used RStudio software Version 1.2.5033.

# 276 **3. Results**

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### 3.1 Characteristics of 178 countries/regions with reported cases of COVID-19

- As of April 6, 2020, a total of 178 countries/regions worldwide had reported data and were
- included in this study (Table S1). The three countries/regions with the highest IR worldwide
- were Andorra (Southern Europe, IR=313.80), Iceland (Northern Europe, IR=215.90) and
- 281 Gibraltar (United Kingdom) (Southern Europe, IR=178.52). The three countries/regions with the
- highest CMR worldwide were San Marino (Southern Europe, CMR=947.17), Spain (Southern
- Europe, IR=285.53) and Italy (Southern Europe, IR=273.42). The three countries/regions with
- the highest DCI worldwide were the United States (North America, DCI=4823.87), Spain
- 285 (Southern Europe, DCI=2070.83) and Italy (Southern Europe, DCI=1978.31).

# 286 3.2 Spatial clustering evaluation for COVID-19

- 3.2.1 Test results for global spatial correlation
- The number and distribution of first-order neighbors in different countries/regions are shown in
- 289 Figure 2. The number of neighboring countries/regions was mainly concentrated in 0-6,
- accounting for 87.08% of the total number of neighboring countries. Among them, China and
- 291 Russia had the largest number of neighboring countries/regions.
- Table S2 shows the global spatial Moran's I indexes of the IR, CMR and DCI of 178
- 293 countries/regions worldwide according to the one-order spatial contiguity matrix. The Moran's I
- indexes of IR, CMR and DCI were all positive, and all index values were significant at the level
- of 1%, thus indicating that the IR, CMR and DCI of 178 countries/regions worldwide had strong
- 296 spatial aggregation effects. Meanwhile, the Moran's I index of different indicators showed
- 297 significant differences, thus indicating to some extent that IR, CMR and DCI have different
- 298 aggregation effects in different countries/regions.
- 299 3.2.2 Test results for local spatial correlation
- A total of 37 countries/regions were strongly opposite from the IR index "spatial autocorrelation"
- 301 hypothesis," including 11 countries/regions with high-high patterns, mainly concentrated in
- Western Europe, southern Europe and Canada; 24 countries/regions with low-low patterns,
- mainly concentrated in parts of Africa, parts of Asia (China, India, Laos); Cuba with a low-high
- pattern; and Diibouti with a high-low pattern. Simultaneously, 29 countries/regions were
- strongly opposite from the CMR index "spatial autocorrelation hypothesis," which was suitable
- for 10 countries with high-high patterns, mainly in Western Europe and southern Europe (e.g.,
- France, Italy and Spain); 16 countries/regions with low-low patterns, mainly concentrated in
- parts of Africa and China; and three countries with low-high patterns, including Morocco and
- 309 Slovenia. In addition, 39 countries/regions strongly did not support the hypothesis of "no spatial
- autocorrelation" of the DCI index, among which six countries/regions had high-high patterns
- 311 (Canada, France, Portugal, Belgium, the Netherlands, and Switzerland), and 22
- 312 countries/regions had low-low patterns, mainly in parts of Africa and Honduras. Eleven

- countries were in the low-high pattern category, including Mexico, Cuba, Morocco, Denmark
- and Luxembourg, etc. The above results are consistent with the global spatial autocorrelation
- test results, thus indicating that IR, CMR and DCI indicators in some countries/regions may be
- affected by the COVID-19 epidemic in neighboring countries/regions and may show clear
- 317 geographical characteristics.
- To directly reflect the local spatial characteristics of IR, CMR and DCI, LISA scatter diagrams of
- the three indexes are shown in Figure 3. Most of the three indicators fell into the third quadrant
- 320 (low-low), but the countries/regions whose IR and DCI index fell into the first quadrant (high-
- high) and the second quadrant (low-high) had indicator values exceeding the CMR. Thus,
- among the 178 countries/regions worldwide, the countries/regions with low IR, CMR and DCI
- indicators showed a spatial agglomeration effect, as did the countries/regions with high IR, CMR
- and DCI indicators. In addition, some neighboring countries/regions showed some differences in
- 325 IR, CMR and DCI (high-low and low-high).

# 3.3 Analysis of the influence of socio-ecological factors on COVID-19 risk

- 3.3.1 Correlation analysis of socio-economic factors
- To eliminate the influence of the collinearity between the socio-economic indicators on the
- estimation effect of the model, we established a correlation matrix of the socio-economic
- indicators (Table S3). The indexes with strong correlation (> 0.8) were screened, and one of the
- 331 effective indexes was reserved for model analysis. We excluded eight socio-economic
- indicators in Table 2, numbered 7 (current health expenditure per capita), 12 (total life
- expectancy at birth), 13 (maternal mortality ratio), 14 (infant mortality rate), 17 (access to basic
- handwashing facilities including soap and water), 20 (population growth), 21 (proportion of the
- population spending more than 10% of household consumption or income on out-of-pocket
- health care expenditure) and 26 (technicians in R&D), and we retained 20 socio-economic
- 337 indicators.

- 338 3.3.2 Negative binomial regression analysis of socio-ecological factors on COVID-19 risk
- 339 We analyzed the effects of socio-ecological factors on COVID-19 risk in 178 countries. The
- results of single-factor and multi-factor negative binomial regression analysis are shown in
- 341 Table 4.
- The IR was significantly positively associated with GDP per capita (aIRR=1.029, 95%CI: 1.013–
- 343 1.045), use of at least basic sanitation services (aIRR=1.022, 95%CI: 1.005-1.039) and
- 344 coverage of social insurance programs (aIRR=1.047, 95%CI: 1.009-1.086), and was
- significantly negatively associated with the proportion of the population spending more than 25%
- of household consumption or income on out-of-pocket health care expenses (aIRR=0.846,
- 95%CI: 0.750–0.955) and the poverty headcount ratio at national poverty lines (aIRR=0.970,
- 348 95%CI: 0.948-0.993).
- The CMR was significantly positively associated with urban populations (aIRR=1.027, 95%CI:
- 350 1.010-1.044), GDP per capita (alRR=1.031, 95%Cl: 1.021-1.041) and current health
- expenditure (aIRR=1.211, 95%Cl: 1.040-1.410), and was significantly negatively associated
- with the number of hospital beds (alRR=0.799, 95%Cl: 0.696-0.916), number of nurses and
- midwives (aIRR=0.837, 95%CI: 0.749-0.936) and poverty headcount ratio at the national
- 354 poverty lines (aIRR=0.960, 95%CI: 0.940-0.982).

- 355 The DCI was significantly positively associated with urban populations (aIRR=1.021, 95%CI:
- 1.009-1.034), population density (aIRR=1.000, 95%CI: 1.000-1.000) and researchers in R&D
- 357 (aIRR=1.000, 95%CI: 1.000-1.001), and was significantly negatively associated with the
- number of hospital beds (aIRR=0.731, 95%CI: 0.641-0.833), number of nurses and midwives
- (aIRR=0.904, 95%CI: 0.820-0.997) and poverty headcount ratio at the national poverty lines
- 360 (alRR=0.963, 95%CI: 0.945-0.982).
- The results of the sensitivity analysis are reported in Table S4 and Table S5: we used the
- 362 maximum and minimum temperatures instead of the average temperature, and then
- incorporated the two climate factors into the single-factor and multi-factor negative binomial
- regression. The results showed that the significance of different socio-ecological factors was
- essentially consistent. We found that only the variable of poverty headcount ratio at the national
- poverty lines (percentage of population) became significant after sensitivity analysis on IR, thus
- indicating that the analysis results were relatively reliable.

#### 4. Discussion

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- By evaluating the spatial aggregation characteristics of three indicators—IR, CMR and DCI—on
- 371 COVID-19 risk in 178 countries, Western Europe, Southern Europe, East Asia and some African
- countries, we found that all showed relatively large spatial correlations, thus indicating that
- 373 COVID-19 broadly affects these countries/regions.
- Because COVID-19 is highly contagious, after an outbreak occurs in a country/region, the virus
- tends to spread rapidly in surrounding countries. Italy was the first country in Europe to have a
- large outbreak of COVID-19, but the Italian health system adopted several control measures,
- such as timely intervention and containment measures brought about by decentralization, flexible financing mechanisms, private and public sector partnerships, and human resources
- nexible intaining medianisms, produce and public sector participants, and numer resources
- mobilization, so that the IR and DCI could be effectively controlled [51]. However, because
- some European countries did not perform effective prevention and control measures, such as
- blockading countries or cities, in early stages of the outbreak, the epidemic gradually broke out in countries including France, Germany, Spain and Portugal. In North America, the development
- of COVID-19 presents progressive characteristics (high–high and low–high mode), and Canada
- is also significantly affect clearly the United States by the COVID-19 outbreak, but the DCI in
- Mexico and other countries/regions in Central America remained relatively low. The United
- 386 States also recently closed its border with Canada and Mexico and decreased the flow of
- people across the border. Because, blockading and quarantining provide very good protection,
- taking these measures in countries or cities is very important to decrease the risk of COVID-19
- multinational spread. The potential transmission of COVID-19 in South America must not be
- 390 ignored.
- 391 Second, both IR and CMR presented low-low patterns in China, thus indicating that China and
- some neighboring countries (such as South Korea and Singapore) have effectively reduced the
- risk to neighboring countries by implementing strong prevention and control measures against
- 394 COVID-19 transmission and have also acquired valuable experience useful to other countries in
- fighting COVID-19 virus [52–56]. However, notably, the IR of COVID-19 in India presents a low-
- low model, thus indicating that India is at low risk of COVID-19 transmission from surrounding
- countries, and consequently has a low DCI. However, as the world's second most populous
- country, India may have a high risk of COVID-19 transmission because of inadequate medical
- conditions and detection levels. Simultaneously, China, South Korea and other countries must

strengthen screening of imported cases from other countries, reduce social contact among travelers and prevent the possible secondary transmission of COVID-19 [52,57,58].

Third, most countries/regions in Africa remain in a low-low mode, but the short distance and frequent contacts between Western and Southern Europe and North Africa may place North Africa at high risk of COVID-19 spread; Morocco currently has a low-high mode representing an early warning, and COVID-19 viruses must further be prevented from entering other parts of Africa. Although African countries took measures to prevent the Ebola outbreak in 2014, Africa remains one of the poorest countries worldwide, and it has a shortage of health resources to quickly control the outbreak. Studies have shown that the current spread of COVID-19 in West Africa urgently requires action to control the further spread of COVID-19 and improve the response capacity of affected countries in West Africa [59]. Although most parts of Africa are in the low-low mode, they may also face threats. Many COVID-19 cases may be undetected, thus potentially explaining the current low-level indicators (IR, CMR and DCI).

We found that, in terms of urban development, both CMR and DCI were significantly positive associated with the urban population (percentage home of total population), and people per sq. km of land area had significant positive effects on the DCI. Non-drug intervention measures have already been implemented, and if traffic restrictions, social isolation and family measures are not ensured, the increase in population density and urbanization may result in many problems, such as public traffic, rural population health inequities, poor housing conditions, inadequate freshwater supply, and poor sanitation and ventilation systems, thus accelerating the spread of the COVID-19 virus, in agreement with previous research [60,61]. The higher the urban population (percentage of total population), the faster the urbanization process of the country/region; consequently, aging and young people participating in social activities become more likely to aggravate the spread of the virus and increase the burden on the health system, in agreement with the results of one study [62]. In addition, studies have shown that, with urbanization, the risk of infection and the chances of survival after COVID-19 infection among older individuals with complications is greatly increased, thus resulting in a significant increase in the CMR in the country/region [63–64].

In terms of the economy and growth, we found that GDP per capita (current 1,000 US\$) was significantly positive associated with the IR and CMR of COVID-19, possibly because the GDP per capita tends to reflect a country's economic development level: with higher GDP per capita, governments can invest more in screening and treatment of patients with mild and severe cases of COVID-19. Consequently, with more confirmed cases and deaths, classification strategies can be considered for COVID-19 in low-income groups. Especially in economically underdeveloped areas such as Africa, similar symptoms can be used as a basis to implement a series of diagnostic tests [65]. This method of raising clinical diagnostic standards was used in Wuhan, China.

In terms of health, we found that increasing the proportion of residents using at least basic sanitation services was significantly positive associated with the IR of COVID-19. For example, improving basic sanitation services and increasing contact between primary health workers and potential and diagnosed COVID-19 patients is very important. In particular, the government of Wuhan, China implemented nucleic acid testing on each resident via hospitals and primary health workers, thus enabling COVID-19 detection in a larger proportion and facilitating rapid control of COVID-19 risk transmission. Second, the numbers of hospital beds (per 1,000 people), nurses and midwives (per 1,000 people) were significantly negative associated with the IR and CMR of COVID-19, thus suggesting that COVID-19 risk should be controlled, and the number of hospital beds and nurses should be increased in a short period of time. The increase in the numbers of hospital beds and nurses can help achieve standardized management of patients

and allow more medical resources to be concentrated on the treatment of severe cases. Some research has shown that some countries, such as Italy, China and the United States, have established Fangcang shelter hospitals or field hospitals and increased the numbers of regular hospital beds, intensive care beds and medical workers (by transferring resources from other regions and the military), reopened closed hospitals, and considered use of medical volunteers in the treatment of mild and severe COVID-19 cases; these measures are effective ways to reduce the IR and CMR [66, 67]. Third, among people infected with COVID-19, the proportion of the population spending more than 25% of household consumption or income on out-of-pocket health care expenses were significantly negative associated with the IR, whereas coverage with social insurance plans positively influences the IR. Higher income, enhanced health insurance coverage and decreased burden of medical treatment significantly increase the IR, thus suggesting that governments and health insurance providers should cooperate in the prevention and control of COVID-19. In addition to financial subsidies, the government should also reduce or grant exemptions for patient co-payments, to increase the possibility of COVID-19 patients receiving testing and treatment.

In science and technology, the number of researchers in R&D (per million people) was significantly positive associated with the DCI. This improvement includes facilitating health science and technology input, strengthening basic life science research, fostering international cooperation between science and technology (such as in the development and use of effective drugs), providing more convenient testing technology, shortening testing times, expanding the scale of detection, improving treatment technology and performing ongoing vaccine development to reduce present and future COVID-19 transmission. In addition, the poverty headcount ratio at the national poverty lines (percentage of population) was significantly negative associated with the IR, CMR and DCI. Increases in the population in poverty and in racial discrimination greatly diminish accessibility to medical services. Government and society must address these problems through economic stimulus plans, unemployment relief programs, welfare and health safeguarding measures, and plans to decrease health spending by these groups [68].

We also found that climatic factors (temperature, RH, precipitation and wind speed) were not significantly associated with COVID-19 risk, in agreement with the results of some studies [69]. However, previous studies have primarily considered the effects of single climate factors, thus potentially affecting the estimates of the results [70–72]. There is no sufficient evidence indicating that climate factors have specific effects on the spread of COVID-19. This study also shows that in the measurement of COVID-19 risk, the influences of other factors should be considered—such as the constraints of economic development, transportation and other factors—to improve understanding of the mechanisms underlying interrelationships among factors.

#### 5. Limitations

This study has several limitations. First, we selected cross-sectional data for spatial analysis and regression modeling; therefore, the results may not reflect more changes in time, thus potentially decreasing the statistical ability to detect the relationships among various factors and COVID-19 risk. Second, owing to data matching across databases, some aspects of country/region data may have been lost, thus potentially affecting the spatial weight matrix estimation and regression modeling results. Third, because of the socio-ecological study design, we were unable to access data at the individual level, such as age, sex, occupation, economic and health status, and the actual exposure temperature of each person. However, future studies

could adopt hybrid study designs, which use individual-level data from subpopulations to improve ecological extrapolation.

#### 6. Conclusion

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By using the data from 178 countries/regions, we found that socio-economic factors can significantly reduce the risk of COVID-19. As a next step in COVID-19 prevention, different countries/regions should focus on controlling urban populations, providing economic subsidies and medical resource supplies, and taking broad views of social welfare. Strategies may include population isolation, travel restrictions, case screening, cross-regional or national science and technology exchange to promote diagnosis and treatment, public welfare policy improvement, as well as decreasing the burden of low-income groups in obtaining medical treatment. Simultaneously, we must be alert to the COVID-19 risk in some countries in Africa and Asia, and must curb the second wave of COVID-19 transmission.

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### **Contributors**

- DS, XZ contributed to the conception and design of the project; DS, TZ, KH, XZ contributed to
- the analysis and interpretation of the data; MT, YZ contributed to the data acquisition and
- 521 provided statistical analysis support; DS drafted the article. DS and XZ are the guarantors. The
- 522 corresponding author attests that all listed authors meet authorship criteria and that no others
- 523 meeting the criteria have been omitted.

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### **Declaration of interests**

All other authors declare no competing interests.

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Patient and public involvement This research was done without patient involvement. Patients were not invited to comment on the study design and were not consulted to develop patient relevant outcomes or interpret the results. Patients were not invited to contribute to the writing or editing of this document for readability or accuracy. Patient consent for publication Not required. **Ethics approval** This study was approved by the Ethics Committee of the Tongji Medical College, Huazhong University of Science and Technology (IORG No: IORG0003571). **Data sharing statement** The data used for the analyses are publicly available from the Johns Hopkins University Center for Systems Science and Engineering (https://github.com/CSSEGISandData/COVID-19), the World Bank (https://datacatalog.worldbank.org/dataset/world-development-indicators) and National Oceanic and Atmospheric Administration, Department of Commerce (https://catalog.data.gov/dataset/global-surface-summary-of-the-day-gsod). References [1] Cleaveland, S., M. K. Laurenson, and L. H. Taylor. "Diseases of humans and their domestic mammals: pathogen characteristics, host range and the risk of emergence." Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences 356.1411 (2001): 991-999. [2] Halliday, Jo EB, et al. "Driving improvements in emerging disease surveillance through locally relevant capacity strengthening." Science 357.6347 (2017): 146-148. [3] Schneider, Maria Cristina, and Gustavo Machado. "Environmental and socioeconomic drivers in infectious disease." The Lancet Planetary Health 2.5 (2018): e198-e199. [4] Daszak, Peter, Andrew A. Cunningham, and Alex D. Hyatt. "Emerging infectious diseases of wildlife--threats to biodiversity and human health." science 287.5452 (2000): 443-449. [5] Weiss, Robin A., and Anthony J. McMichael. "Social and environmental risk factors in the emergence of infectious diseases." Nature medicine 10.12 (2004): S70-S76.

- [6] Woolhouse, Mark EJ, and Sonya Gowtage-Sequeria. "Host range and emerging and
- reemerging pathogens." Emerging infectious diseases 11.12 (2005): 1842.
- [7] Patz, Jonathan A., et al. "Unhealthy landscapes: policy recommendations on land use
- 570 change and infectious disease emergence." Environmental health perspectives 112.10 (2004):
- 571 1092-1098.
- 572 [8] Kuhn, K., et al. "Using climate to predict infectious disease outbreaks: A review." World
- 573 Health Organization (2004).
- [9] Wu, XiaoXu, et al. "Impact of global change on transmission of human infectious diseases."
- 575 Science China Earth Sciences 57.2 (2014): 189-203.
- [10] Hamrick, Patricia Najera, et al. "Geographic patterns and environmental factors associated
- 577 with human yellow fever presence in the Americas." PLoS neglected tropical diseases 11.9
- 578 (2017): e0005897.
- 579 [11] Muñoz-Zanzi, Claudia, et al. "Leptospira contamination in household and environmental
- water in rural communities in southern Chile." International journal of environmental research
- and public health 11.7 (2014): 6666-6680.
- [12] Semenza, Jan C., et al. "Linking environmental drivers to infectious diseases: the European
- environment and epidemiology network." PLoS neglected tropical diseases 7.7 (2013).
- [13] Froment, A., et al. "Biodiversity and health: the place of parasitic and infectious diseases.
- Biodiversity change and human health." (2009): 211-227.
- [14] Yang, Hyun M., and Marcelo U. Ferreira. "Assessing the effects of global warming and local
- 587 social and economic conditions on the malaria transmission." Revista de saude publica 34.3
- 588 (2000): 214-222.
- [15] Martens, Pim, and Susanne C. Moser. "Health impacts of climate change." Science
- 590 292.5519 (2001): 1065-1066.
- 591 [16] McMichael, Anthony J., and Rosalie E. Woodruff. "Detecting the health effects of
- environmental change: scientific and political challenge." (2005): 1-3.
- [17] Casman, Elizabeth A., and Hadi Dowlatabadi, eds. The contextual determinants of malaria.
- Resources for the Future, 2002.
- 595 [18] Tol, Richard SJ, and Hadi Dowlatabadi. "Vector-borne diseases, development & climate
- 596 change." Integrated Assessment 2.4 (2001): 173-181.
- 597 [19] Epstein, Paul R. "Climate change and emerging infectious diseases." Microbes and
- 598 infection 3.9 (2001): 747-754.
- 599 [20] Wu, Xiaoxu, et al. "Impact of climate change on human infectious diseases: Empirical
- evidence and human adaptation." Environment international 86 (2016): 14-23.
- [21] Wu, XiaoXu, et al. "Impact of global change on transmission of human infectious diseases."
- 602 Science China Earth Sciences 57.2 (2014): 189-203.

- [22] Parham, Paul E., and Edwin Michael. "Outbreak properties of epidemic models: The roles
- of temporal forcing and stochasticity on pathogen invasion dynamics." Journal of theoretical
- 605 biology 271.1 (2011): 1-9.
- 606 [23] Turell, Michael J., Lee W. Cohnstaedt, and William C. Wilson. "Effect of Environmental
- Temperature on the Ability of Culex tarsalis and Aedes taeniorhynchus (Diptera: Culicidae) to
- Transmit Rift Valley Fever Virus." Vector-Borne and Zoonotic Diseases (2020).
- 609 [24] Kioutsioukis, Ioannis, and Nikolaos I. Stilianakis. "Assessment of West Nile virus
- 610 transmission risk from a weather-dependent epidemiological model and a global sensitivity
- analysis framework." Acta tropica 193 (2019): 129-141.
- [25] Peci, Adriana, et al. "Effects of absolute humidity, relative humidity, temperature, and wind
- speed on influenza activity in Toronto, Ontario, Canada." Appl. Environ. Microbiol. 85.6 (2019):
- 614 e02426-18.
- [26] Sung, Minki, et al. "Airflow as a Possible Transmission Route of Middle East Respiratory
- 616 Syndrome at an Initial Outbreak Hospital in Korea." International journal of environmental
- 617 research and public health 15.12 (2018): 2757.
- 618 [27] Huang, Chaolin, et al. "Clinical features of patients infected with 2019 novel coronavirus in
- 619 Wuhan, China." The Lancet 395.10223 (2020): 497-506.
- [28] Chen, Nanshan, et al. "Epidemiological and clinical characteristics of 99 cases of 2019
- novel coronavirus pneumonia in Wuhan, China: a descriptive study." The Lancet 395.10223
- 622 (2020): 507-513.
- [29] Wang, Dawei, et al. "Clinical characteristics of 138 hospitalized patients with 2019 novel
- 624 coronavirus-infected pneumonia in Wuhan, China." Jama (2020).
- 625 [30] Guan, Wei-jie, et al. "Clinical characteristics of coronavirus disease 2019 in China." New
- 626 England Journal of Medicine (2020).
- 627 [31] Liu, Ying, et al. "The reproductive number of COVID-19 is higher compared to SARS
- 628 coronavirus." Journal of travel medicine (2020).
- [32] Parham, Paul E., et al. "Understanding and modelling the impact of climate change on
- 630 infectious diseases–progress and future challenges." Climate Change—Socioeconomic Effects
- 631 (2011).
- 632 [33] Caldwell, John C. "Rethinking the African AIDS epidemic." Population and development
- 633 review 26.1 (2000): 117-135.
- 634 [34] Butler, Colin. "HIV and AIDS, poverty, and causation." The Lancet 356.9239 (2000): 1445-
- 635 **1446**.
- [35] Auvert, Betran, et al. "Ecological and individual level analysis of risk factors for HIV infection
- 637 in four urban populations in sub-Saharan Africa with different levels of HIV infection." Aids 15
- 638 (2001): S15-S30.
- [36] Weiss, Robin A., and Anthony J. McMichael. "Social and environmental risk factors in the
- emergence of infectious diseases." Nature medicine 10.12 (2004): S70-S76.

- [37] Houéto, D. "The social determinants of emerging infectious diseases in Africa." MOJ Public
- 642 Health 8.2 (2019): 57-63.
- [38] Wu, Xiaoxu, et al. "Impact of climate change on human infectious diseases: Empirical
- evidence and human adaptation." Environment international 86 (2016): 14-23.
- [39] Kovats, Sari, et al. Climate change and human health: impact and adaptation. World Health
- 646 Organization (WHO), 2000.
- [40] Houéto, D. "The social determinants of emerging infectious diseases in Africa." MOJ Public
- 648 Health 8.2 (2019): 57-63.
- [41] Parham, Paul E., et al. "Climate, environmental and socio-economic change: weighing up
- 650 the balance in vector-borne disease transmission." Philosophical Transactions of the Royal
- 651 Society B: Biological Sciences 370.1665 (2015): 20130551.
- [42] Zhang S, Diao M Y, Yu W, et al. Estimation of the reproductive number of Novel
- 653 Coronavirus (COVID-19) and the probable outbreak size on the Diamond Princess cruise ship:
- A data-driven analysis[J]. International Journal of Infectious Diseases, 2020, 93: 201-204.
- 655 [43] Li, Qun, et al. "Early transmission dynamics in Wuhan, China, of novel coronavirus-infected
- 656 pneumonia." New England Journal of Medicine (2020).
- 657 [44] Xie X, Zhong Z, Zhao W, et al. Chest CT for typical 2019-nCoV pneumonia: relationship to
- 658 negative RT-PCR testing[J]. Radiology, 2020: 200343.
- [45] Dong, Ensheng, Hongru Du, and Lauren Gardner. "An interactive web-based dashboard to
- track COVID-19 in real time." The Lancet Infectious Diseases (2020).
- [46] Chen, Biging, et al. "Roles of meteorological conditions in COVID-19 transmission on a
- 662 worldwide scale." medRxiv (2020).
- 663 [47] Anselin, Luc. "A local indicator of multivariate spatial association: extending Geary's C."
- 664 Geographical Analysis 51.2 (2019): 133-150.
- [48] Elhorst, J. Paul, Donald J. Lacombe, and Gianfranco Piras. "On model specification and
- 666 parameter space definitions in higher order spatial econometric models." Regional Science and
- 667 Urban Economics 42.1-2 (2012): 211-220.
- [49] Phung, Dung, et al. "The effects of socioecological factors on variation of communicable
- diseases: A multiple-disease study at the national scale of Vietnam." PloS one 13.3 (2018).
- [50] Hondula, David M., and Adrian G. Barnett. "Heat-related morbidity in Brisbane, Australia:
- spatial variation and area-level predictors." Environmental health perspectives 122.8 (2014):
- 672 831-836.
- [51] Armocida, Benedetta, et al. "The Italian health system and the COVID-19 challenge." The
- 674 Lancet Public Health (2020).
- 675 [52] Leung, Kathy, et al. "First-wave COVID-19 transmissibility and severity in China outside
- 676 Hubei after control measures, and second-wave scenario planning: a modelling impact
- 677 assessment." The Lancet (2020).

- [53] Kraemer, Moritz UG, et al. "The effect of human mobility and control measures on the
- 679 COVID-19 epidemic in China." Science (2020).
- 680 [54] Chinazzi, Matteo, et al. "The effect of travel restrictions on the spread of the 2019 novel
- 681 coronavirus (COVID-19) outbreak." Science (2020).
- [55] Prem, Kiesha, et al. "The effect of control strategies to reduce social mixing on outcomes of
- the COVID-19 epidemic in Wuhan, China: a modelling study." The Lancet Public Health (2020).
- [56] Koo, Joel R., et al. "Interventions to mitigate early spread of SARS-CoV-2 in Singapore: a
- 685 modelling study." The Lancet Infectious Diseases (2020).
- [57] Xu, Shunqing, and Yuanyuan Li. "Beware of the second wave of COVID-19." The Lancet
- 687 (2020).
- [58] Niehus, Rene, et al. "Using observational data to quantify bias of traveller-derived COVID-
- 19 prevalence estimates in Wuhan, China." The Lancet Infectious Diseases (2020).
- 690 [59] Martinez-Alvarez, Melisa, et al. "COVID-19 pandemic in west Africa." The Lancet Global
- 691 Health (2020).
- 692 [60] Lee, Vernon J., et al. "Epidemic preparedness in urban settings: new challenges and
- 693 opportunities." The Lancet Infectious Diseases (2020).
- [61] Dowd, Jennifer Beam, et al. "Demographic science aids in understanding the spread and
- fatality rates of COVID-19." medRxiv (2020).
- 696 [62] Sajadi, Mohammad M. and Habibzadeh, Parham and Vintzileos, Augustin and Shokouhi,
- 697 Shervin and Miralles-Wilhelm, Fernando and Amoroso, Anthony, Temperature, Humidity and
- 698 Latitude Analysis to Predict Potential Spread and Seasonality for COVID-19 (March 5, 2020).
- 699 Available at SSRN: https://ssrn.com/abstract=3550308 or
- 700 http://dx.doi.org/10.2139/ssrn.3550308
- 701 [63] Ruan, Shigui. "Likelihood of survival of coronavirus disease 2019." The Lancet Infectious
- 702 Diseases (2020).
- 703 [64] Fang, Lei, George Karakiulakis, and Michael Roth. "Are patients with hypertension and
- diabetes mellitus at increased risk for COVID-19 infection?." The Lancet. Respiratory Medicine
- 705 (2020).
- 706 [65] Ayebare, Rodgers R., et al. "Adoption of COVID-19 triage strategies for low-income
- 707 settings." The Lancet Respiratory Medicine (2020).
- 708 [66] Chen, Simiao, et al. "Fangcang shelter hospitals: a novel concept for responding to public
- 709 health emergencies." The Lancet (2020).
- 710 [67] Miani, Alessandro, et al. "The Italian war-like measures to fight coronavirus spreading: Re-
- 711 open closed hospitals now." EClinicalMedicine (2020).
- 712 [68] McCloskey, Brian, et al. "Mass gathering events and reducing further global spread of
- 713 COVID-19: a political and public health dilemma." Lancet (London, England) 395.10230 (2020):
- 714 1096.

- 715 [69] Yao, Y., Pan, J., Liu, Z., Meng, X., Wang, W., Kan, H., & Wang, W. (2020). No Association
- of COVID-19 transmission with temperature or UV radiation in Chinese cities. The European
- 717 respiratory journal, 2000517. Advance online publication.
- 718 https://doi.org/10.1183/13993003.00517-2020
- 719 [70] Islam, Nazrul, Sharmin Shabnam, and A. Mesut Erzurumluoglu. "Meteorological factors and
- 720 Covid-19 incidence in 310 regions across the world." medRxiv (2020).
- 721 [71] Zhu, Yongjian, and Jingui Xie. "Association between ambient temperature and COVID-19
- infection in 122 cities from China." Science of The Total Environment (2020): 138201.
- 723 [72] Wang, Mao, et al. "Temperature significant change COVID-19 Transmission in 429 cities."
- 724 medRxiv (2020).

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# 725 Tables and Figures

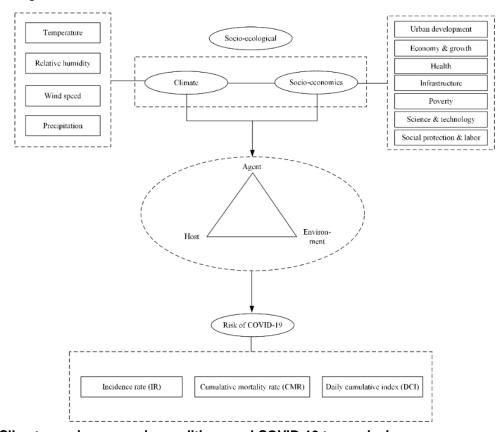


Figure 1. Climate, socio-economic conditions and COVID-19 transmission

Table 1 The calculation process of outcome variables for COVID-19

Outcome variables	Calculation process
Incidence rate (IR)	$IR = \frac{\text{Number of new cases of COVID-19 in a given time period}}{\text{×1,000,000}}$
incluence rate (IK)	Total population at risk during the follow-up period
Cumulative morality	$CMR = \frac{\text{number of COVID-19 deaths in a given time period}}{\times 1,000,000}$
rate (CMR)	total population during a given time period

Daily cumulative	DCI = cumulative COVID-19 confirmed cases
index (DCI)	number of days between the first reported case until now

Table 2. Socioeconomic indicators influencing the spread of COVID-19

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Dimensions	Indicators	No.					
	Urban population (% of total population)	(1)					
Urban Development	Urban population growth (annual %)	(2)					
	Population density (people per sq. km of land area)	(3)					
Economy & Growth	GDP per capita (current US\$)	(4)					
Health	People using at least basic sanitation services (% of population)	(5)					
	Current health expenditure (% of GDP)	(6)					
	Current health expenditure per capita (current US\$)	(7)					
	Death rate, crude (per 1,000 people)	(8)					
	Domestic private health expenditure (% of current health expenditure)	(9)					
	Domestic private health expenditure per capita (current US\$)	(10)					
	Hospital beds (per 1,000 people)	(11)					
	Life expectancy at birth, total (years)	(12)					
	Maternal mortality ratio (national estimate, per 100,000 live births)						
	Mortality rate, infant (per 1,000 live births)	(14)					
	Net migration	(15)					
	Nurses and midwives (per 1,000 people)	(16)					
	People with basic handwashing facilities including soap and water (% of population)	(17)					
	Physicians (per 1,000 people)	(18)					
	Population aged 65 and above (% of total population)	(19)					
	Population growth (annual %)	(20)					
	Proportion of population spending more than 10% of household consumption or income on out-of-pocket health care expenses (%)	(21)					
	Proportion of population spending more than 25% of household consumption or income on out-of-pocket health care expenses (%)	(22)					
Infrastructure	Railways, passengers carried (million passenger-km)	(23)					
Poverty	Poverty headcount ratio at national poverty lines (% of population)	(24)					
Science & Technology	Researchers in R&D (per million people)	(25)					
Science & Technology	Technicians in R&D (per million people)	(26)					
Cooled Drotection 9 Labor	Coverage of social insurance programs (% of population)	(27)					
Social Protection & Labor	Unemployment, total (% of total labor force) (national estimate)	(28)					

# Table 3 Characteristics of UN geographical divisions with reported cases of COVID-19 as of 6 April 2020

			-			-
UN geographical divisions	No. of Countries/regions	IR†	CMR‡	DCI§	Total population	Total days since first reported case
Africa						
Eastern Africa	17	0.18	0.04	2.85	451173502	325
Middle Africa	8	0.12	0.21	4.96	168910830	189
Northern Africa	5	1.92	1.85	25.03	194924933	179

Southern Africa	3	0.50	0.21	26.28	62482003	65
Western Africa	13	0.35	0.16	4.93	343169384	299
Asia						
Central Asia	3	4.55	0.21	19.63	57547699	68
East Asia	4	0.40	2.29	355.28	1574064564	273
Southeast Asia	9	1.47	0.78	26.75	600191804	525
Southern Asia	9	2.18	2.09	159.97	1896189013	436
Western Asia	14	11.32	1.67	36.21	138585525	586
Europe						
Eastern Europe	10	6.91	1.85	64.50	292450026	379
Northern Europe	12	51.86	60.72	153.93	104678611	528
Southern Europe	14	64.24	204.80	535.26	148744007	541
Western Asia	1	38.24	7.88	1119.15	82319724	27
Western Europe	9	57.69	77.55	628.85	196616151	442
North America						
Caribbean	16	3.35	2.99	7.62	38841019	338
Central America	8	2.86	1.03	24.87	175471759	203
North America	4	83.30	30.53	2027.60	364346283	189
Oceania						
Australia and New Zealand	2	5.92	1.37	62.19	29877869	111
Melanesia	5	0.49	0.00	1.92	22465856	106
South America	12	4.74	2.39	74.46	423398995	367

<sup>†</sup>IR, incidence rate (per 10 million people).

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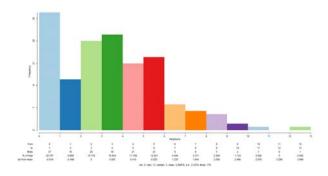


Figure 2. Number of first-order neighbors in different countries/regions

<sup>‡</sup>CMR, cumulative mortality rate (per 10 million people).

<sup>§</sup>DCI, daily cumulative index (%)

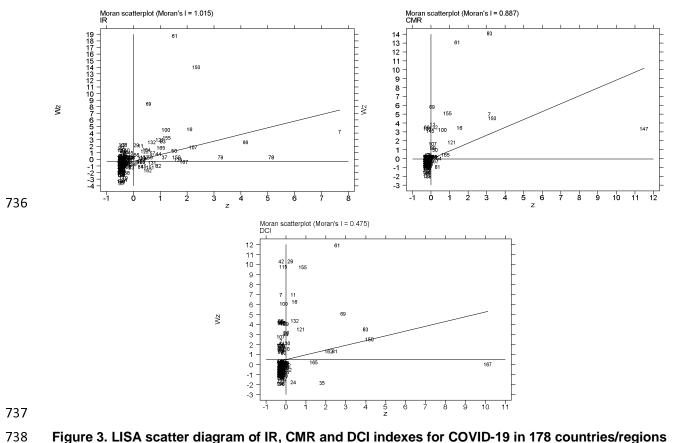


Figure 3. LISA scatter diagram of IR, CMR and DCI indexes for COVID-19 in 178 countries/regions (z is the value of the variable, and Wz is the local Moran's li value of the variable.)

Table 4. The results of single-factor and multi-factor negative binomial regression analysis for COVID-19 in 178 countries/regions

				Incidenc	e rate (IR)	)					Cum	ulative mor	tality rate	(CMR)	<u> </u>	riv pi			Dai	ily cumulati	ive index	(DCI)		
Indicators	IRR*	95%CI† (Lower)	95%CI (Upper)	p-value	alRR‡	95%CI (Lower)	95%CI (Upper)	p-value	IRR	95%CI (Lower)	95%CI (Upper)	p-value	alRR	95%CI (Lower)	95%CI	eprint doi:	IRR	95%CI (Lower)	95%CI (Upper)	p-value	alRR	95%CI (Lower)	95%CI (Upper)	p-value
Urban Development																:://dc								
Urban population (% of total population)	1.048	0.992	1.106	0.096					1.055	1.027	1.083	<0.001	1.027	1.010	1.04 <u>4</u>	0.001	1.073	1.055	1.091	<0.001	1.022	1.010	1.034	<0.001
Urban population growth (annual %)	1.053	1.039	1.066	< 0.001	0.866	0.670	1.120	0.273	0.287	0.203	0.405	<0.001	0.751	0.507	1.112	0.153	0.407	0.312	0.530	<0.001	0.993	0.734	1.343	0.963
Population density (people per sq. km of land area)	1.000	1.000	1.000	0.179					1.000	1.000	1.000	0.633			nade av	.1101/	1.000	1.000	1.000	<0.001	1.000	1.000	1.000	0.020
Economy & Growth															avail	202								
GDP per capita (current 1,000 US\$)	1.054	1.038	1.071	<0.001	1.029	1.013	1.045	<0.001	1.086	1.056	1.117	<0.001	1.031	1.021	1.04	<0.001	1.045	1.019	1.072	0.001	0.998	0.987	1.009	0.696
Health															thor.	1.23								
People using at least basic sanitation services (% of population)	1.063	1.048	1.078	<0.001	1.022	1.005	1.039	0.010	1.088	1.065	1.111	<0.001	1.001	0.985	1.01% a	.77	1.056	1.045	1.066	<0.001	1.011	0.998	1.025	0.102
Current health expenditure (% of GDP)	1.186	1.045	1.345	0.008	1.088	0.956	1.238	0.203	1.501	1.245	1.809	<0.001	1.211	1.040	1.4100 ⋽	0.013	1.416	1.216	1.648	<0.001	1.080	0.968	1.206	0.169
Death rate, crude (per 1,000 people)	0.954	0.862	1.057	0.371					1.097	0.857	1.403	0.462			BY-I	:.t	1.187	0.978	1.439	0.082				
Domestic private health expenditure (% of current health expenditure)  Domestic private health expenditure per	0.955	0.933	0.978	<0.001	0.988	0.972	1.004	0.135	0.937	0.906	0.969	<0.001	0.986	0.970	1.003 8	ersi	0.951	0.933	0.970	<0.001	1.010	0.994	1.027	0.207
capita (current US\$)	1.003	1.002	1.003	<0.001	1.001	1.000	1.001	0.119	1.005	1.003	1.008	<0.001	1.001	1.000	1.00 1	g 0.104 B	1.003	1.001	1.004	<0.001	1.000	1.000	1.001	0.438
Hospital beds (per 1,000 people)	1.246	1.034	1.502	0.021	0.906	0.790	1.039	0.156	1.798	1.067	3.030	0.028	0.799	0.696	0.91	0.001	1.302	1.022	1.659	0.033	0.731	0.641	0.833	<0.001
Net migration	1.000	1.000	1.000	<0.001	1.000	1.000	1.000	0.954	1.000	1.000	1.000	0.001	1.000	1.000	1.00 뜻	<u>د</u> 0.530	1.000	1.000	1.000	0.005	1.000	1.000	1.000	0.103
Nurses and midwives (per 1,000 people)	1.239	1.149	1.337	< 0.001	0.901	0.813	1.002	0.052	1.499	1.268	1.773	< 0.001	0.837	0.749	0.93€ ≷	্ট্র 0.002	1.290	1.111	1.498	0.001	0.904	0.820	0.997	0.044
Physicians (per 1,000 people)	1.938	1.393	2.698	< 0.001	1.005	0.750	1.347	0.972	3.389	2.652	4.331	< 0.001	1.725	1.191	2.49	0.004	2.600	1.739	3.886	<0.001	0.951	0.758	1.192	0.661
Population ages 65 and above (% of total population) Proportion of population spending more	1.111	1.054	1.171	<0.001	0.981	0.913	1.055	0.609	1.235	1.151	1.326	<0.001	1.066	0.968	e to	020.192 Th	1.233	1.144	1.328	<0.001	1.062	0.988	1.141	0.102
than 25% of household consumption or income on out-of-pocket health care expenditure (%)	0.802	0.675	0.953	0.012	0.846	0.750	0.955	0.007	0.794	0.626	1.007	0.057			display tr	he copyright	0.898	0.715	1.129	0.357				
Infrastructure Railways, passengers carried (million passenger-km)	1.000	1.000	1.000	<0.001	1.000	1.000	1.000	0.323	1.000	1.000	1.000	0.679			ne prepri	ht holder for	1.000	1.000	1.000	0.498				
Poverty															DI II	r for								
Poverty headcount ratio at national poverty lines (% of population)	0.924	0.900	0.949	<0.001	0.970	0.948	0.993	0.011	0.894	0.872	0.916	<0.001	0.960	0.940	0.982	ਜ਼ਿੱ<0.001 ਬੁ	0.908	0.889	0.926	<0.001	0.963	0.945	0.982	<0.001
Science & Technology															Ĕ	<u>e</u>								
Researchers in R&D (per million people)	1.000	1.000	1.001	<0.001	1.000	1.000	1.000	0.159	1.000	1.000	1.001	0.034	1.000	1.000	1.000♀	ੜ੍ਹੋਂ 0.115	1.001	1.001	1.001	<0.001	1.000	1.000	1.001	0.012
Social Protection & Labor																								
Coverage of social insurance programs (% of population)	1.060	1.041	1.079	<0.001	1.047	1.009	1.086	0.014	1.036	0.992	1.082	0.110					1.091	1.072	1.110	<0.001	1.015	0.991	1.039	0.214
Unemployment, total (% of total labor force) (national estimate)  Climate	0.902	0.828	0.982	0.018	0.956	0.909	1.004	0.072	1.002	0.861	1.166	0.984					0.986	0.866	1.122	0.828				
Mean temperature (Celsius)	0.934	0.897	0.972	0.001	1.039	0.992	1.088	0.105	0.975	0.887	1.071	0.592					0.834	0.800	0.869	<0.001	0.978	0.939	1.018	0.280
Relative humidity (%)	1.011	0.994	1.027	0.204					1.025	0.995	1.056	0.108					0.990	0.960	1.022	0.538				
Mean wind speed (.1 knots);	1.210	1.111	1.317	<0.001	1.040	0.957	1.130	0.358	1.155	0.951	1.403	0.146					0.958	0.836	1.097	0.533				
Precipitation amount (.01 inches).	0.082	0.016	0.003	0.003	0.477	0.126	1.808	0.276	0.019	0.001	0.377	0.009	0.425	0.123	1.471	0.177	0.204	0.005	8.409	0.402				
*IRR, incidence rate ratio.				000							2.0		0							<b>-</b>				

<sup>\*</sup>IRR, incidence rate ratio. †CI is short for confidence interval. ‡aIRR, adjusted incidence rate ratio.

Table S1 Characteristics of 178 countries/regions with reported cases of COVID-19 as of 6 April 2020

Continents	UN geographical divisions	Countries/regions	IR†	CMR‡	DCI§	Total population	Days since first reported case
Africa	Eastern Africa	Burundi	0.00	0.00	0.43	11175378	7
		Djibouti	32.33	0.00	4.50	958920	20
		Eritrea	0.62	0.00	1.82	3213972	17
		Ethiopia	0.01	0.02	1.76	109224559	25
		Kenya	0.31	0.12	6.32	51393010	25
		Madagascar	0.38	0.00	4.56	26262368	18
		Malawi	0.06	0.00	1.00	18143315	5
		Mauritius	13.44	5.53	12.20	1265303	20
		Mozambique	0.00	0.00	0.63	29495962	16
		Rwanda	0.08	0.00	4.38	12301939	24
		Seychelles	10.34	0.00	0.46	96762	24
		Somalia	0.00	0.00	0.32	15008154	22
		Sudan	0.00	0.05	0.48	41801533	25
		Tanzania	0.04	0.02	1.09	56318348	22
		Uganda	0.00	0.00	3.06	42723139	17
		Zambia	0.00	0.06	1.95	17351822	20
		Zimbabwe	0.07	0.07	0.56	14439018	18
	Middle Africa	Angola	0.06	0.06	0.89	30809762	18
		Cameroon	0.32	0.36	20.56	25216237	32
		Central African Republic	0.00	0.00	0.35	4666377	23
		Chad	0.00	0.00	0.47	15477751	19
		Congo (Brazzaville)	0.00	0.95	1.96	5244363	23
		Congo (Kinshasa)	0.08	0.21	5.96	84068091	27
		Equatorial Guinea	0.00	0.00	0.70	1308974	23
		Gabon	1.42	0.47	1.00	2119275	24
	Northern Africa	Algeria	2.44	4.10	33.88	42228429	42
		Egypt	1.51	0.86	24.94	98423595	53
		Libya	0.15	0.15	1.36	6678567	14
		Morocco	2.75	2.22	31.11	36029138	36
		Tunisia	1.90	1.90	17.53	11565204	34

	Southern Africa	Botswana	0.00	0.44	0.75	2254126	8
		Namibia	0.00	0.00	0.67	2448255	24
		South Africa	0.54	0.21	51.09	57779622	33
	Western Africa	Benin	0.35	0.09	1.18	11485048	22
		Burkina Faso	0.96	0.91	13.00	19751535	28
		Gambia	0.00	0.44	0.19	2280102	21
		Ghana	0.00	0.17	8.92	29767108	24
		Guinea-Bissau	0.00	0.00	1.38	1874309	13
		Liberia	0.21	0.62	0.64	4818977	22
		Mali	0.10	0.26	3.62	19077690	13
		Mauritania	0.00	0.23	0.25	4403319	24
		Niger	3.07	0.45	14.06	22442948	18
		Nigeria	0.03	0.03	6.10	195874740	39
		Senegal	0.25	0.13	6.28	15854360	36
		Sierra Leone	0.00	0.00	0.86	7650154	7
		Togo	1.77	0.38	1.81	7889094	32
Asia	Central Asia	Kazakhstan	4.27	0.33	26.48	18276499	25
		Kyrgyzstan	10.93	0.63	10.80	6315800	20
		Uzbekistan	3.49	0.06	19.87	32955400	23
	Eastern Asia	China	0.05	2.39	965.56	1392730000	86
		Japan	4.07	0.67	44.56	126529100	82
		Korea, South	0.91	3.60	133.56	51635256	77
		Mongolia	0.32	0.00	0.54	3170208	28
	South-Eastern Asia	Brunei	0.00	2.33	4.66	428962	29
		Cambodia	0.00	0.00	1.61	16249798	71
		Indonesia	0.81	0.78	69.19	267663435	36
		Laos	0.14	0.00	0.86	7061507	14
		Malaysia	4.16	1.97	51.96	31528585	73
		Philippines	3.88	1.53	53.82	106651922	68
		Singapore	11.71	1.06	18.33	5638676	75
		Thailand	0.73	0.37	26.43	69428524	84
		Vietnam	0.04	0.00	3.27	95540395	75

Southern Asia	Afghanistan	0.48	0.30	8.53	37172386	43
	Bangladesh	0.22	0.07	4.10	161356039	30
	Bhutan	0.00	0.00	0.16	754394	32
	India	0.88	0.10	70.26	1352617328	68
	Iran	27.82	45.71	1260.42	81800269	48
	Maldives	0.00	0.00	0.63	515696	30
	Nepal	0.00	0.00	0.12	28087871	73
	Pakistan	2.87	0.25	91.85	212215030	41
	Sri Lanka	0.09	0.23	2.51	21670000	71
Western Asia	Armenia	3.73	2.71	22.51	2951776	37
	Azerbaijan	5.73	0.70	17.32	9942334	37
	Bahrain	35.70	2.55	17.58	1569439	43
	Cyprus	15.98	7.57	16.03	1189265	29
	Georgia	3.75	0.54	4.59	3731000	41
	Iraq	1.82	1.67	23.98	38433600	43
	Israel	53.41	6.42	193.57	8883800	46
	Jordan	0.40	0.60	9.97	9956011	35
	Kuwait	26.35	0.24	15.47	4137309	43
	Lebanon	2.04	2.77	11.76	6848925	46
	Oman	6.83	0.41	7.70	4829483	43
	Qatar	82.02	1.44	48.21	2781677	38
	Saudi Arabia	6.02	1.13	72.36	33699947	36
	Turkey	38.26	7.88	1119.15	82319724	27
	United Arab Emirates	28.77	1.14	30.09	9630959	69
Eastern Europe	Belarus	14.55	1.37	17.95	9485386	39
	Bulgaria	2.56	3.13	18.30	7024216	30
	Czechia	22.13	7.34	130.32	10625695	37
	Hungary	1.13	3.89	21.88	9768785	34
	Moldova	28.49	5.36	32.17	3545883	30
	Poland	8.19	2.82	129.79	37978548	34
	Romania	9.91	9.04	98.95	19473936	41
	Russia	6.60	0.33	94.67	144478050	67

Europe

	Slovakia	9.00	0.37	16.69	5447011	32
	Ukraine	0.25	0.85	37.69	44622516	35
Northern Europe	Denmark	53.86	32.26	117.03	5797446	40
	Estonia	8.33	14.38	27.70	1320884	40
	Faroe Islands (Denmark)	41.40	0.00	5.38	48497	34
	Finland	45.14	4.89	31.54	5518050	69
	Iceland	215.90	16.97	40.05	353574	39
	Ireland	76.32	35.85	141.16	4853506	38
	Isle of Man (United Kingdom)	142.96	11.89	7.72	84077	18
	Latvia	4.67	0.52	15.06	1926542	36
	Lithuania	11.47	5.38	21.62	2789533	39
	Norway	33.53	14.30	143.05	5314336	41
	Sweden	36.95	46.84	107.55	10183175	67
	United Kingdom	57.23	80.81	770.27	66488991	67
Southern Europe	Albania	5.58	7.33	13.00	2866376	29
	Andorra	313.80	272.71	14.58	77006	36
	Bosnia and Herzegovina	6.02	8.72	20.42	3323929	33
	Croatia	9.78	3.91	29.10	4089400	42
	Gibraltar (United Kingdom)	178.52	0.00	3.21	33718	34
	Greece	1.86	7.36	42.80	10727668	41
	Italy	59.69	273.42	1978.31	60431283	67
	Malta	28.97	0.00	7.77	483530	31
	Montenegro	30.54	3.21	11.10	622345	21
	Portugal	44.01	30.25	325.83	10281762	36
	San Marino	0.00	947.17	6.65	33785	40
	Serbia	41.83	8.31	68.75	6982084	32
	Slovenia	11.61	14.51	30.94	2067372	33
	Spain	107.95	285.53	2070.83	46723749	66
Western Europe	Austria	27.84	24.87	292.79	8847037	42
	Belgium	98.50	142.88	330.38	11422068	63
	France	77.31	133.03	1324.46	66987244	74
	Germany	39.25	21.83	1455.97	82927922	71

		Liechtenstein	0.00	26.38	2.26	37910	34
		Luxembourg	64.48	67.46	74.82	607728	38
		Monaco	103.61	25.85	2.03	38682	38
		Netherlands	55.31	108.35	470.08	17231017	40
		Switzerland	65.57	89.83	515.64	8516543	42
North America	Caribbean	Antigua and Barbuda	0.00	0.00	0.60	96286	25
		Bahamas	2.59	12.97	1.32	385640	22
		Barbados	13.96	6.98	2.86	286641	21
		British Virgin Islands (United Kingdom)	0.00	0.00	0.30	29802	10
		Cayman Islands (United Kingdom)	62.37	15.58	1.56	64174	25
		Cuba	2.65	0.79	13.46	11338138	26
		Dominica	13.96	0.00	0.94	71625	16
		Dominican Republic	7.81	8.09	49.41	10627165	37
		Grenada	0.00	0.00	0.75	111454	16
		Haiti	0.27	0.09	1.33	11123176	18
		Jamaica	0.00	1.02	2.15	2934855	27
		Saint Kitts and Nevis	0.00	0.00	0.77	52441	13
		Saint Lucia	0.00	0.00	0.58	181889	24
		Saint Vincent and the Grenadines	0.00	0.00	0.29	110210	24
		Trinidad and Tobago	0.72	5.76	4.38	1389858	24
		Turks and Caicos Islands (United Kingdom)	79.67	26.55	0.80	37665	10
	Central America	Belize	5.22	2.61	0.47	383071	15
		Costa Rica	2.60	0.40	14.59	4999441	32
		El Salvador	1.09	0.62	3.63	6420744	19
		Guatemala	0.52	0.17	2.92	17247807	24
		Honduras	3.13	2.29	11.04	9587522	27
		Mexico	2.00	0.74	54.95	126190788	39
		Nicaragua	0.00	0.15	0.32	6465513	19
		Panama	44.79	12.93	71.00	4176873	28
	Northern America	Bermuda (United Kingdom)	31.28	31.27	2.05	63968	19
		Canada	21.76	9.12	229.89	37058856	72
		Greenland (Denmark)	0.00	0.00	0.50	56025	22

		US	90.40	32.96	4823.87	327167434	76
Oceania	Australia and New Zealand	Australia	4.40	1.60	80.51	24992369	72
		New Zealand	13.72	0.20	28.36	4885500	39
	Melanesia	Fiji	2.26	0.00	0.74	883483	19
		French Polynesia (France)	3.60	0.00	1.68	277679	25
		Guinea	0.56	0.00	5.12	12414318	25
		New Caledonia (France)	0.00	0.00	0.95	284060	19
		Papua New Guinea	0.12	0.00	0.11	8606316	18
South America	South America	Argentina	2.31	1.08	44.40	44494502	35
		Bolivia	2.29	0.97	6.78	11353142	27
		Brazil	4.92	2.69	296.61	209469333	41
		Chile	18.37	1.98	137.57	18729160	35
		Colombia	1.89	0.93	49.34	49648685	32
		Ecuador	5.91	11.18	101.27	17084357	37
		Guyana	8.99	5.13	1.19	779004	26
		Paraguay	1.29	0.72	3.77	6956071	30
		Peru	8.75	2.88	80.03	31989256	32
		Suriname	0.00	1.74	0.42	575991	24
		Uruguay	1.74	1.74	16.92	3449299	24
		Venezuela	0.21	0.24	6.88	28870195	24

<sup>†</sup>IR, incidence rate (per 10 million people).

<sup>‡</sup>CMR, cumulative mortality rate (per 10 million people).

<sup>§</sup>DCI, daily cumulative index (%)

Table S2. The Global Moran's I index of IR, CMR and DCI for COVID-19

Variables	1	E(I)	sd(I)	Z	p-value
IR	0.339	-0.006	0.056	6.171	<0.001
CMR	0.297	-0.006	0.040	7.535	<0.001
DCI	0.159	-0.006	0.049	3.379	0.001

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)		RAN)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
)	1.000																		pre  vas									
)	-0.420*	1.000																	preprint vas not									
)	0.188*	-0.075	1.000																do:									
	0.444*	-0.360*	0.488*	1.000															doi: https									
	0.585*	-0.717*	0.111	0.448*	1.000														os://doi <b>d by p</b>									
	0.218*	-0.289*	-0.148*	0.175*	0.243*	1.000																						
	0.468*	-0.327*	0.099	0.656*	0.421*	0.574*	1.000											<u>~</u>	org/10									
	-0.110	-0.335*	-0.061	-0.052	-0.086	0.239*	0.060	1.000										ma	/10.1101 review) i									
)	-0.328*	0.178*	-0.064	-0.368*	-0.269*	-0.219*	-0.404*	-0.011	1.000									de a	<u>\$</u> [01]									
))	0.436*	-0.376*	0.106	0.580*	0.439*	0.514*	0.890*	0.013	-0.194*	1.000								vaik	2020 the									
)	0.376*	-0.602*	0.293*	0.407*	0.497*	0.195*	0.304*	0.380*	-0.296*	0.268*	1.000							able	).04 aut									
2)	0.573*	-0.653*	0.106	0.559*	0.858*	0.345*	0.557*	-0.158*	-0.383*	0.536*	0.454*	1.000						und	23.2 hor/f									
3)	-0.503*	0.632*	-0.085	-0.367*	-0.858*	-0.110	-0.351*	0.106	0.283*	-0.360*	-0.462*	-0.807*	1.000					er a	2007 und									
1)	-0.521*	0.690*	-0.116	-0.455*	-0.861*	-0.302*	-0.457*	0.107	0.381*	-0.455*	-0.534*	-0.913*	0.858*	1.000				ç	754 er, w									
5)	0.217*	-0.033	0.006	0.228*	0.164*	0.397*	0.426*	0.050	-0.353*	0.279*	0.163*	0.193*	-0.120	-0.191*	1.000				5.th									
)	0.503*	-0.493*	0.288*	0.659*	0.567*	0.416*	0.758*	0.182*	-0.419*	0.649*	0.613*	0.616*	-0.507*	-0.600*	0.285*	1.000		N C	l/2020.04.23.20077545.this version point the author/funder, who has granted									
)	0.534*	-0.674*	0.088	0.405*	0.875*	0.289*	0.401*	-0.063	-0.221*	0.412*	0.451*	0.837*	-0.825*	-0.832*	0.132	0.568*	1.000	S	rsion									
5)	0.556*	-0.662*	0.218*	0.497*	0.660*	0.441*	0.571*	0.276*	-0.339*	0.525*	0.600*	0.676*	-0.594*	-0.690*	0.190*	0.747*	0.658*	1.000	n po ted									
)	0.388*	-0.715*	-0.059	0.358*	0.607*	0.546*	0.594*	0.524*	-0.340*	0.540*	0.587*	0.702*	-0.558*	-0.662*	0.219*	0.650*	0.606*	===	me #00									
)	-0.274*	0.931*	-0.038	-0.249*	-0.606*	-0.246*	-0.230*	-0.427*	0.133	-0.272*	-0.544*	-0.561*	0.564*	0.613*	0.055	-0.390*	-0.594*	-0.569*	₹03* ××××××××××××××××××××××××××××××××××××	1.000								
)	-0.018	-0.069	0.028	-0.088	0.026	0.273*	-0.071	0.090	0.335*	0.045	0.016	0.026	0.065	0.021	-0.177*	-0.063	0.073	<u>w</u>	<u>a</u> 0 <u>.</u> 267	-0.093	1.000							
)	-0.105	0.056	0.003	-0.110	-0.103	0.235*	-0.097	0.050	0.280*	-0.013	-0.105	-0.105	0.193*	0.160*	-0.174*	-0.135	-0.061	Ф	%67 ≥ 000 ≥ 000 < 000 <000 <000 <000 <000 <000 <000 <000 <000 <000 <000 <000 <000 <000 <000 <000 <000 <000 <000 <000 <000 <00	0.011	0.883*	1.000						
3)	-0.065	0.020	-0.006	-0.051	-0.026	-0.078	-0.031	0.019	0.147*	-0.038	-0.010	-0.020	-0.011	0.010	-0.347*	-0.027	0.004	-0.026	\$6.508 \$7	-0.050	0.133	0.116	1.000					
1)	-0.355*	0.453*	0.027	-0.237*	-0.639*	-0.222*	-0.341*	0.045	0.189*	-0.312*	-0.371*	-0.676*	0.658*	0.660*	-0.111	-0.456*	-0.727*		<u>ල</u> 07540* ග්ර	0.447*	-0.080	0.018	-0.101	1.000				
5)	0.459*	-0.399*	0.040	0.509*	0.447*	0.486*	0.778*	0.217*	-0.375*	0.666*	0.419*	0.584*	-0.392*	-0.501*	0.275*	0.724*	0.449*	0.600*	<del>g</del> 0 <del>g</del> 28*	-0.329*	-0.029	-0.108	-0.004	-0.439*	1.000			
3)	0.368*	-0.324*	-0.020	0.542*	0.381*	0.509*	0.828*	0.200*	-0.399*	0.703*	0.341*	0.533*	-0.339*	-0.440*	0.281*	0.730*	0.373*		<b>∄</b> 67*	-0.260*	-0.076	-0.108	-0.009	-0.362*	0.838*	1.000		
7)	0.498*	-0.598*	0.033	0.368*	0.586*	0.451*	0.544*	0.350*	-0.285*	0.482*	0.551*	0.630*	-0.568*	-0.640*	0.249*	0.704*	0.664*		<u>\$0₹82*</u>	-0.534*	0.089	-0.055	0.036	-0.586*	0.693*	0.617*	1.000	
	-0.019	-0.031	-0.052	-0.203*	0.013	0.019	-0.175*	0.053	0.141	-0.113	-0.039	-0.118	-0.015	0.049	-0.013	-0.144	-0.096	-0.114	<u>≒</u> œ68	-0.041	0.050	-0.004	-0.067	0.167*	-0.183*	-0.167*	-0.110	1.000

Table S4. The sensitive analysis of single-factor negative binominal regression for the risk of COVID-19

			IR			С	MR			DCI					
Indicators	IRR†	95%CI‡ (Lower)	95%CI (Upper)	p-value	IRR	95%CI (Lower)	95%CI (Upper)	p-value	IRR	95%CI (Lower)	95%CI (Upper)	p-value			
Max temperature (Celsius)	0.911	0.881	0.942	<0.001	0.960	0.860	1.072	0.470	0.838	0.801	0.877	<0.001			
Min temperature (Celsius)	0.939	0.908	0.971	<0.001	0.983	0.900	1.075	0.713	0.845	0.812	0.880	<0.001			

<sup>†</sup>IRR is short for incidence rate ratio.

<sup>‡</sup>CI is short for confidence interval.

Table S5. The sensitive analysis of multiple-factor negative binominal regression for the risk of COVID-19

		Incidend	ce rate (IR)		C	umulative mo	rtality rate (Cl	Daily cumulative index (DCI)					
Indicators	alRR†	95%CI‡ (Lower)	95%CI (Upper)	p-value	alRR	95%CI (Lower)	95%CI (Upper)	p-value	alRR	95%CI (Lower)	95%CI (Upper)	p-value	
Urban Development													
Urban population (% of total population)					1.027	1.010	1.044	0.001	1.023	1.011	1.035	0.000	
Urban population growth (annual %)	0.823	0.651	1.040	0.102	0.751	0.507	1.112	0.153	1.020	0.759	1.371	0.896	
Population density (people per sq. km of land area)									1.000	1.000	1.000	0.017	
Economy & Growth													
GDP per capita (current 1,000 US\$)	1.023	1.007	1.040	0.006	1.031	1.021	1.041	0.000	0.998	0.986	1.010	0.712	
Health													
People using at least basic sanitation services (% of population)	1.019	1.001	1.036	0.038	1.001	0.985	1.018	0.897	1.013	0.999	1.026	0.061	
Current health expenditure (% of GDP)	1.119	0.983	1.273	0.088	1.211	1.040	1.410	0.013	1.068	0.962	1.186	0.215	
Death rate, crude (per 1,000 people)													
Domestic private health expenditure (% of current health expenditure)	0.986	0.970	1.003	0.100	0.986	0.970	1.003	0.102	1.011	0.995	1.027	0.180	
Domestic private health expenditure per capita (current US\$)	1.001	1.000	1.001	0.114	1.001	1.000	1.001	0.104	1.000	1.000	1.001	0.408	
Hospital beds (per 1,000 people)	0.899	0.782	1.034	0.137	0.799	0.696	0.916	0.001	0.719	0.627	0.824	0.000	
Net migration	1.000	1.000	1.000	0.538	1.000	1.000	1.000	0.530	1.000	1.000	1.000	0.075	
Nurses and midwives (per 1,000 people)	0.937	0.845	1.039	0.218	0.837	0.749	0.936	0.002	0.900	0.818	0.990	0.031	
Physicians (per 1,000 people)	1.009	0.739	1.376	0.956	1.725	1.191	2.498	0.004	0.940	0.751	1.176	0.587	
Population ages 65 and above (% of total population)	0.976	0.905	1.052	0.519	1.066	0.968	1.173	0.192	1.080	1.000	1.167	0.051	
Proportion of population spending more than 25% of household consumption or income on out-of- pocket health care expenditure (%)	0.822	0.719	0.939	0.004									
Infrastructure													
Railways, passengers carried (million passenger-km)	1.000	1.000	1.000	0.242									
Poverty													
Poverty headcount ratio at national poverty lines (% of population)	0.971	0.949	0.994	0.014	0.960	0.940	0.982	0.000	0.962	0.944	0.980	0.000	
Science & Technology	4 005	4 000	4 000	0.400	4 000	4 000	4 000	0.445	4 000	4 000	4.007	0.047	
Researchers in R&D (per million	1.000	1.000	1.000	0.103	1.000	1.000	1.000	0.115	1.000	1.000	1.001	0.017	

people)												
Social Protection & Labor												
Coverage of social insurance programs (% of population)	1.042	1.002	1.084	0.042					1.014	0.991	1.037	0.239
Unemployment, total (% of total labor force) (national estimate)	0.942	0.896	0.990	0.019								
Climate												
Max temperature (Celsius)	0.909	0.806	1.027	0.125					1.042	0.976	1.112	0.218
Min temperature (Celsius)	1.122	0.999	1.258	0.051					0.940	0.872	1.012	0.101
Relative humidity (%)	0.993	0.972	1.015	0.533								
Mean wind speed (.1 knots);	0.999	0.915	1.092	0.989								
Precipitation amount (.01 inches).	0.281	0.064	1.235	0.093	0.425	0.123	1.471	0.177				

<sup>†</sup>IRR is short for incidence rate ratio.

<sup>‡</sup>CI is short for confidence interval.