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Original article

An analytical study of the factors that influence COVID-19 spread

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ABSTRACT

The outbreak of the coronavirus disease 2019 (COVID-19) continues to constitute an international public health emergency. Seasonality is a long-recognized attribute of many viral infections of humans. Nevertheless, the relationship between environmental factors and the spread of infection, particularly for person-to-person communicable diseases, remains poorly understood. This study explores the relationship between environmental factors and the incidence of COVID-19 in 188 countries with reported COVID-19 cases as of April 13, 2020. Here we show that COVID-19 growth rates peaked in temperate zones in the Northern Hemisphere during the outbreak period, while they were lower in tropical zones. The relationships between COVID-19 and environmental factors were resistant to the potentially confounding effects of air pollution, sea level, and population. To prove the effect of those factors, study, and analysis of the prevalence of COVID-19 in Italy, Spain, and China was undertaken. A fuzzy logic system was designed to predict the effects of that variables on the rate of viral spread of COVID-19.

1. Introduction

One of the earliest accounts of a winter infectious respiratory disease epidemic can be found in the "Book of Epidemics," an ancient Greek record written by Hippocrates around 400 BCE (Pappas et al., 2008). Since then, many respiratory viruses have been identified as the etiological agents of such epidemics. The first coronaviruses (CoV) were identified in the 1930s in domestic poultry with acute respiratory diseasecaused by the avian infectious bronchitis virus (IBV). Two more coronaviruses affecting animals were discovered in the 1940 s, i.e., mouse hepatitis virus (MHV) and transmissible gastroenteritis virus (TGEV), the latter of which infects pigs (Virus Taxonomy, 2019). Sometimes a coronavirus that infect animals can evolve to cause illness in humans, thus becoming a new human coronavirus. The discovery of human coronaviruses dates to the mid-1960 (Simmons et al. 2013). Coronaviruses are named for the crown-like spikes on their surface, and they belong to the large family of Coronaviridae; these enveloped viruses, which have a positive-sense single-stranded RNA genome, can be classified into four major sub-groups (Snijder et al. 2013). The four main sub-groupings of coronaviruses are known as alpha, beta, gamma, and delta. The earliest human coronaviruses to be intensely studied were from human patients with the common cold, which were later named human coronavirus 229E and human coronavirus OC43 (Pica and Bouvier, 2012). Common human coronavirus types are 229E (alpha coronavirus), NL63 (alpha coronavirus), OC43 (beta coronavirus), and HKU1 (beta coronavirus). The beta coronavirus type includes MERS-CoV and SARS-CoV. In January 2020, Chinese health authorities announced that they had isolated the virus spreading in Wuhan city. This novel coronavirus was initially referred to as 2019-nCoV or the Wuhan coronavirus. The World Health Organization (WHO) announced COVID-19 as the name of this new coronavirus disease in February 2020 (Novel Coronavirus 2019).

COVID-19 cases have been reported in more than 188 countries worldwide. Some countries have been experiencing limited growth and spread of COVID-19 cases, while others are suffering widespread community transmission and fast, nearly exponential increase in the number of infections (Dong et al. 2020). Understanding the environmental drivers of early growth rates is pivotal for predicting the potential severity of disease outbreaks (i.e., the disease impact in the absence of containment measures), given the importance of environmental factors in the transmission of many pathogens. Environmental factors affect host susceptibility by modulating airway defense mechanisms and can influence the

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viability and transmission of respiratory viruses (Moriyama et al. 2020).

Some studies have suggested that COVID-19 has a significant relationship with environmental factors (Yip et al. 2007; Thai et al. 2015; Ng and Cowling 2014; Lowen and Steel 2014; Bi et al. 2007; Barreca and Shimshack 2012; Moriyama and Ichinohe 2019). As in (Casanova et al. 2010; Chan et al. 2011; Van Doremalen et al. 2013) have claimed that the survival time of coronaviruses on surfaces affected with temperature increases or decreases; therefore, temperature could affect the virus transmission risk. The results of some studies focused on non-tropical countries (Hastie and Tibshirani, 1990; Zhu and Xie 2020; Wang et al. 2020; Le et al. 2020; Bukhari and Jameel 2020; Yongjiana et al. 2020) established the relationship between lower temperature and increasing numbers of confirmed cases, while a study in the tropical heat of Brazil showed that there was a negative linear relationship between temperature and the number of confirmed cases (Núñez-Delgado 2020).

Population density has a marked impact on spread of the pandemic. Population density can be defined as a measurement of the average number of individuals per unit of geographic area and overpopulation increases air pollution (Liu et al. 2020). The higher the population density, the faster diseases can spread. Population density is likely just one of many key factors that determine the vulnerability of a specific location to the virus. Around the world, COVID-19 has taken root and hit hard in several types of sites. One type is typified by sizeable, dense, superstar cities like New York and London, with large flows of visitors and tourists, diverse global populations, and dense residential areas. A second type includes industrial centers like Wuhan, Detroit, and Northern Italy, which are connected via supply chains. A third type comprises global tourist meccas like the ski slopes of Italy, Switzerland and France, and their counterparts in the Colorado Rockies. In smaller communities, the virus has targeted nursing homes and funeral parlors, and of course cruise ships, which are like dense small cities at sea.

Air pollution is a type of environmental pollution that contaminates the air with harmful particles and gases, e.g., carbon dioxide (CO_2). Before the COVID-19 pandemic of 2020, CO_2 emissions rose by approximately 1% per year over the previous decade. Daily global CO_2 emissions decreased by 17% (11 to 25%) by early April 2020 compared with the mean 2019 levels, and just under half of this effect has been attributed to changes in surface transport. In the period of maximum decline, the average emissions in individual countries decreased by 26% (Rosenberg 2011).

Sea level affects humans, as those at higher altitudes have increased exposure to sunlight, the primary source of vitamin D. Vitamin D has essential functions beyond its roles in calcium and bone homeostasis, including modulation of the innate and adaptive immune responses (Quéré et al. 2020). On the other hand, as the altitude increases, atmospheric pressure decreases, thus reducing the oxygen level (Chen et al. 2008). The lack of oxygen above 2,400 m can cause increased severity respiratory infectious diseases (Peacock and Andrew 1998).

Fuzzy logic systems have been used to diagnose human diseases. For example, a system was developed to serve as a web-based clinical tool to improve the quality of the exchange of health information between health care professionals and patients, and it exhibited satisfactory results (Hasan et al. 2010).

A computerized behavioral model was created to predict the impaired reaction condition of Huntington's disease (HD) patients. A mobile application based on a fuzzy logic system and a neural network was designed to evaluate the reaction condition of healthy individuals and HD patients. The best results were achieved using backpropagation of the neural network and a fuzzy logic system (Lauraitis et al. 2018).

A fuzzy logic system was developed using the Visual Prolog programming language to improve medical diagnoses. One study found that a fuzzy logic system appeared to be the best solution for managing the enormous responsibilities related to the diagnostic process carried out by medical personnel based on patient registration and maintenance of patient details (Awotunde et al. 2014).

A fuzzy logic model was also developed to predict of cholera disease. This model was used to examine the variables that cause cholera. It also generated a predictive model to forecast the likelihood of cholera disease to help environmental health workers educate people, and it assisted in effective decision-making (Aroyehun et al. 2018).

A fuzzy logic system suitable for diagnosing Ebola Virus Disease (EVD) before it becomes contagious has also been developed. This system obtains responses related to symptoms (e.g., temperature, vomiting, bleeding, diarrhea, muscle pain) from people suspected of being infected and processes the responses using a fuzzy classification to determine the probability of EVD. This system provides a quick response alternative to slow manual laboratory diagnostic approaches and helps to reduce the likelihood that an uninfected person is quarantined (Emokhare and Igbape 2015).

2. Methods

2.1. Data collection

Stated numbers of COVID-19 cases were taken from the database created by undergraduates at Stanford University, University of Virginia, and Virginia Tech (data available at https://www.track-corona.live/api). We gathered the CO_2 emission data from the International Energy Agency (data available at http://energyatlas.iea.org/#!/tellmap/1378539487). Additional analyses were conducted to examine the association between weather and COVID-19 incidence. All models were adjusted for COVID-19 prevalence and other environmental factors (e.g., air pollution, sea level, and population data). In the present work, we studied, discussed, and analyzed the effects of air pollution at industrial sites, sea level, temperature related to latitude, and population density on COVID-19 spread. Three countries (i.e., Italy, Spain, and China) were used as case studies, and their data were analyzed as examples of countries with the highest prevalence of COVID-19. Statistical analysis of the data and a fuzzy logic system were used to predict the COVID-19 infection patterns in these countries.

Quantitative data were statistically analyzed in terms of the minimum, maximum, and mean values, and the standard deviations (SD). In the present study, the Mann-Whitney Test was used to compare two nonparametric groups and the Kruskal-Wallis test was used to compare more than two nonparametric groups. Correlations between multiple variables were established using the Spearman rank correlation coefficient (R). Probability values (p-values) less than or equal to 0.05 were considered significant. All statistical analyses were performed using the statistical software SPSS (Statistical Product and Service Solutions).

The present work study, discuss, and analysis the effects of air pollution at industrial sites, sea level, temperature related to latitude, and population density on COVID-19 spread at Italy, Spain, and Chinaas the highest prevalence of COVID-19. Statistical analysis of the data and a fuzzy logic system were used to predict the COVID-19 infection patterns in these countries.

2.2. Case studies

In this section, data related to the spread of COVID-19 in Italy, Spain, and China will be analyzed and discussed to better understand the effects of air pollution, sea level, temperature, and population density in these countries.

2.2.1. Italy

Italy located at south-central Europe with approximately 60 million inhabitants. It consists of a peninsula delimited by the Alps and is surrounded by several islands. The first confirmed incidence of COVID-19 spread to Italy occurred on 31 January 2020 when two Chinese tourists in Rome tested positive for the virus. One week later an Italian man repatriated from Wuhan, China, was hospitalized and confirmed as Italy's third case. A cluster of cases was later detected, starting with 16 confirmed cases in Lombardia on 21 February and 60 additional cases and the first deaths on 22 February. By the beginning of March, COVID-19 had spread to all regions of Italy. In February, Italy were identified as the centers of the two main Italian clusters and were placed under quarantine. Most positive cases in other regions could be traced back to these two clusters. As of 11 April 2020, Italy was one of the world's centers of active COVID-19 cases with 100,269 active cases. The total number of confirmed cases at the time of this study was 152,271, with 19,468 deaths, and 32,534 recoveries or dismissals (36). A map of Italy's regions as well as maps of its distribution of COVID-19-infected people and COVID-19 deaths are provided in (Fig. 1). The Lombardia, Emilia-Romanga, Piemonte, and Veneto regions had the highest incidence of coronavirus infection, as shown in Table 1.

The relationhips between COVID-19 spread and the effective variables (pollution or CO_2 level, sea level, temperature or latitude, and population) in Italy are shown in (Fig. 2). The graph shows that population had the most robust effect on COVID-19 spread, with CO_2 level coming second, followed by sea level and latitude, which had nearly the same effect.

2.2.2. Spain

The Kingdom of Spain is a country in Southwestern Europe with a population exceeding 46 million, making it the sixth-most populous European country. The 2020 COVID-19 pandemic was confirmed to have spread to Spain on 31 January 2020 when a German tourist tested positive for COVID-19 in La Gomera, Canary Islands (37). By 24 February, Spain confirmed multiple cases related to the Italian cluster that were brought by a medical doctor from Lombardy, Italy, who was on holiday in Tenerife (38). Other cases involving individuals who visited Italy were also discovered in Peninsular Spain (39, 40). On 25 March 2020, the death toll in Spain surpassed that reported in mainland China. On 2 April, 950 people had died of COVID-19. As of 12 April 2020, Spain had 166,831 confirmed cases with 62,391 recoveries and 17,209 deaths. A map of Spain's regions as well as maps of its distribution of COVID-19-infected people and COVID-19 deaths are show in (Fig. 3). The regions of Catalonia, Madrid, Galicia and Castilla and Leon had the highest incidence of COVID-19 infection, as shown in Table 2.

The relationships between COVID-19 spread and the effective variables (pollution or CO_2 level, sea levelsea levelsea level, temperature or latitude, and population) in Spain are shown in (Fig. 4). The graph shows that population had robust effect on COVID-19 spread, with CO_2 level coming second, followed by sea level and latitude, which had nearly the same effect.

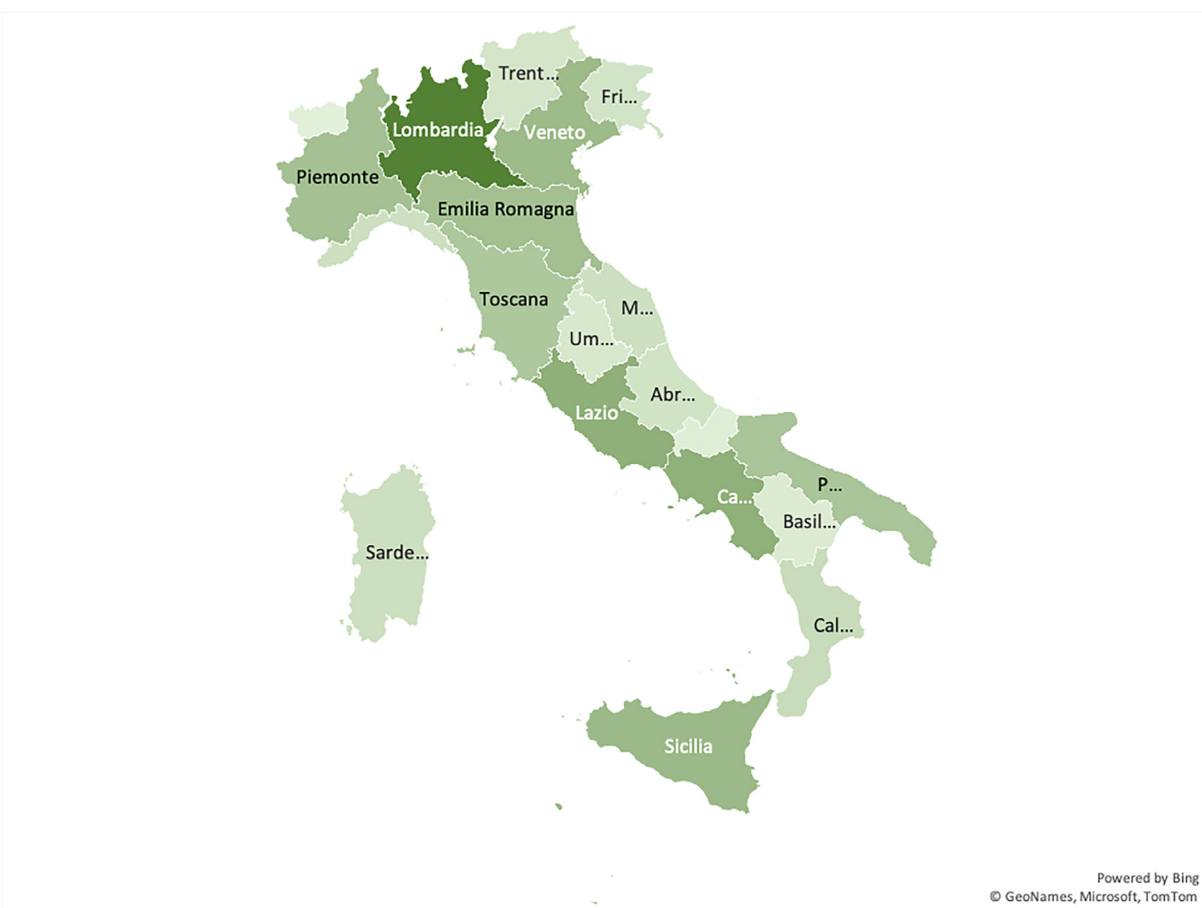

Fig. 1. Italian regions (a), Regions of COVID-19 spread (b), Regions of death due to COVID-19 (c).

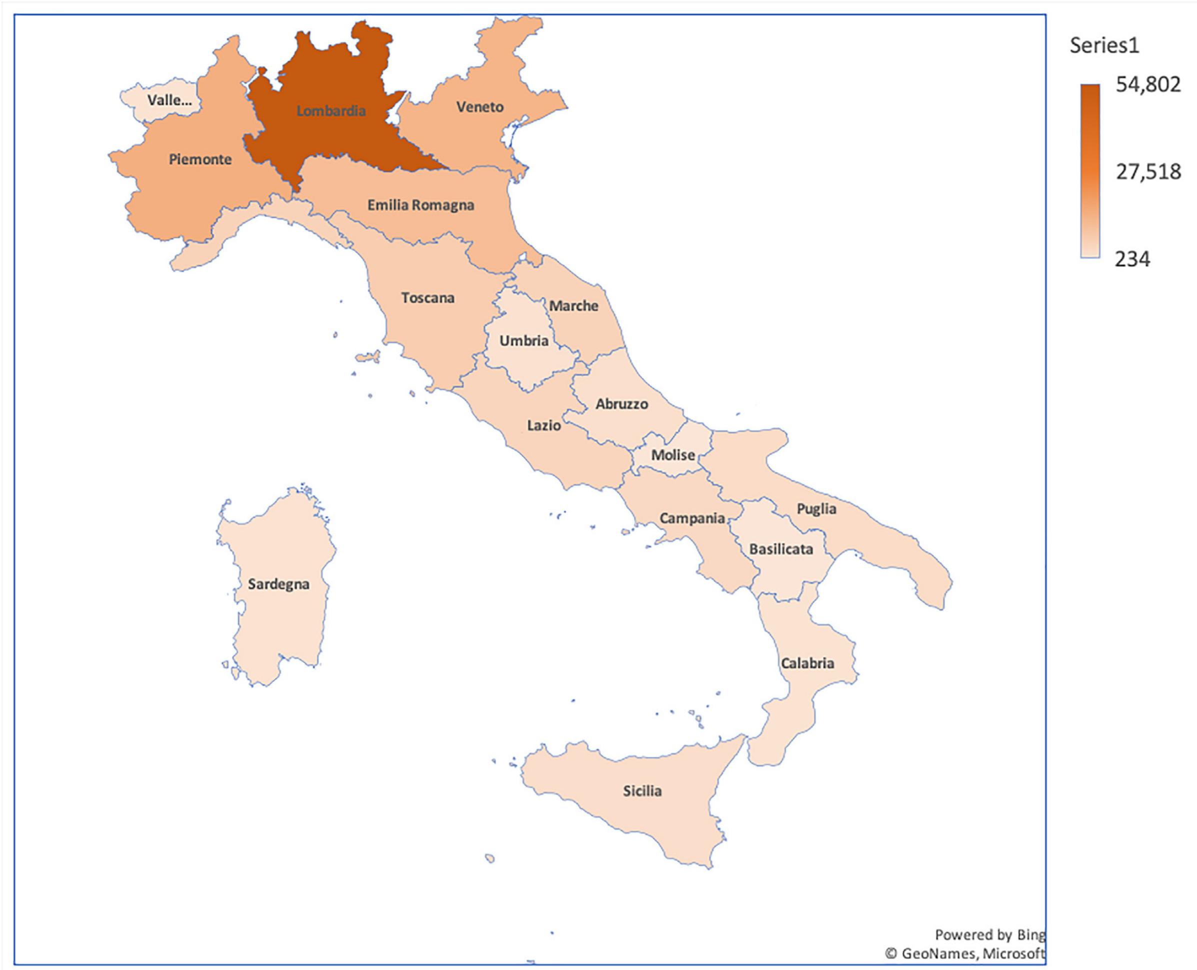

Fig. 1 (*continued*)

2.2.3. China

China is a country in East Asia with a population of around 1.40005 billion (2019), making it the world's most populous country. It covers approximately 9.6 million square kilometers.

On 31 December 2019, Chinese health officials reported 41 patients with a mysterious form of pneumonia. Chinese authorities identified the virus that caused the pneumonia-like illness as a new type of (CoV) on 7 January 2020. On 11 January 2020, China recorded its first death linked to the novel coronavirus. 811 deaths were recorded in China during February 2020. On 19 March 2020, China reported no new locally spread infections for the first time since the pandemic began. A map of China's regions as well as maps of its distribution of COVID-19-infected people and COVID-19 deaths are provided in (Fig. 5). Guangdong, Henan, Hubei, and Zhejiang regions had the highest incidence of COVID-19 infection, as shown in Table 3.

The relationships between COVID-19 spread and the effective variables (pollution or CO_2 sea level, temperature or latitude, and population) in China are shown in (Fig. 6) as appeared in the graph population had good impact on COVID-19 spread, with CO_2 level coming second, followed by sea level and latitude, which had nearly the same effect.

2.3. Data analysis

The characteristics (pollution, which originates from industrial activity; pressure, which is related to sea level; temperature, which is related to latitude and longitude; and population density) that likely influence coronavirus spread were analyzed statistically using SPSS (Statistical Package for the Social Sciences). The data for the individual countries examined here (Italy, Spain, and China) are shown in Table 4.

The data analysis highlighted the effects of population and air pollution on increasing COVID-19 infection. Weather temperature and mean sea level also had effects, but they were smaller than those of population and pollution.

2.3.1. Prediction of COVID-19 spread via a fuzzy logic system

Fuzzy logic systems can handle problems with imprecise and incomplete data or that are complex in nature; furthermore, such systems can also model nonlinear functions of arbitrary sets. A fuzzifier (fuzzification) and a defuzzifier (defuzzification), IF-THEN rules (fuzzy rule base), and an inference engine are the main mechanisms of fuzzy systems (Fig. 7) (41).

In this work, a fuzzy logic system was used to predict the spread of coronavirus in Italy, Spain, and China. This prediction was based on an analysis of the variables that effect viral spread (i.e., population, pollution, mean sea level, and weather temperature). Prediction process achieved by designing a COVID-19 fuzzy logic system with four inputs (affected variables) that generates an output to predict viral spread (Fig. 8).

MATLAB software was used to build the COVID-19 fuzzy logic system. Fuzzification, Defuzzification, and IF-THEN rules are the main process of fuzzy logic system (42).

Fig. 1 (*continued*)

Table 1
COVID-19 in Italy.

Region	Affected Variables			COVID-19	
	Air pollution	Mean sea level	Population density	No. of COVID-19 cases	No. of deaths
Lombardy	The main industrial area of the country	200 *m*	10,088,484 people 420/km^2	57,592	10,511
Emilia-Romanga	Food processing industry and motor industry (Ferrari, Maserati, Lamborghini, and Ducati)	~120 *m*	4,011,400 people 200/km^2	19,635	2,481
Piemonte	Tobacco industry (cigarettes and pipe tobacco products) and information technology industry (computers)	113–390 *m*	4,377,941 people 170/km^2	16,008	1,633
Veneto	Large metallurgical and chemical plants, the largest center of glass production in the world, and the fashion industry	95–416 *m*	4,865,380 people 270/km^2	13,768	831

The first step in the fuzzification process involves the conversion of the input data (affected variables) into a fuzzy set via fuzzy linguistic variables and membership functions (triangular membership functions with Low, Medium, and High parameters), as shown in (Fig. 9) (a, b). Next, the inference process is carried out via IF-THEN rules (Fig. 10).

Lastly, the defuzzification step is implemented, and the process is completed using membership functions to obtain predicted spread values (Fig. 11).

The triangular membership function, which is specified by the three parameters a, b and c, represents the z coordinates of the three vertices in a fuzzy set L (a and c are the lower and upper boundaries, where the membership degree is 0; b is the center, where the membership degree is 1, as given by the following equation:

$$\mu_L(x) = \begin{cases} 0 & if\ z \le a \\ \frac{z-a}{b-a} & if\ a \le z \le b \\ \frac{c-z}{c-b} & if\ b \le z \le c \\ 0 & if\ z \ge c \end{cases}$$

Table 5 shows the values of the inputs and outputs for the three adopted ranges used in the coronavirus fuzzy logic system.

Based on multiple IF-THEN rules, inference processes are used to establish the relationships between the input and output variables. Table 6 shows a few examples of the IF-THEN rules used in

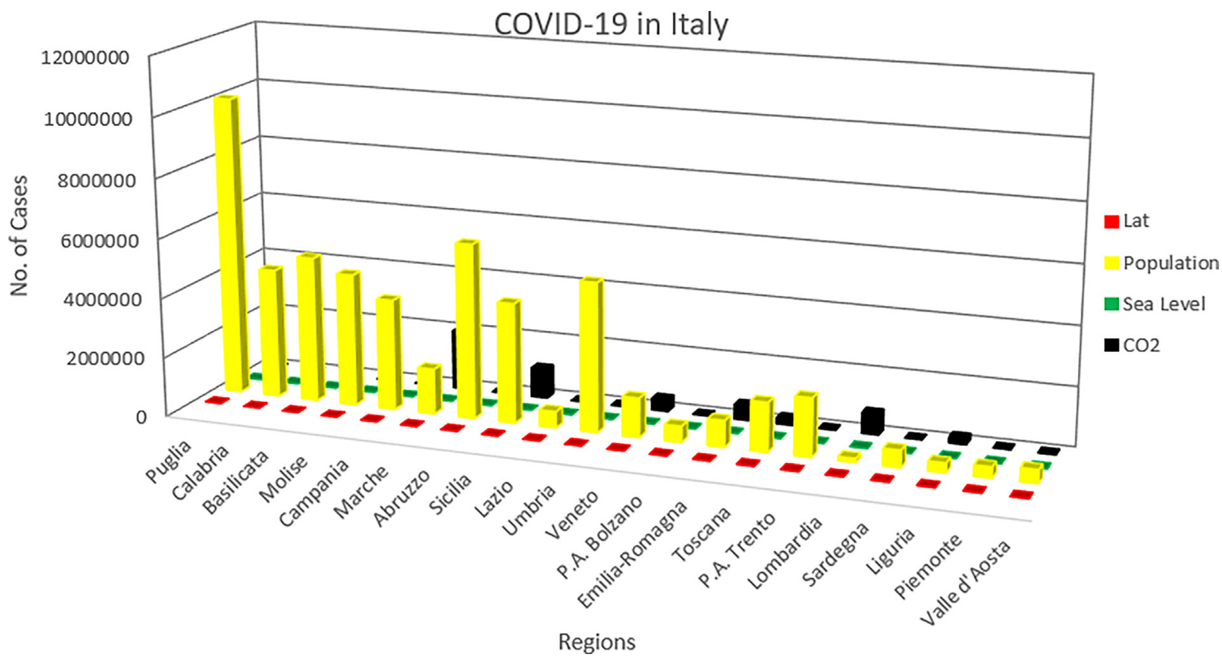

Fig. 2. Relationship between CO_2 level, sea level, latitude, and population and COVID-19 in Italy.

Fig. 3. Spanish regions (a), Regions of COVID-19 spread (b), Regions of death due to COVID-19 (c).

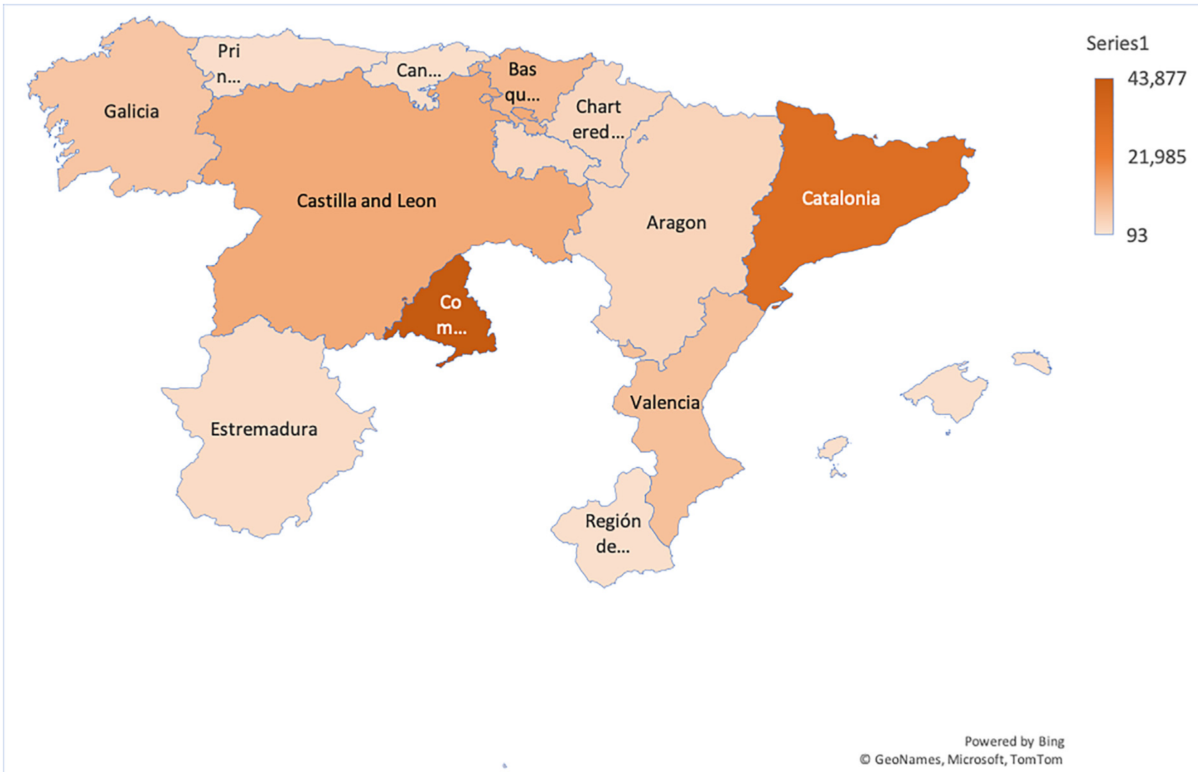

Fig. 3 (*continued*)

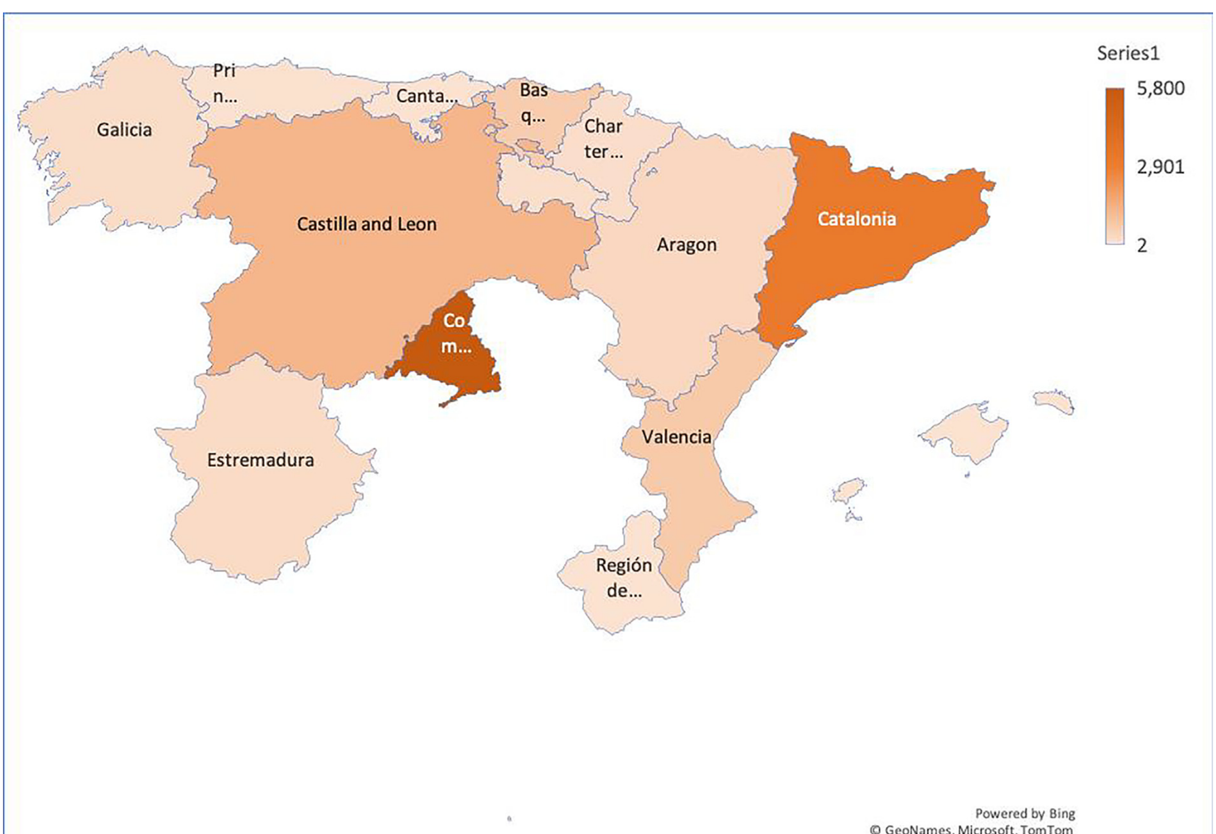

Fig. 3 (*continued*)

Table 2
COVID-19 in Spain.

Region	Affected Variables			COVID-19	
	Air pollution	Mean sea level	Population density	No. of COVID-19 cases	No. of deaths
Catalonia	Manufacturing of motor vehicles, aircraft, chemicals, pharmaceuticals, processed food, printed materials, and leather goods	667 *m*	6,661,949 people 829.62/km^2	43,877	5,800
Madrid	Manufacturing of motor vehicles and accessories, chemicals, food, electrical household, IT equipment	125 *m*	7,522,596 people 234/km^2	31,043	3,148
Galicia	Manufacturing of motor vehicles, paper, aeronautics, chemicals, and food industry	738 *m*	2,04,631 people 26/km^2	12,489	1,322
Castilla and Leon	Manufacturing of motor vehicles	830 *m*	2,04,833people	18,631	1,922

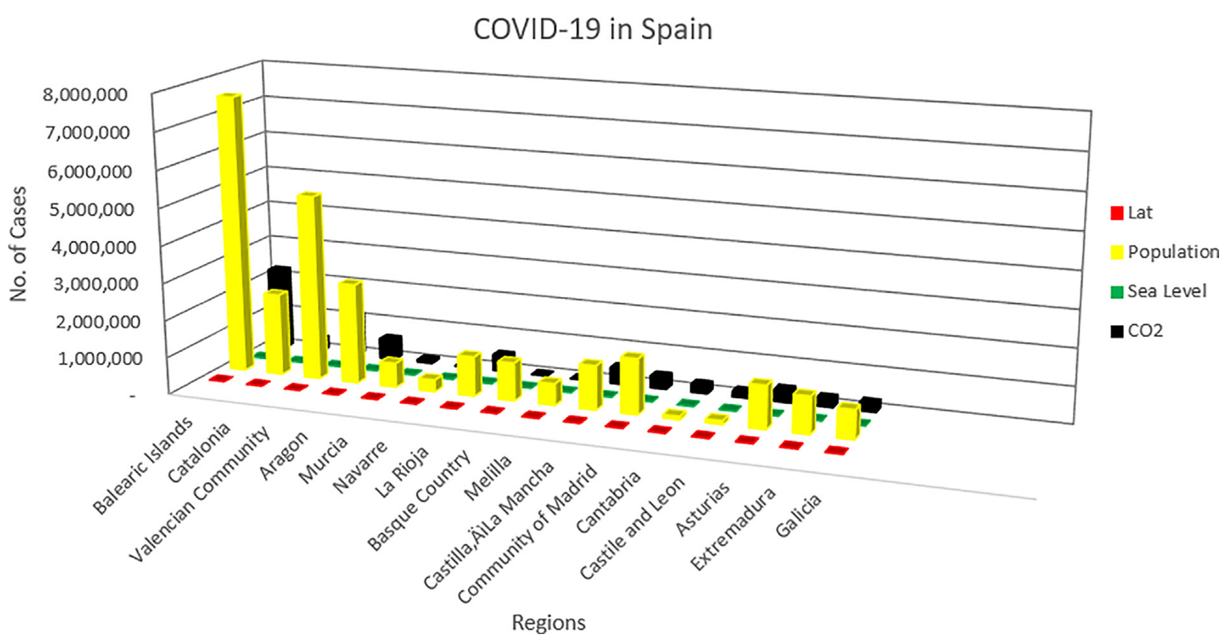

Fig. 4. Relationship between CO_2 level, sea levelsea levelsea level, latitude, and population and COVID-19 in Spain.

this investigation. In total, 53 IF-THEN rules were used in this analysis to predict coronavirus spread.

3. Results and discussion

(Fig. 12) shows descriptive statistics for the number sof confirmed COVID-19 cases in the top 20 countries worldwide with the highest numbers of reported cases on April 13, 2020. We found that all 20 of these countries are located in the temperate zone (latitudes 23.5°N–66.5°N).

To study the effects of temperature and air pollution variables on confirmed COVID-19 variables, Spearman's rank correlation coefficient (R) was used (as explained earlier), and values less than or equal to 0.05 or 0.01 were selected to denote statistical significance.

(Fig. 13) shows the populations of the top 20 countries worldwide with the highest numbers of reported cases. The confirmed number of COVID-19 cases and population (P) and population density (P/Km^2) were positively correlated (r = 0.609 and r = 0.205, respectively).

(Fig. 14) shows the CO_2 emissions in the top 20 countries worldwide with the highest numbers of reported cases. The confirmed numbers of COVID-19 cases were positively correlated with air pollution in terms of CO_2 emission (r = 0.823), and CO_2 emission (per m^2) (r = 0.517).

Latitude is one of the main factors that affects temperature. The obtained data are presented as means ± S.D. for the two measured variables for 107 countries. 19 countries are located in the temperate zone (latitudes 23.5°N–66.5°N), and 88 countries are located in the tropic zone (latitudes 0°–23.5°N) (Table 7).

Table 7 shows a comparison of the confirmed numbers of COVID-19 cases and temperature during the study period (April 13, 2020). There was a significantly lower number of confirmed COVID-19 cases in countries located in the tropic zone. The number of confirmed cases in countries located in the temperate zone were higher than in countries located in the tropic zone.

For air pollution (in terms of CO_2 emission data), a trend test showed that the number of COVID-19 confirmed cases increased with increasing air pollution (see Figs. 15 - 16)

Table 8 shows a comparison of the confirmed numbers of COVID-19 cases in 66 regions in these countries and environmental factors during the study period (April 7, 2020).

Fuzzy logic analysis was adopted to predict the spread of coronavirus in Italy, Spain, and China. The fuzzy inputs (air pollution, mean sea level, population density, and weather temperature) were each built using three parameters (Low, Medium, and High)

Fig. 5. Chinese regions (a), Regions of COVID-19 spread (b), Regions of death due to COVID-19 (c).

to assess and calculate the predicted value of COVID-19 spread. Triangular membership functions for each input were calibrated for the spread value. The output values from the fuzzy logic system suggested that the rate of virus spread was higher in industrial and large cities, reflecting the effects of air pollution and population density on COVID-19 infection. On the other hand, weather temperature and mean sea level had little effect on viral spread. Table 9 and (Fig. 17) show the relationships between the values of the inputs for the coronavirus fuzzy logic system and the decreases in the rate of virus infection.

4. Conclusions

COVID-19 appeared in China in December 2019 and spread to most of the world's countries. Industrial countries with high population density have the highest number of infection cases, reflecting some link between air pollution and COVID-19. At the time of this study, Italy, Spain, and China had the highest numbers of COVID-19 infections in the world. Statistical analyses of some characteristics of those countries were performed via SPSS, and a fuzzy logic system was designed for the same purpose. The two techniques confirmed that air pollution (% CO_2 in the air) and population density were the main variables driving increased viral spread. The temperature or air pressure in these countries did not have the same effects as pollution or population. This fuzzy logic system can help to predict viral spread in any country depending on the variables of pollution and population.

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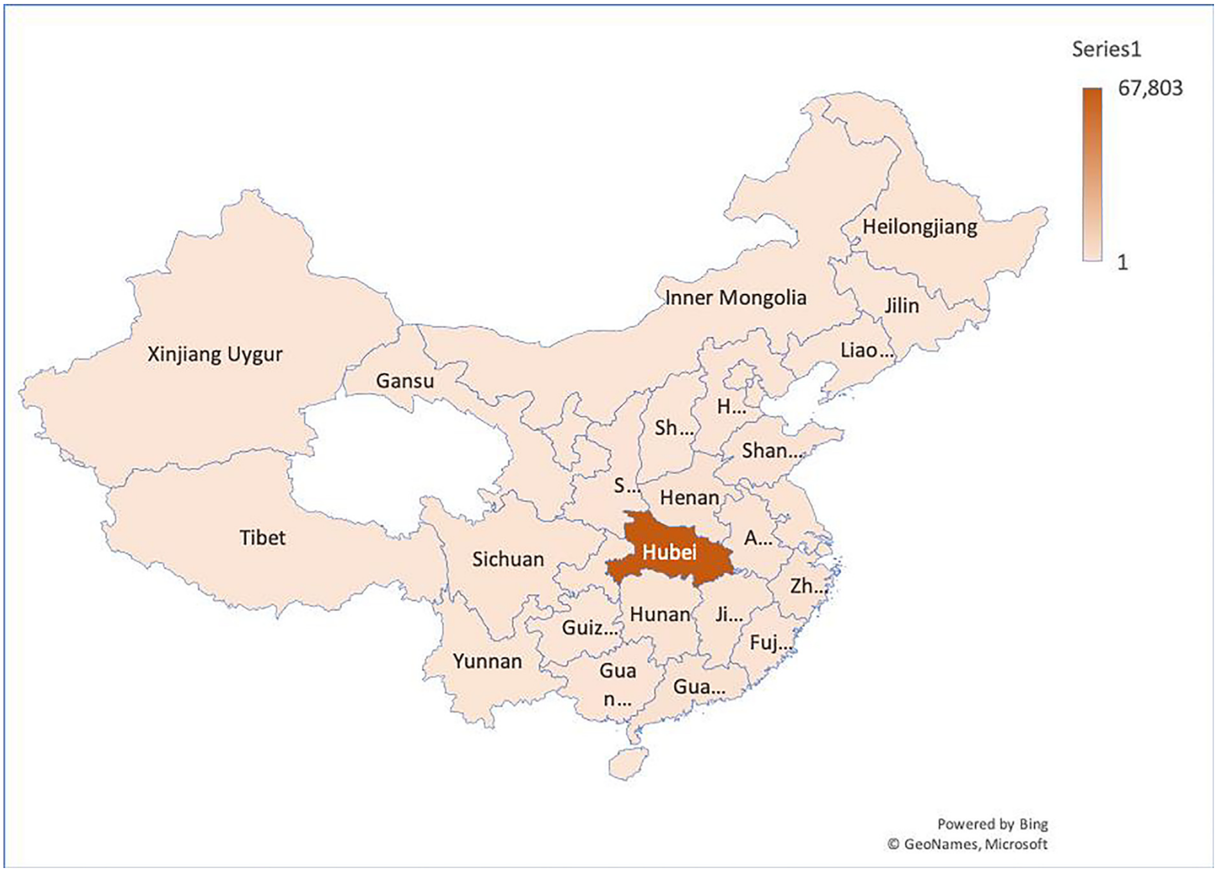

Fig. 5 (*continued*)

Fig. 5 (*continued*)

Table 3
COVID-19 in China.

Region	Affected Variables			COVID-19	
	Air pollution	Mean sea level	Population density	No. of COVID-19 cases	No. of deaths
Guangdong	Manufacturing of motor vehicles, electronics, and pharmaceuticals.	1,902 *m*	140,460,012 people	1539	8
Henan	Manufacturing of heavy machinery, electronics, oil and fats, machinery, and wood crushers.	2,413.8 *m*	94,0401,11	1267	22
Hubei	Manufacturing of semiconductors, electronics, fiber lasers, and fiber optic materials.	37 *m*	11,081,110	67,803	3212
Zhejiang	Manufacturing of heavy equipment (pumps, gunite machinery, gunning machines, and wood crushers)	21,152 *m*	67,370,112	1264	1

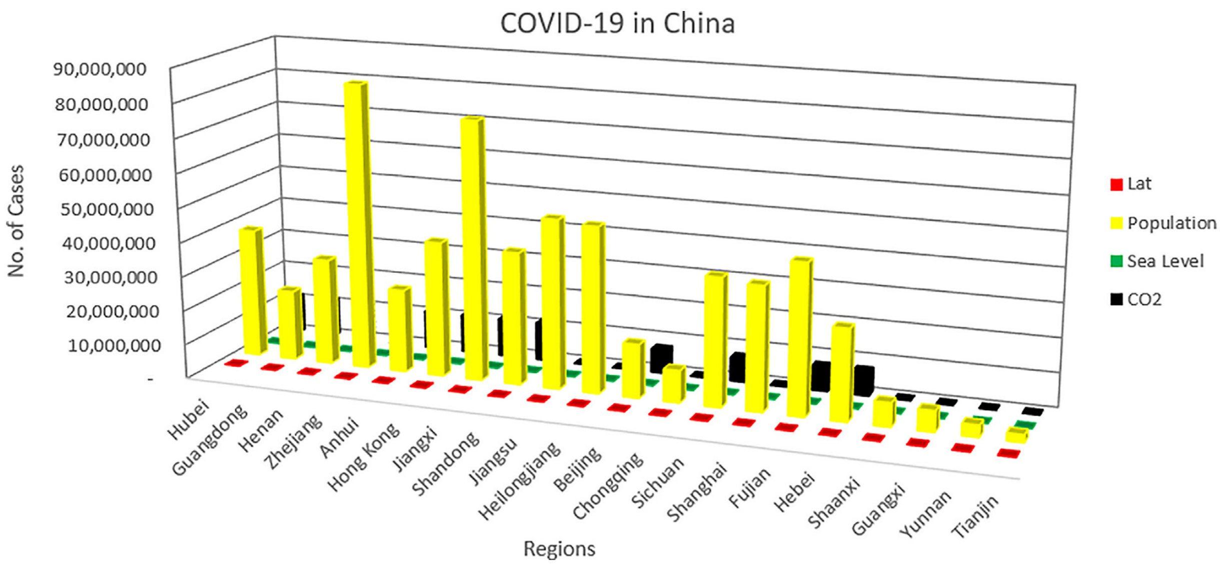

Fig. 6. Relationship between CO_2 level, sea level, latitude, and population and COVID-19 in China.

Table 4
Data for Italy, Spain, and China.

Industrial City	Sea Level	Population	Temperature	Conformed	Death
Yes	Mixed + Low	10,060,574	Moderate	54,802	10,022
No	Mixed + Low	4,356,406	Moderate	14,522	1454
Yes	Mixed + Low	4,905,854	Moderate	12,933	756
Yes	Sea + Sand	4,459,477	Moderate	10,766	1538
Yes	Sea + Sand	3,729,641	Moderate	6552	408
Yes	Sea + Sand	1,525,271	Moderate	4955	669
No	Mixed + Low	5,879,082	Moderate	4429	253
No	High + Half	4,029,053	Moderate	2716	225
No	Mixed + Low	541,098	Moderate	2708	268

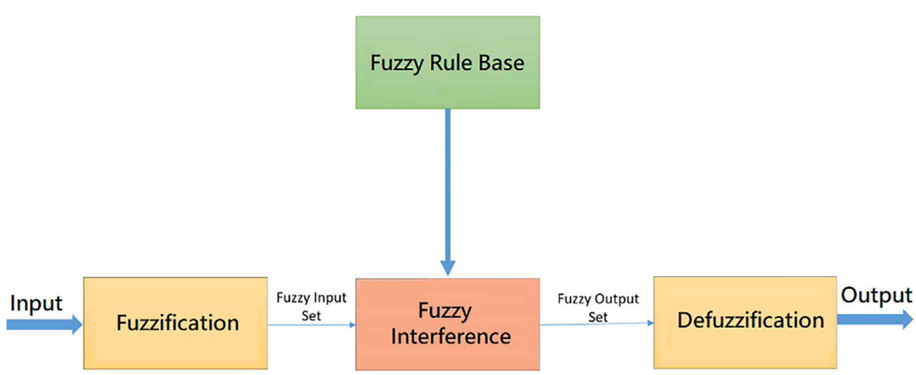

Fig. 7. Fuzzy logic architecture.

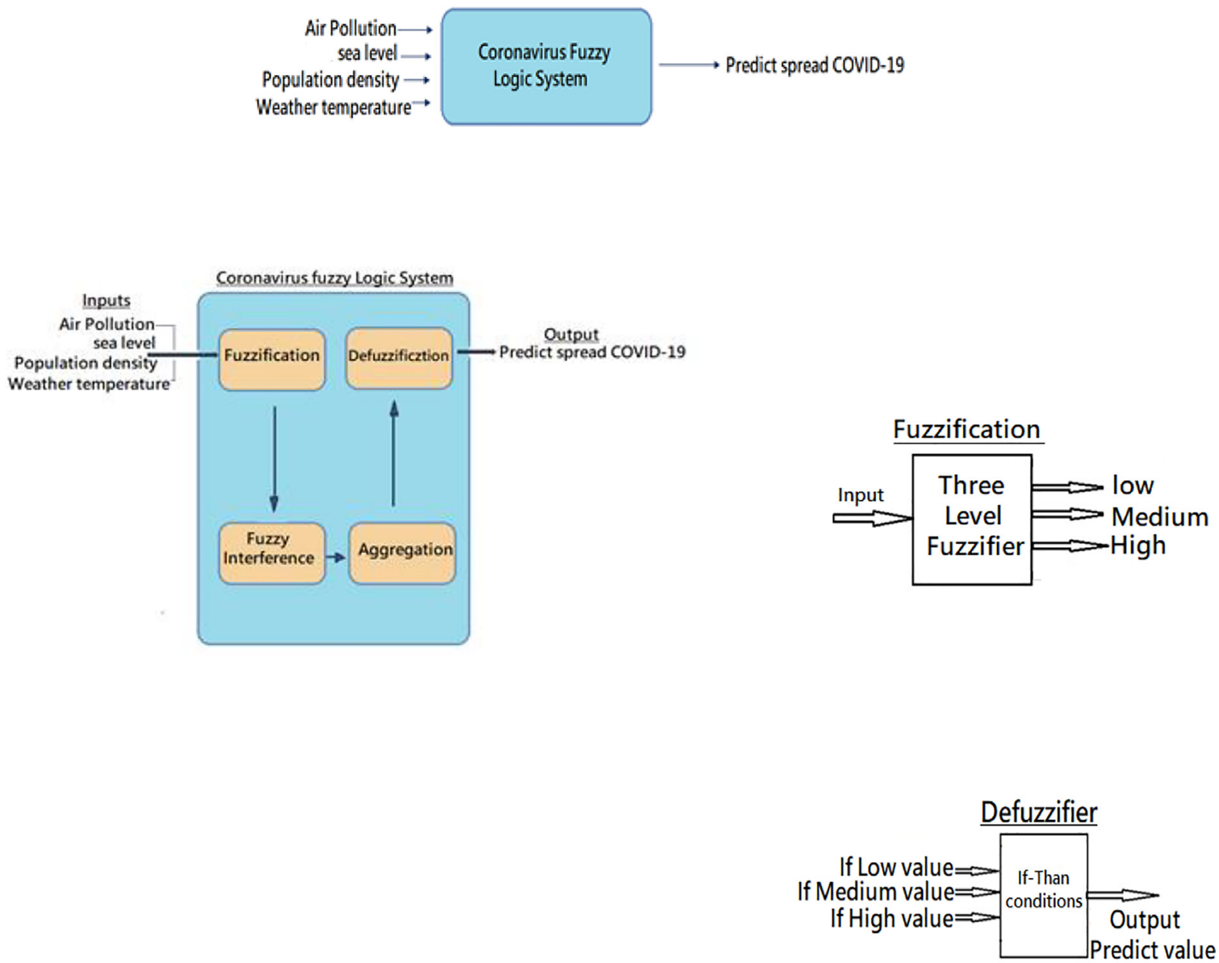

Fig. 8. COVID-19 fuzzy logic system.

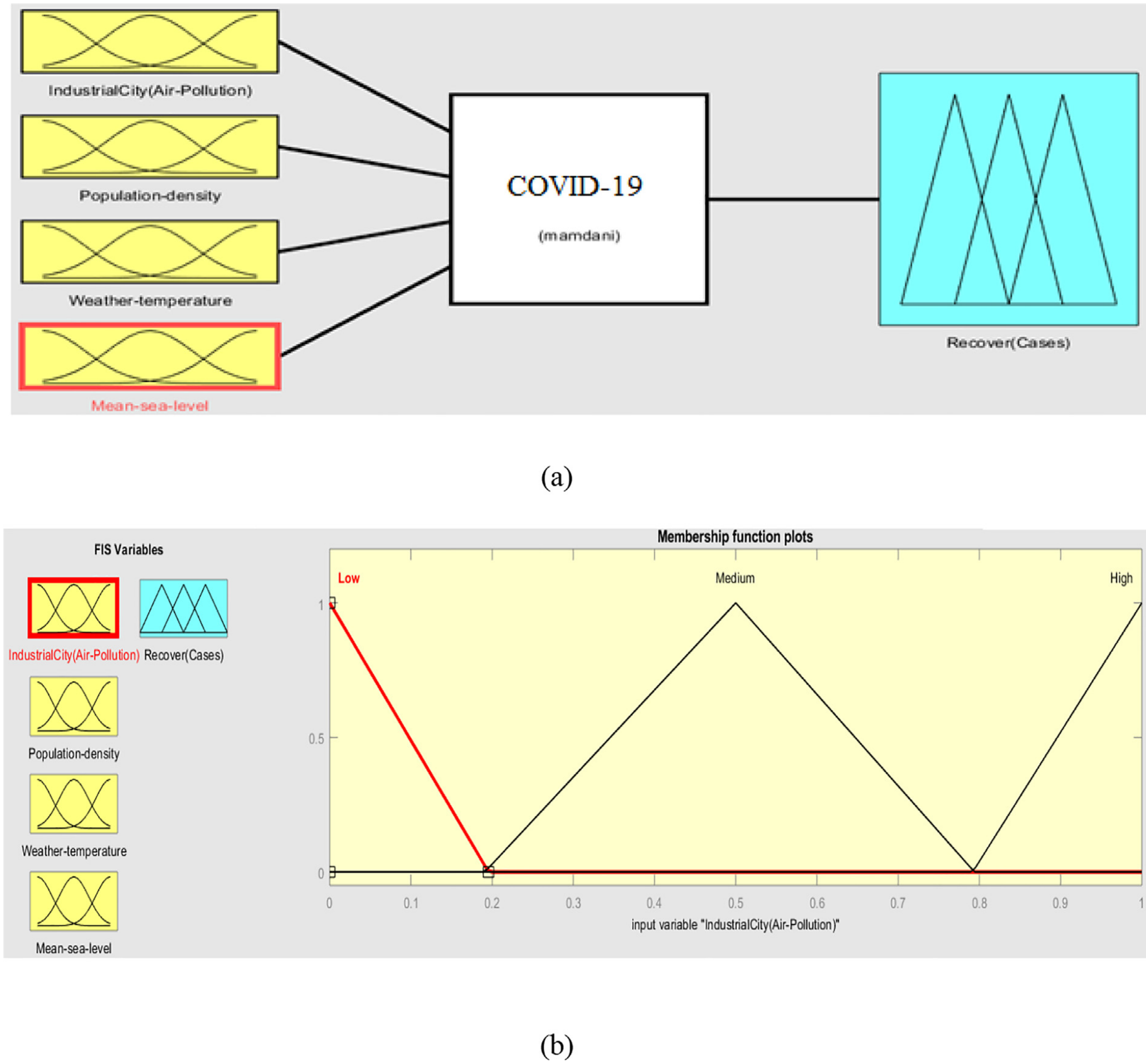

Fig. 9. (a) COVID-19 fuzzy logic system, (b) input variables (in triangular membership function).

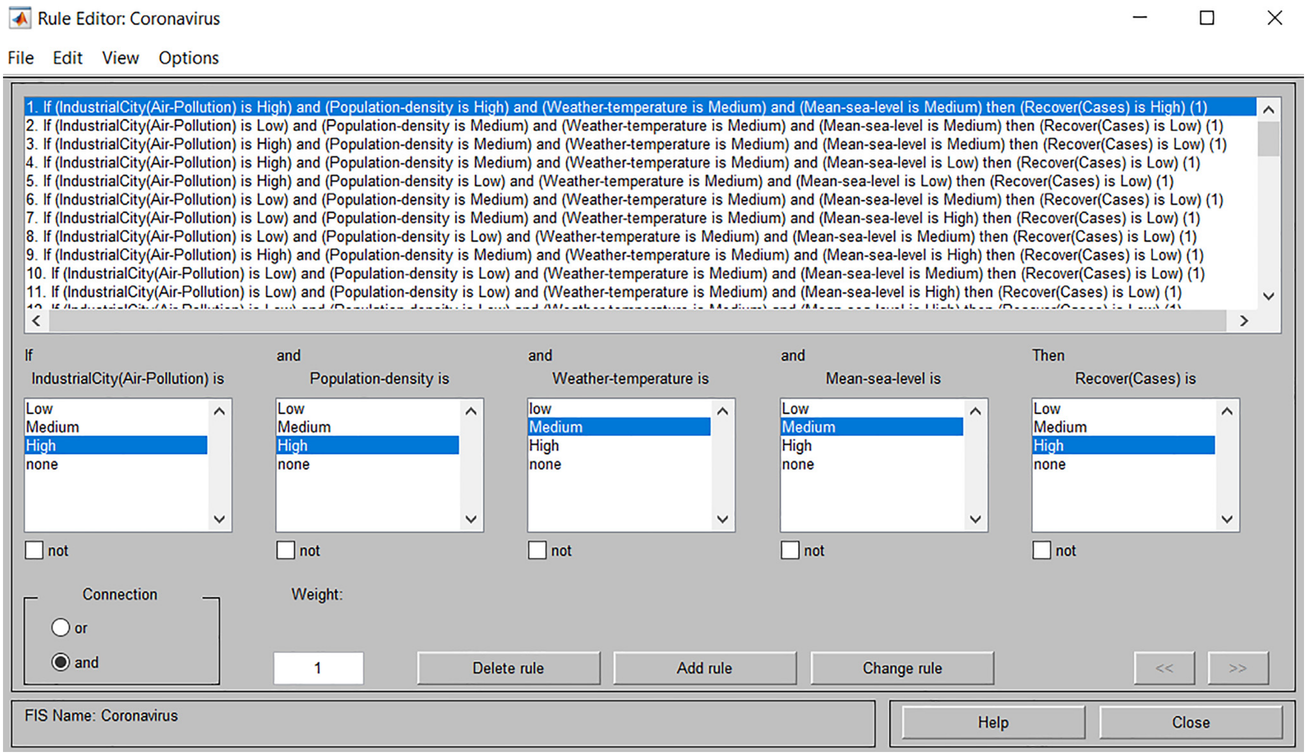

Fig. 10. IF-THEN rules for the COVID-19 fuzzy logic system.

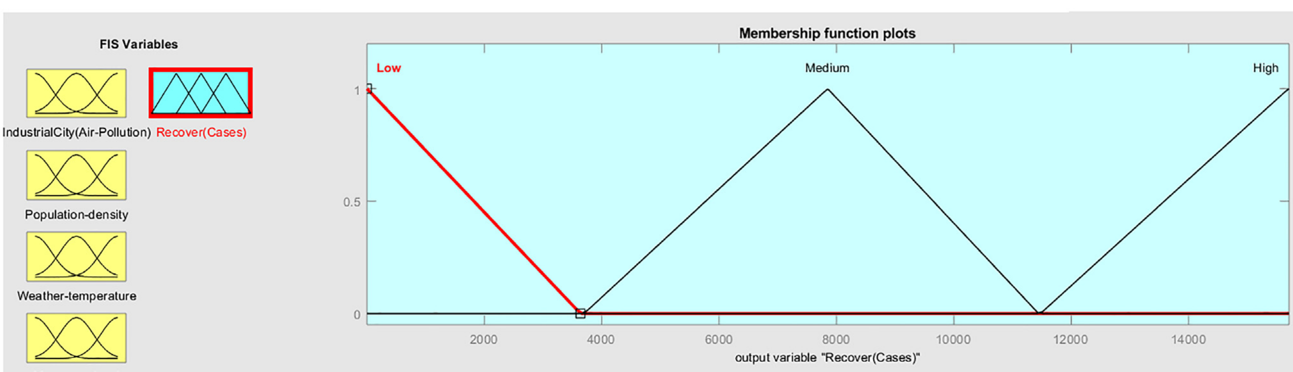

Fig. 11. Output variable in triangular membership function.

Table 5
Levels of COVID-19 Fuzzy System Input Values.

Input Variables	Low	Medium	High
Air pollution (CO_2)	0.0 – 0.1956	0.191 – 0.793	0.792 – 1.4
Mean sea level	0.0 – 0.2442	0.242 – 0.752	0.754 – 1.4
Population density	0.0 – 2.41	2.42 – 7.44	7.48 – 10.5
Weather temperature	0.0 – 0.236	0.238 – 0.737	0.756 – 1.4

Table 6
Example COVID-19 fuzzy system rules.

Fuzzy Rules (IF-THEN rules) – relationship between inputs and output
If (Industrial City (Air-Pollution) is High) and (Population-density is High) and (Weather-temperature is Medium) and (Mean-sea-level is Medium) then (Recover (Cases) is High) (1) If (Industrial City (Air-Pollution) is High) and (Population-density is Medium) and (Weather-temperature is Medium) and (Mean-sea-level is Medium) then (Recover (Cases) is Low) (1) If (Industrial City (Air-Pollution) is High) and (Population-density is Low) and (Weather-temperature is Medium) and (Mean-sea-level is Low) then (Recover (Cases) is Low) (1)
If (Industrial City (Air-Pollution) is Low) and (Population-density is Medium) and (Weather-temperature is Medium) and (Mean-sea-level is High) then (Recover (Cases) is Low) (1) If (Industrial City (Air-Pollution) is High) and (Population-density is Medium) and (Weather-temperature is Medium) and (Mean-sea-level is High) then (Recover (Cases) is Low) (1)
If (Industrial City (Air-Pollution) is Low) and (Population-density is Low) and (Weather-temperature is Medium) and (Mean-sea-level is High) then (Recover (Cases) is Low) (1)

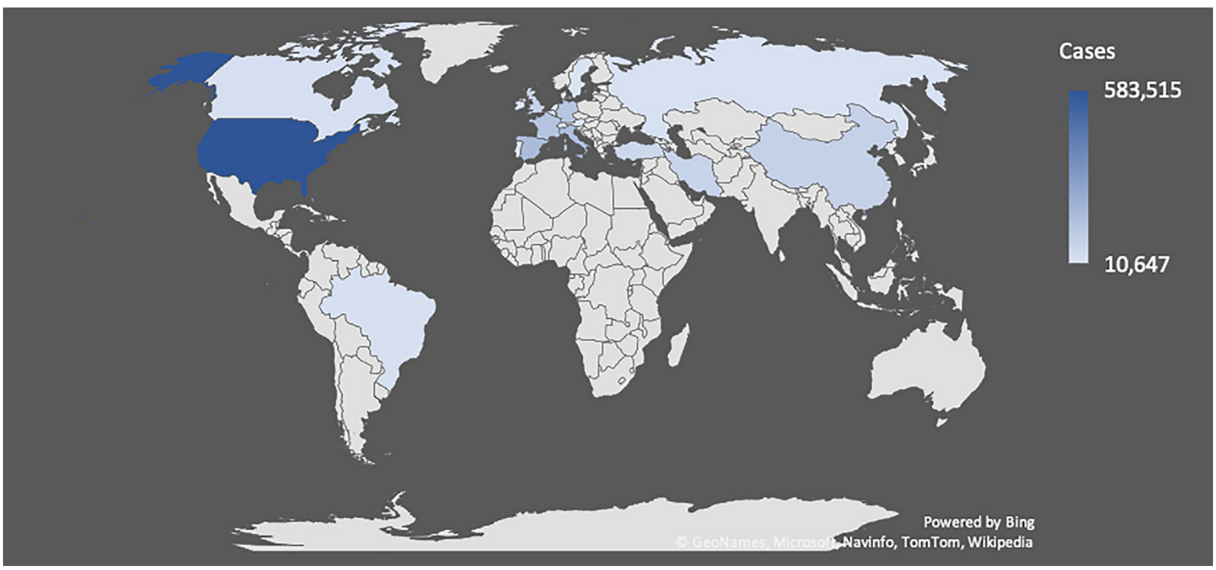

Fig. 12. Confirmed COVID-19 cases by date (April 13, 2020) based on data available at https://www.trackcorona.live/api (n = 20).

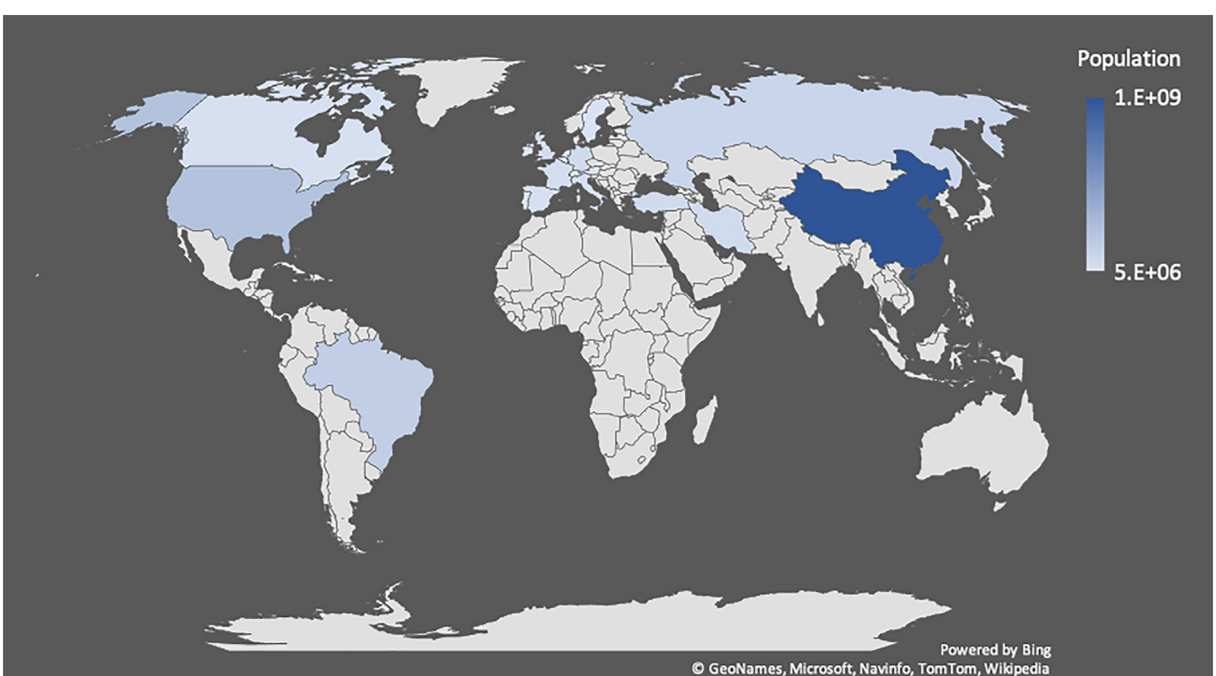

Fig. 13. Confirmed COVID-19 cases by date (April 13, 2020) based on data available at https://www.trackcorona.live/api (n = 20).

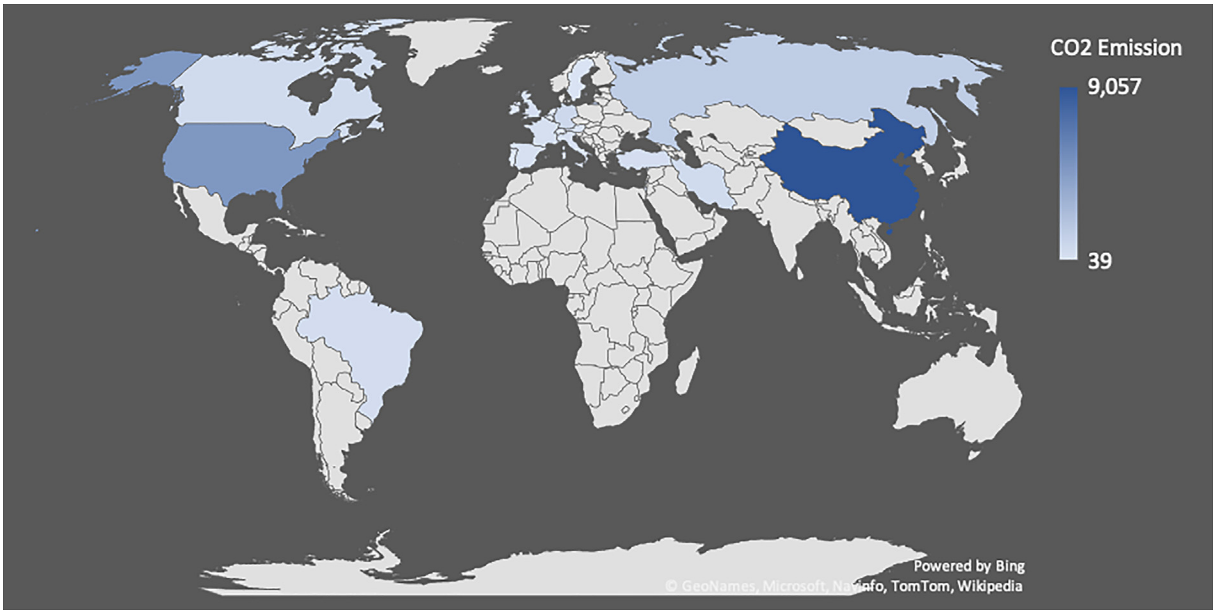

Fig. 14. Confirmed COVID-19 cases by date (April 13, 2020) based on data available at https://www.trackcorona.live/api (n = 20).

Table 7
Confirmed COVID-19 cases by date (April 13, 2020) based on data available at https://www.trackcorona.live/api (n = 107)[a].

Parameters	Groups	N	Minimum	Maximum	Mean ± S.D.	P value
Latitude	Temperate	19	10647.00	583515.00	88216.21 ± 131337.00	0.001
	Tropic	88	1.00	23430.00	797.11 ± 2836.90	

[a] Comparing between Lat groups using the Mann-Whitney test (non-parametric data).

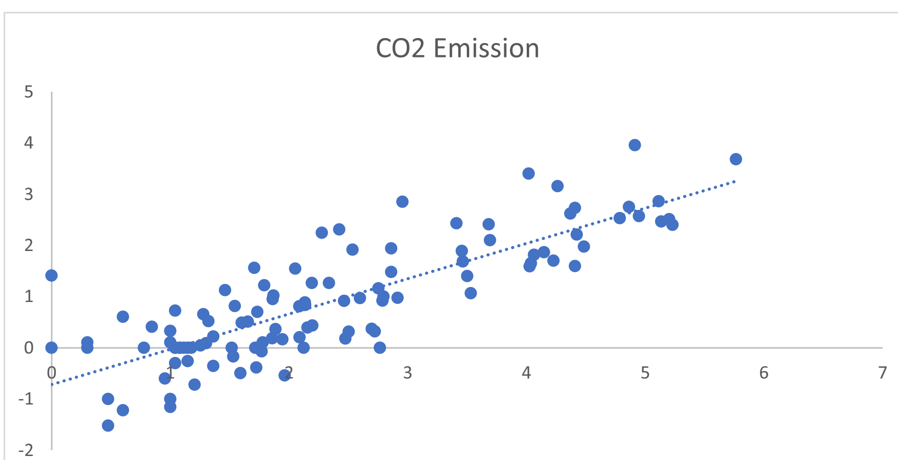

Fig. 15. Confirmed COVID-19 cases by date (April 13, 2020) based on data available at https://www.trackcorona.live/api (n = 107).

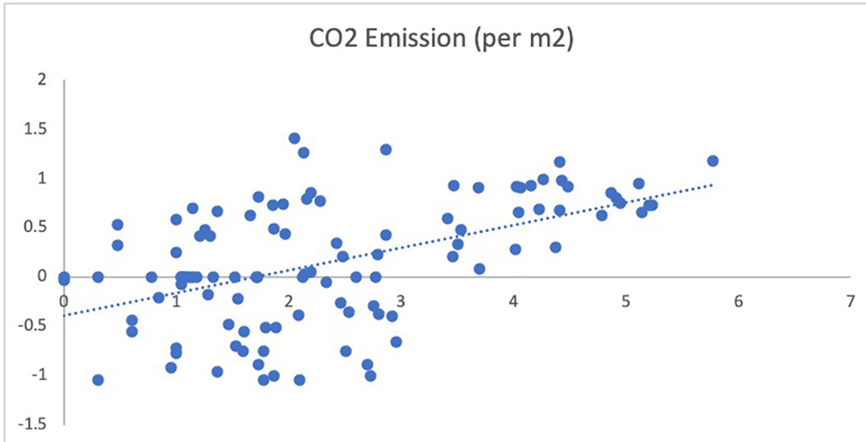

Fig. 16. Confirmed COVID-19 cases by date (April 13, 2020) based on data available at https://www.trackcorona.live/api) (n = 107).

Table 8
Confirmed COVID-19 cases by date (April 7, 2020) based on data available at https://www.trackcorona.live/api (n = 66) [a].

Parameters	Groups	N	Minimum	Maximum	Mean ± S.D.	P value
Altitude	Low level	18	139.00	67803.00	9925.00 ± 19326.08	0.031
	Sea level	18	75.00	31043.00	4381.67 ± 7396.21	
	High level	30	1.00	2716.00	990.33 ± 896.81	
Latitude	Temperate	64	1.00	67803.00	4470.14 ± 11388.53	0.001
	Tropic	89	1.00	10453.00	537.72 ± 1439.57	
Air pollutant	Industrial	29	75.00	67803.00	7975.41 ± 16147.58	0.035
	Non Industrial	37	1.00	14522.00	1511.97 ± 2476.65	

[a] Comparing between Level groups for Con using the Kruskal-Wallis test (non-parametric data) and comparing between Lat groups and NDS groups using the Mann-Whitney test (non-parametric data).

Table 9
Output values related to the inputs in the fuzzy logic system.

Input variables for the COVID-19 fuzzy logic system				Output of the fuzzy logic system
Industrial city	Population density	Weather temperature	Mean sea level	Recovered cases
No	Low density	Moderate	High	Low number of cases
Yes	Low density	Moderate	High	Low number of cases
Yes	High density	Moderate	Medium	High number of cases

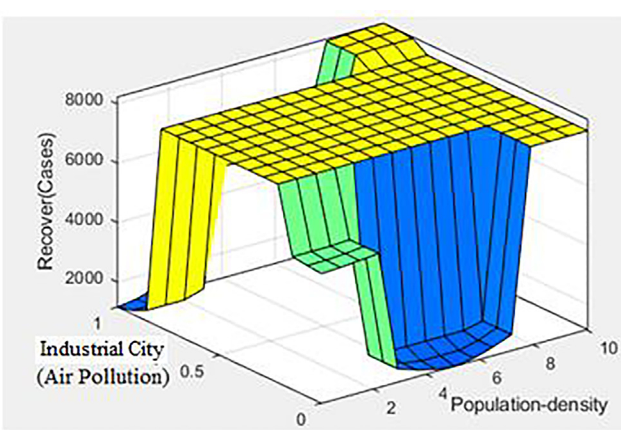

Fig. 17. . Output results of the COVID-19 fuzzy logic system.

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