# Exponential phase of COVID-19 expansion is driven by airport connections

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The pandemic state of COVID-19 caused by the SARS CoV-2 put the world in quarantine, led to hundreds of thousands of deaths and is causing an unprecedented economic crisis. However, COVID-19 is spreading in different rates at different countries. Here, we tested the effect of three classes of predictors, i.e., socioeconomic, climatic and transport, on the rate of daily increase of COVID-19. We found that global connections, represented by countries' importance in the global air transportation network, is the main explanation for the growth rate of COVID-19 in different countries. Climate, geographic distance and socioeconomics had a milder effect in this big picture analysis. Geographic distance and climate were significant barriers in the past but were surpassed by the human engine that allowed us to colonize most of our planet land surface. Our results indicate that the current claims that the growth rate of COVID-19 may be lower in warmer and humid tropical countries should be taken very carefully, at risk to disturb well-established and effective policy of social isolation that may help to avoid higher mortality rates due to the collapse of national health systems.

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## Abstract

The pandemic state of COVID-19 caused by the SARS CoV-2 put the world in quarantine, led to hundreds of thousands of deaths and is causing an unprecedented economic crisis. However, COVID-19 is spreading in different rates at different countries. Here, we tested the effect of three classes of predictors, i.e., socioeconomic, climatic and transport, on the rate of daily increase of COVID-19. We found that global connections, represented by countries' importance in the global air transportation network, is the main explanation for the growth rate of COVID-19 in different countries. Climate, geographic distance and socioeconomics had a milder effect in this big picture analysis. ~~Geographic distance and climate were significant barriers in the past but were surpassed by the human engine that allowed us to colonize most of our planet land surface.~~ Our results indicate that the current claims that the growth rate of COVID-19 may be lower in warmer and humid tropical countries should be taken very carefully, ~~at risk to~~ disturb well-established and effective policy of social isolation that may help to avoid higher mortality rates due to the collapse of national health systems.

## Introduction

With the worldwide spread of the novel Coronavirus Disease 2019 (COVID-19), caused by the SARS-CoV-2 virus, we are experiencing a declared pandemic. One of the largest preoccupations about this new virus ~~regards~~ its notable ability to spread given the absence of any effective treatment, vaccine and immunity in human populations. Epidemiologists quantify the ability of infectious agents to spread by estimating the basic reproduction number (*R0*) statistic (Delamater et al., 2019), which measures the average number of people each contagious person infects. According to the World Health Organization (2020), the new coronavirus is transmitting at an *R0* around *1.4-2.5,* which is greater than seasonal influenza viruses that spread every year around the planet (median *R0* of 1.28, Biggerstaff et al., 2014). To anticipate the timing and magnitude of public interventions and mitigate the adverse consequences on public health and economy, understanding the factors associated with the survival and transmission of SARS-CoV-2 is urgent.

Because previous experimental (Lowen et al., 2007), epidemiological (Shaman et al., 2010, Barreca & Shimshack 2012) and modeling (Zuk et al., 2009) studies show the critical role of temperature and humidity on the survival and transmission of viruses, recent studies are testing the effect of environmental variables on SARS-CoV-2 (Wang et al., 2020, Sajadi et al., 2020) and forecasting monthly scenarios of the spread of the new virus based on climate suitability (Araújo & Naimi 2020, *but see* Chipperfield et al., 2020). Although temperature and humidity ~~are known to~~ affect the spread and survival of other coronaviruses (i.e., SARS-CoV and MERS-CoV, Tan et al., 2005, Chan et al., 2011, Doremalen et al., 2013, Gaunt et al., 2010) using the current occurrences of SARS-CoV-2 cases to build correlative climatic suitability

models without ~~taking into consideration~~, connectivity among different locations and socioeconomic conditions might be inadequate.

Many factors might influence the distribution of diseases at different spatial scales. Climate might affect the spread of viruses given its known effect on biological processes that influences many biogeographical patterns, including the distribution of diseases and human behavior (e.g., Murray et al., 2018). Geographic distance represents the geographical space where the disease spread following the distribution of hosts and has also ~~been found to~~ explain biogeographic patterns (Pulin 2003, Nekola & White 2004, Warren 2014). Socioeconomic characteristics of countries could be viewed as a proxy for the ability to identify and treat infected people and for the governability necessary to make fast political decision and avoid the spread of new diseases. Finally, the global transportation network might surpass other factors as it can reduce the relative importance of geographic distance and facilitate the spread of viruses and their vectors (Brockmann & Helbing 2013, Pybus et al., 2015). According to the International Air Transport Association (2019) more than 4 billion passengers traveled abroad in 2018. This amount of travelers reaching most of our planet's surface represents a human niche construction (~~i.e. global transportation network;~~ Boivin et al., 2016) that facilitates the global spread of viruses and vectors (Brockmann & Helbing 2013) in the same way it facilitated the spread of invasive species and domesticated animals over modern human history (Boiving et al., 2016).

The spread of SARS-CoV-2 from central China to other locations might be strongly associated with inter-country connections, which might largely surpass the effect of climate suitability. Thus, at this point of the pandemic, there is still a distributional disequilibrium that can generate very biased predictions based on climatic correlative modeling (De Marco et al.,

2008). ~~Thus,~~ here we used an alternative macroecological approach (Burnside et al., 2012), based on the geographical patterns of exponential growth rates of the disease at country level, to investigate variations ~~on~~ the growth rates of SARS-CoV-2. We studied the effect of environment, socioeconomic and global transportation controlling for spatial autocorrelation that could bias model significance. By analyzing these factors, we show that the exponential growth of COVID-19 at global scale is explained mainly by country's importance in global transportation network (~~i.e., air transportation).~~

## Material & Methods

We collected the number of people infected by ~~the~~ COVID-19 per day from the John Hopkins (Dong et al., 2020) and European Centre for Disease Prevention and Control (ECDC, 2020). ~~This~~ data ~~is~~ available for 204 countries, for which 65 had more than 100 cases recorded and for which time series had at least 30 days after the 100$^{th}$ case. We also performed the analysis considering countries with more than 50 cases, but it did not qualitatively change our results. Thus, we only show the results for countries with more than 100 cases.

In our analysis, we only used the exponential portion of the time series data (i.e. number of people infected per day) and excluded days after stabilization or decrease in total number of cases. We empirically modelled each time series using an exponential growth model for each country and calculated both the intrinsic growth rate (r) and the regression coefficient of the log growth series to be used as the response variable in our models. Because both were highly correlated (Person's r = 0.97), we used only the regression coefficient to represent the growth rate of COVID-19 in our study.

To investigate potential correlates of the virus growth rate, we downloaded climatic and socioeconomic data of each country. We used climatic data represented by monthly average minimum and maximum temperature (°C) and total precipitation (mm) retrieved from the WorldClim database (https://www.worldclim.org) (Fick & Hijmans 2017). We used monthly available data for the most recent year available in WorldClim. We extracted climatic data from the months of January, February, March, and December to represent the climatic conditions of the winter season in the Northern Hemisphere and the summer season in the Southern Hemisphere. From these data, we computed the mean value of climatic variables across each country. Finally, minimum and maximum temperatures were combined to estimate monthly mean temperature for December, January, February, and March, which was used in the model along with total precipitation for the same months. However, using different combinations of these variables (i.e., using means of minimum or maximum temperatures, as well as minimum or maximum for each month) did not qualitatively affect our results.

We extracted socioeconomic data for each country. Human Development Index (HDI) rank, mean number of school years in 2015, gross national income (GNI) per capita in 2011, population size in 2015 and average annual population growth rate between 2010-2015 were used in our study and downloaded from the United Nations database (http://hdr.undp.org/en/data). We also obtained a mean value of health investment in each country by averaging the annual health investments between 2005-2015 obtained from the World Health Organization database (http://apps.who.int/gho/data/node.home). Due to the strong collinearity among some of these predictors, HDI rank and mean number of school years were removed from our final model.

Finally, we also downloaded air transportation data from the OpenFlights (2014) database regarding the airports of the world, which informs where each airport is located including country location (7,834 airports), and whether there is a direct flight connecting the airports (67,663 connections). We checked the Openfligths database to make the airports and connections compatible by including missing or fixing airport codes and removing six unidentified airport connections resulting in a total of 7,834 airports and 67,657 connections. We used this information to build an air transportation network that reflects the existence of a direct flight between the airports while considering the direction of the flight. Thus, the airport network is a unipartite, binary, and directed graph where airports are nodes and flights are links (Fig 1, Fig S1). In the following step, we collapsed the airports' network into a country-level network using the country information to merge all the airports located in a country in a single node (e.g., United States had 613 airports that were merged in a single vertex representing the country). The country-level network (Fig 1, Fig S1) is a directed weighted graph where the links are the number of connections between 226 countries which is collapsed for the 65 countries that had more than 100 cases and for which time series data had at least 30 days after the 100$^{th}$ case . Afterward, we measured the countries centrality in the network using the Eigenvector Centrality (Bonacich, 1987), ~~hereafter centrality,~~ that weights the importance of a country in the network considering the number of connections with other countries and how well connected these countries are to other countries – indirect connections. All networks analyses were generated using package *igraph* (Csardi & Nepusz, 2006).

We evaluated the relationship between the predictors (climatic, socioeconomic and transport data) and our growth rate parameter using a standard multiple regression (OLS) after ~~taking into consideration~~ the distribution of the original predictors as well as the normality of

model residuals. Moreover, OLS residuals were inspected to evaluate the existence of spatial autocorrelation that could upward bias the significance of predictor variables on the model using Moran's I correlograms (Legendre & Legendre 2013). Prior to the analysis, we applied logarithmic (mean precipitation, total population size, and network centrality) and square root (mean health investments) transformations to the data to approximate a normal distribution.

## Results

The models used to estimate COVID-19 growth rate on different countries showed an average $R^2$ of 0.91 (SD = 0.04), varying from 0.78 to 0.99, indicating an overall excellent performance on estimating growth rates. The geographical patterns in the growth rates of COVID-19 cases do not show a clear trend, at least in terms of latitudinal variation, that would suggest a climatic effect at macroecological scale (Fig. 2A).

We build one model including only climate and socioeconomic variables, which explained *only 14%* of the variation on growth rates. This model did not have spatial autocorrelation in the residuals. When we added country centrality (i.e. country importance in global transportation network) as a predictor, the $R^2$ increased to 48.6%. In this model, annual population growth and precipitation had positive and significant effects (Table 1, P = 0.036, P =0.041, Fig 2), while health investments had a negative and significant effect on growth rate (Table 1, P= 0.035, Fig 2). Here, exponential growth rates increased *strongly* in response to countries importance in the transportation network which has more than two times the effect size of any significant variable (Table 1). However, it is also important to note that growth rates of COVID-19 weakly increases with increases of annual population growth and precipitation, and

174 decreases with higher investments in health (Table 1). Statistical coefficients were not upward
175 biased by spatial autocorrelation.
176

177 ## Discussion

178 ~~The pandemic state of SARS CoV-2 is killing hundreds of thousands of people, put the~~
179 ~~world in quarantine and is causing an unprecedented economic crisis. The rates of increase of~~
180 ~~new cases of COVID-19 is faster in some countries than others. To understand why growth rates~~
181 ~~are different among countries we investigate the effect of climatic, socioeconomical and human~~
182 ~~transportation variables that could have important roles on the exponential phase of COVID-19.~~
183 At global scale, temperature, population size and Gross National Income had no significant
184 effect on the exponential phase of COVID-19. However, annual population growth, health
185 investments and precipitation show significant, but weak effects on growth rates. Countries'
186 importance in the global transportation network has a key role on the severity of COVID-19
187 pandemic in different countries as it is strongly associated with the growth rates of the disease
188 ~~(Fig 2).~~

189 The centrality measure is widely used to discover distinguished nodes on ~~many~~ networks,
190 including epidemiological networks (e.g., Madotto & Liu 2016). Our findings reinforce the
191 importance of propagule pressure on disease dissemination (Tian et al., 2017, Chinazzi et al.,
192 2020). Aerial transportation is an important predictor of COVID-19 dissemination in China
193 (Kraemer et al., 2020), in Brazil (Ribeiro et al., 2020), and in Mexico (Dátillo et al., 2020). It is
194 quite likely that further phases of COVID-19 spread, in terms of peak of infections and decrease
195 in mortality rates, will be better related to socioeconomics characteristics of each county and
196 their political decisions when secondary transmissions were identified. We can already clearly

identify the effects of adopting strong social isolation policies in China (see Kraemer et al., 2020) and, on the opposite side of this spectrum, in European countries like Italy, Spain and England (Enserink & Kupfershmidt 2020). Our analyses call attention to the case of Brazil, a well-connected tropical country that presents one of the highest increase rates of COVID-19 in the tropics in its exponential phase ~~(Fig 2A).~~ If decision makers ~~take into consideration~~ yet unsupported claims that growth rates of COVID-19 in its exponential phase might be lower in warmer and humid countries, we might observe terrible scenarios unrolling in tropical countries, especially in those with limited health care structure, such as Brazil. As our results also show, those countries that invested less in health are also the ones with faster growth rates of covid-19 in its exponential phase (~~Fig 2, Table 1~~).

When discussing and modelling the effect of climate on SARS CoV-2 it is important to remember that modern human society is a complex system composed of strongly connected societies that are all susceptible to rare events. It is also critical to consider the negative correlations between climate and local or regional socioeconomic conditions (i.e., inadequate sanitary conditions and poor nutritional conditions) that could easily counteract any potential climatic effect at local scales, such as lower survival rates of viruses exposed to high humidity, temperatures and high UV irradiation (Wang et al., 2020, Duan et al., 2003). Tropical regions will experience mild climate conditions in a couple of months. Thus, regardless of the influence of local environmental conditions, tropical countries could still expect high contagious rates. In addition, our results points to a positive effect of precipitation on growth rates, which is the contrary of what has been suggested by climate suitability models. Finally, climatic suitability models might be ephemeral for very mathematized modelling fields of science such as epidemiology and virology that developed over time very realistic models that enables the

possibility of learning with parameters of similar viruses (i.e. SARS) that can definitely help and instruct decision makers to take actions before it is too late.

Here we showed that countries' importance in the global transportation network has a key role on COVID-19 growth rates in its exponential phase. Our results reinforce board control measures in international airports (Bitar et al., 2009, Nishiura & Kamiya 2011) during exceedingly early stages of pandemics to prevent secondary transmissions that could lead to undesired scenarios of rapid synchronically spread of infectious diseases in different countries. The rapid international spread of the severe acute respiratory syndrome (SARS) from 2002 to 2003 led to extensively assessing entry screening measures at international borders of some countries (Bell et al., 2003, John et al., 2017). The 2019-2020 world spread of COVID-19 highlights that improvements and testing of board control measures (i.e. screening associated with fast testing and quarantine of infected travellers) might be a cheap solution for humanity in comparison to health systems breakdowns and unprecedented global economic crises that the spread of infectious disease can cause. However, it is important to note that board control of potentially infected travellers and how to effectively identify them is still a hotly debated topic in epidemiology and there is still no consensus on accurate methodologies for its application (Sun et al., 2017).

## Conclusions

Here, we show that countries' importance in the global transportation network has a key role on the severity of COVID-19 pandemic in different countries as it is strongly associated with the growth rates of the disease (Fig 2). We do not expect that our results using a macroecological approach at a global scale would have a definitive effect on decision-making in

terms of public health in any particular country, province, or city. However, we expect that our analyses show that current claims that growth of COVID-19 pandemics may be lower in developing tropical countries should be taken very carefully, at risk to disturb well-established and effective policy of social isolation that may help to avoid higher mortality rates due to collapse in national health systems.

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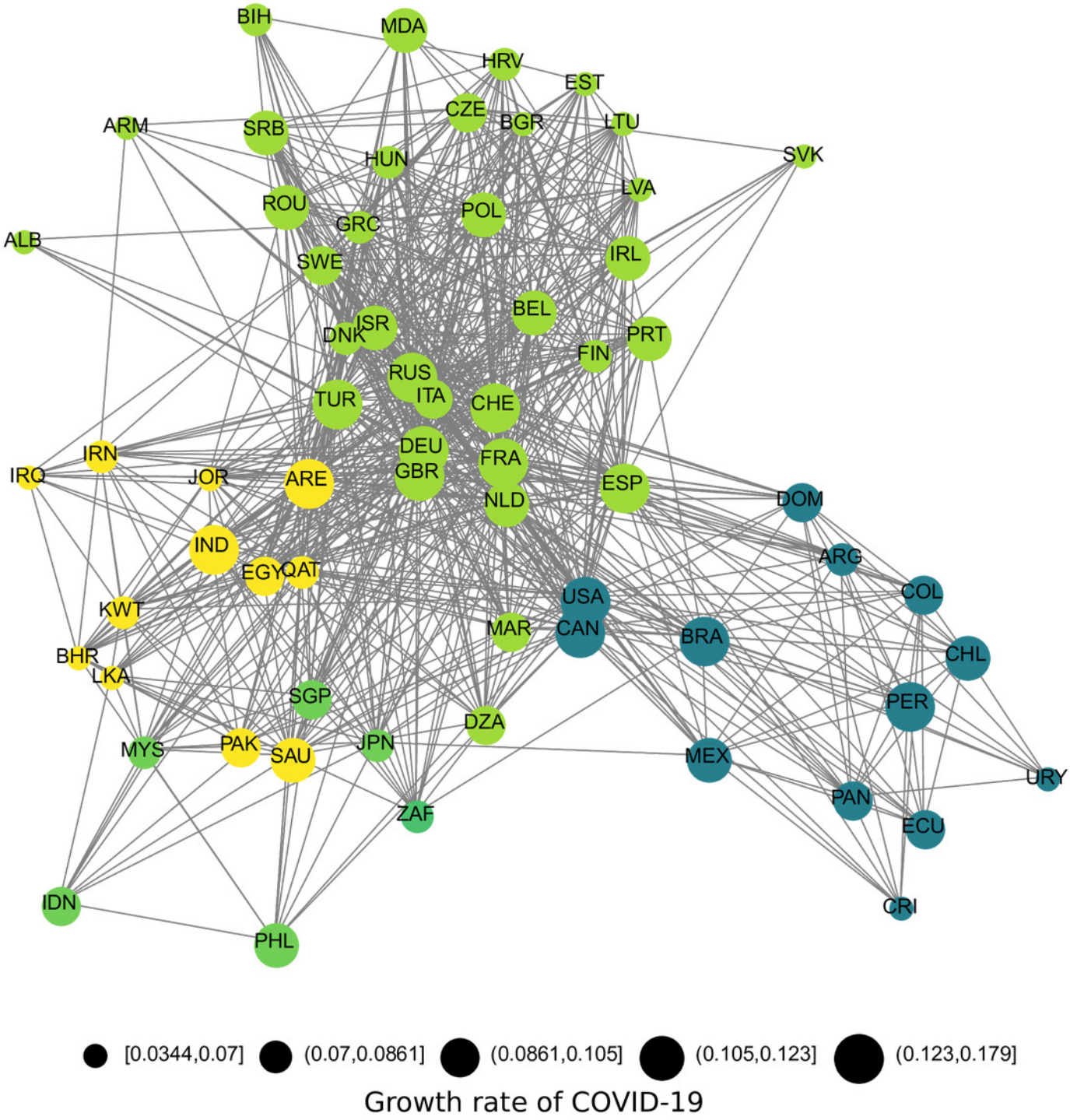
# Figure 1

Air transportation network

**Fig 1**. Air transportation network among 65 countries that had more than 100 cases and for which time series data had at least 30 days after the 100$^{th}$ case. Different colours represent modules of countries that are more connected to each other. Different sizes of each node represent the growth rate of COVID-19 estimated for each country (See results Fig 2).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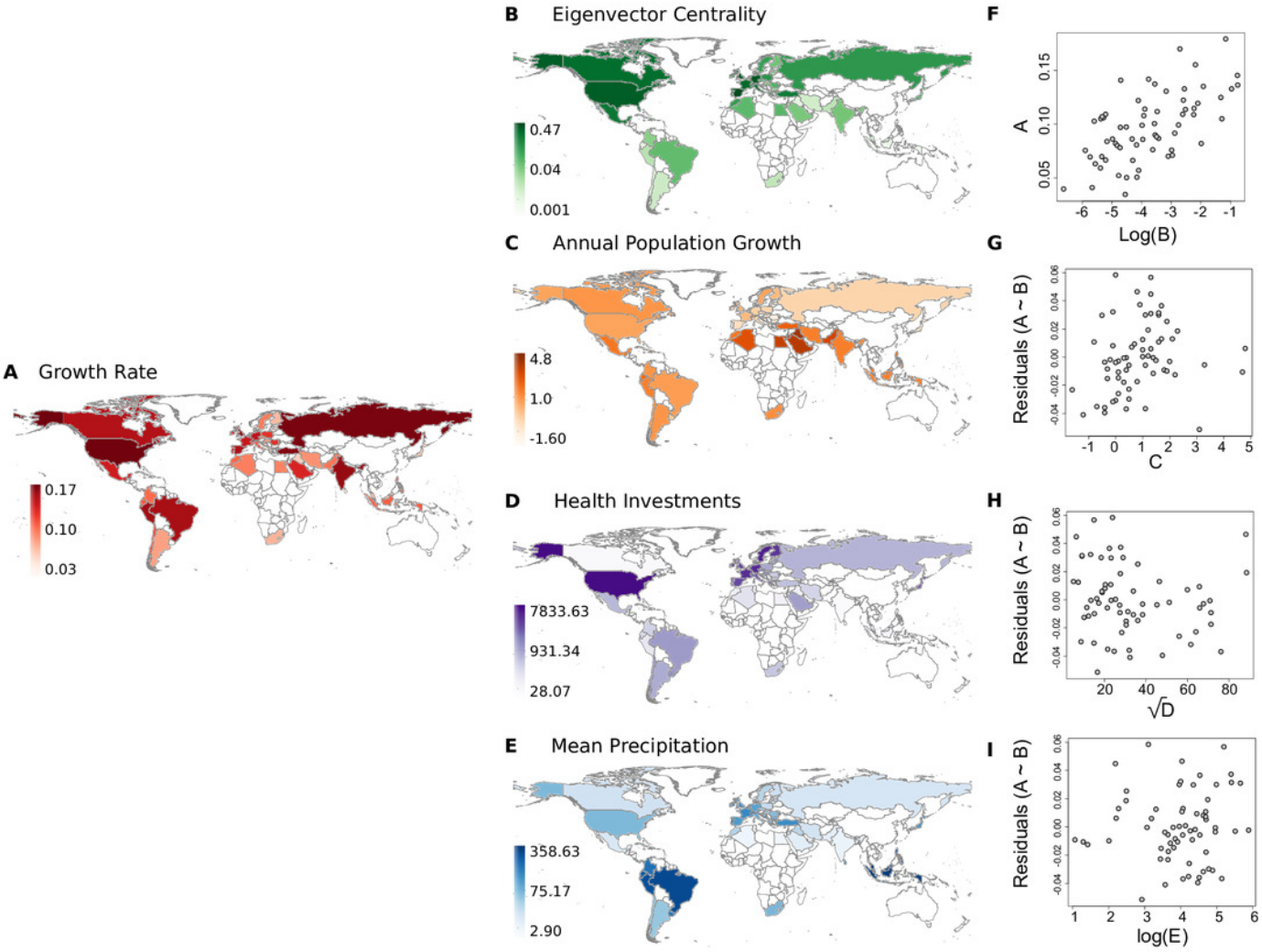
BHR
LKA
SGP
PER
DZA
MYS
PAK
SAU
JPN
MEX
URY
PAN
ZAF
ECU
IDN
CRI
PHL
[0.0344,0.07]
(0.07,0.0861]
(0.0861,0.105]
(0.105,0.123]
(0.123,0.179]
Growth rate of COVID-19

# Figure 2

Geographical patterns of response and significant predictor variables

**Fig 2**. Geographical patterns of growth rate of covid-19 in the exponential phase (**A**), the Eigenvector Centrality that represents countries' importance in global transportation network (**B**), Annual population growth (**C**), health investments (**D**) and mean precipitation (**E**). The relationship between growth rate and the log transformed eigenvector centrality is showed in **F**. **G, H** and **I** are partial plots showing the relationship between the residuals of growth rates vs log transformed eigenvector centrality and annual population growth, health investments and mean precipitation.


A Growth Rate
0.17
0.10
0.03
B Eigenvector Centrality
0.47
0.04
0.001
C Annual Population Growth
4.8
1.0
-1.60
D Health Investments
7833.63
931.34
28.07
E Mean Precipitation
358.63
75.17
2.90
F
A
Log(B)
G
Residuals (A ~ B)
C
H
Residuals (A ~ B)
√D
I
Residuals (A ~ B)
log(E)

## Table 1(on next page)

Model Statistics

**Table 1**. Model statistics for all variables used in the study.

1 **Table 1**. Model statistics for all variables used in the study.

| | Standardized Estimate | Estimate | Std Error | t value | P-value |
|---|---|---|---|---|---|
| ***Intercept*** | | 0.149 | 0.026 | 3.547 | < 0.001 |
| ***Eigenvector Centrality*** | 0.758 | 0.016 | 0.002 | 6.124 | **< 0.001** |
| ***Gross National Income*** | 0.16 | 0.000 | 0.000 | 1.491 | 0.141 |
| ***Population Size*** | -0.096 | -0.004 | 0.004 | -0.953 | 0.344 |
| ***Annual population growth*** | 0.306 | 0.008 | 0.003 | 2.139 | **0.036** |
| ***Heath investment*** | -0.287 | -0.0004 | 0.000 | -2.155 | **0.035** |
| ***Mean Temperature*** | -0.127 | -0.0003 | 0.000 | -0.908 | 0.367 |
| ***Mean Precipitation*** | 0.253 | 0.007 | 0.003 | 2.091 | **0.041** |

2

3