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The Impact of the Average Temperature, Humidity, Wind Speed, Altitude, and Population Density on Daily COVID-19 Infection Evolution †

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Abstract: The aim of this study is to investigate the impact of climate conditions, altitude, and population density on daily COVID-19 infection evolution. For an average wind speed of greater than 25 km/h, the number of daily COVID-19 infections slightly decreased with a rate of 10%, while the temperature, humidity and altitude factors did not affect its evolution. Furthermore, population density strongly affects its progression with an approximate rate of 90%. Finally, we propose a mathematical model to estimate the evolution of COVID-19 infections over time by simultaneously taking into consideration the wind speed and the population density effects.

Keywords: COVID-19 infections; climate conditions; altitude; population density; mathematical model

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1. Introduction

Historically, between 1918 and 1920, the Great Influenza Pandemic which is known as the Spanish Flu caused 39 million deaths which means 2% of the world population [1]. Moreover, other respiratory pandemics have appeared such as Swine Flu, SARS, Ebola, MERS and lately the COVID-19 pandemic which is an infectious disease caused by a newly discovered coronavirus [1–4]. In December 2019, the city of Wuhan in the Hubei province in China attracted worldwide attention because of a new respiratory viral disease outbreak of an unknown cause. By 7 January 2020, Chinese scientists had isolated a novel coronavirus (COVID-19) from patients in Wuhan [5]. On the 10 January 2020, 41 patients contracted COVID-19, 6 of whom recovered, 7 of whom had critical conditions, and the rest of which were in a stable condition [6]. On 30 April 2020, the number of infections reached 3,090,445 with 217,769 deaths and 1,030,715 recoveries [7].

Recently, because of the quick spread of the COVID-19 pandemic around the globe, the World Health Organization announced a state of emergency which has put researchers and scientists from different fields in front of a great challenge; to analyze and uncover the mechanism of the evolution of this serious pandemic, each from their own prospective. Understanding how environmental parameters and population density factors affect the spread of COVID-19 [8–10] is still a vital question that could help the global community to introduce the right solutions as well as inventing new technologies to prevent along with reducing COVID-19 infection progression.

The aim of this paper is to study the impact of the climate parameters (daily average temperature, daily average humidity and daily average wind speed), altitude and population density on the daily number of COVID-19 infections around six different cities: Casablanca (Morocco), New York (USA), Madrid (Spain), Lombardy Milan (Italy), Paris (France), and Wuhan (China) between the first February and 25 April 2020. Consequently, we have proposed a mathematical model to simultaneously estimate the impact of wind speed factor and population density on daily COVID-19 cases.

2. Materials and Methods

The databases of the daily average temperature, humidity, and wind speed across the cities of Casablanca, New York, Madrid, Lombardy-Milan, Paris, and Wuhan were collected between 23 January and 25 April 2020. Moreover, we have determined the average altitude, average annual number of population and visitors plus the daily and cumulated COVID-19 infections' evolution around the six studied cities (Figures A1–A3 and Table A1 in Appendix A).

According to experimental epidemiologists' estimations, 95% of patients had an estimated median incubation period of 4 to 5.1 days and 97.5% of them had symptoms of 11.1 days [11]. Consequently, the duration between the day when a susceptible person will be infected by COVID-19 virus and the day on which the case could be detected is estimated to be 9 days. Thus, we can say that the climate parameters (Temperature: Ti, Humidity: Hi, Wind speed: Wi) on i day show their impacts on N(i + 9) detected cases at (i + 9) days.

We have classified the studied factors into two types of variables:

- Dependent variables: Daily temperature, Ti; Daily humidity, Hi; Daily wind speed, Wi.
- Independent variables: Altitude, average annual population density.

We assume that the average annual population density is constant and given by:

$$P_{total} = P_s + P_t \quad (1)$$

where, P_s is the average annual population density in a city and P_t is the average annual visitors' density across each city.

√Before the lockdown: $P_{total} = P_s + P$
√After the lockdown: $P_{total} = P_s$

The average annual number of populations N(t) in a city could be presented as [12]:

$$N(t) = S(t) + I(t) + R(t) \quad (2)$$

where:

S(t): Number of susceptibles on day (t).
I(t): Number of infected cases on day (t).
R(t): Number of recovered patients on day (t).

The variables S(t), I(t) and R(t) vary over time and they could be presented by a system of three differential equations as follow [13]:

$$\begin{cases} \frac{dS}{dt} = -aS(t)\ (t) \\ \frac{dI}{dt} = aS(t)\ I(t) - bI(t) \\ \frac{dR}{dt} = bI(t) \end{cases} \quad (3)$$

where:

a: Expected number of people an infected person infects per day ($a \approx 1/t_{ip}$).
b: The proportion of recovered patients per day (b = 1/D), while D is the approximate number of days when patient will recover (D = 14 days in our estimations).

tip: The estimated average incubation period (equals 5.75 days in our study) in which an infected patient could infect other susceptible.

3. Results and Discussion

The analysis of the impact of the average daily temperature, average daily humidity, and the average altitude (Figures A4–A6 in Appendix B) shows that these factors have no effect on daily COVID-19 infection evolution for the studied period. While, Hwaiz et al. [14] have presented a study shows that the increase of daily reported cases and mortality rates is due to the increasing of temperature from April to June. Furthermore, their work show also that the increase of temperature has no effect on reducing the number of daily COVID-19 infected cases Other study done by J. dos Santos [15] to measure the effect of climatic conditions on the prevalence rate of COVID-19 in Brazilian states given the exogenous nature of climate variables. The results showed that increases of 1% in the solar incidence, average temperature, and relative humidity of the air reduced COVID-19 prevalence rates by 0.16%, 0.049%, and 0.22%, respectively, considering the 11-day moving average.

In Figure 1 we note that, for an average wind speed of more than 25 Km/h, the amplitude of daily confirmed infections is reduced across the studied cities, which means that the wind speed factor slightly impacts the daily COVID-19 infection evolution compared to the other climatic parameters under study.

Figure 2 shows that the population density factor greatly affects the daily number of COVID-19 infections with a rate of 90%, compared to the other parameters under study. Furthermore, the speed of COVID-19 spread was faster in the area which is highly populated such as NewYork and Wuhan, and the quarantine was the only solution to reduce the progression of COVID-19 infections' evolution (Figures A2 and A3 in Appendix A).

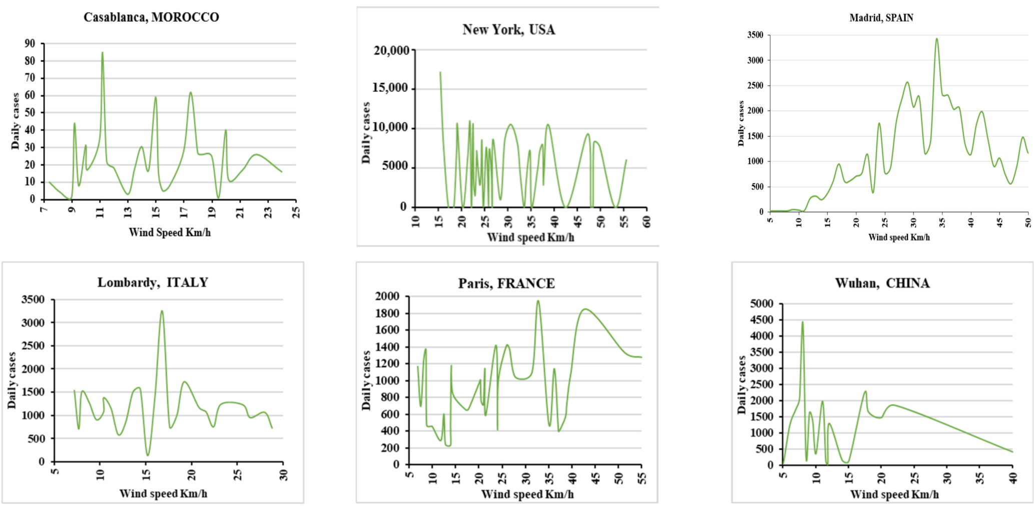

Figure 1. Influence of wind speed on the number of daily cases infected.

Based on those results, the previous system of differential Equations (3) could be rewritten as:

$$\begin{cases} \dfrac{dS}{dt} = -(a+\gamma)S(t-t_{ip}).I(t-t_{ip}) & (4) \\ \dfrac{dI}{dt} = (a+\gamma)S(t-t_{ip}).I(t-t_{ip}) - (b+\gamma)I(t) & (5) \\ \dfrac{dR}{dt} = (b+\gamma)I\ (t) & (6) \end{cases}$$

where γ is the proportion in which wind speed contributes to reducing the number of susceptible people infected.

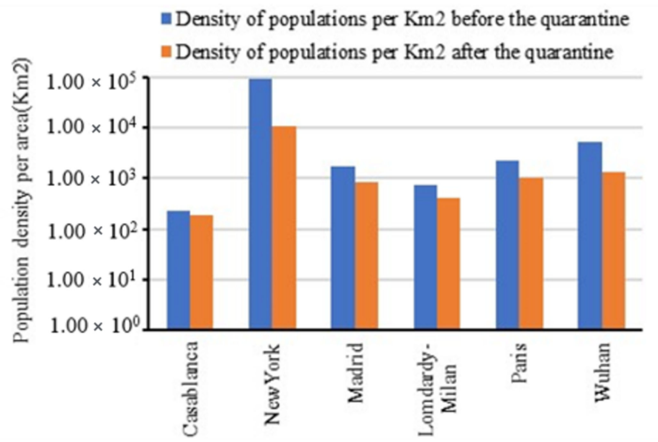

Figure 2. Average population density before and after the quarantine of across the cities under study [16].

Furthermore, the subtracted time-period t_{ip} from t time, means that an infected patient could infect one susceptible person or more after an incubation period of $t_{ip} = 5.75$ days.

The population density factor affects the evolution of infections by 90%, while the wind speed affects it by only 10%, so $\gamma < a$; then, we estimated that $\gamma \simeq \frac{a}{9}$.

So, these conditions could be described mathematically, as follows:

$$\begin{cases} if\ S > \frac{a+\gamma}{b+\gamma}\ so\ \frac{dI}{dt} > 0 \\ ,\ we\ say\ \ that\ the\ COVID19\ epidemic\ grows \\ if\ S < \frac{a}{b}\ so\ \frac{dI}{dt} < 0 \\ ,\ we\ say\ \ that\ the\ COVID19\ epidemic\ shrinks \end{cases} \tag{7}$$

where the coefficient $\frac{a+\gamma}{b+\gamma}$ presents the threshold and the initial conditions of S_0, I_0 and R_0 successively presents the proportions of susceptible people, infected cases, and recovered patients at t_0 in each city, while a = 0.35, b = 0.111, and $\gamma = 0.04$.

Figure 3 shows the comparison between SIR model, where only population density was taken into account, and our estimated model, where we simultaneously implemented the impact of wind speed and population density factors in order to estimate their effects on daily COVID-19 infection evolution.

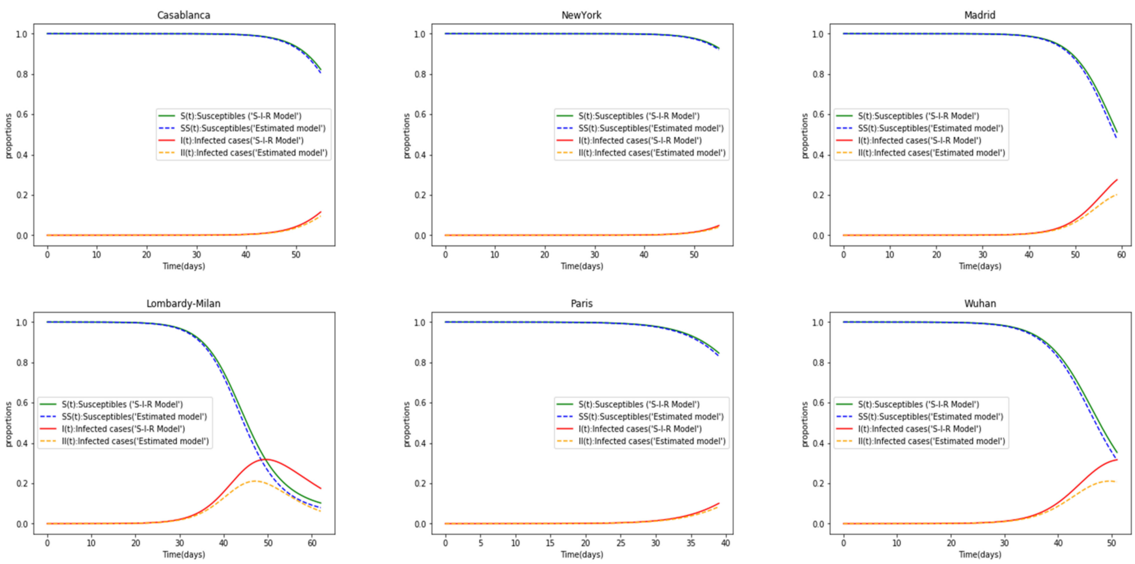

Figure 3. Comparison between SIR model and the proposal mathematical model.

4. Conclusions

The objective of this work is to study the impact of climate parameters, altitude, and population density factors on the daily number of COVID-19 infections over 85 days, between the 1 February the 25 April 2020 around six cities (Casablanca, Paris, Madrid, Lombardy-Milan, New York and Wuhan). The main results of this research showed that:

- The temperature, the humidity and the altitude parameters have no impact on daily COVID-19 infection evolution.
- For an average wind speed of greater than 25 km/h, the number of COVID-19 infections is slightly decreased, with an approximate rate of 10%.
- Population density has a significant impact on the daily COVID-19 spread with a rate of 90%.

Based on this study, a mathematical model is proposed in which we simultaneously considered the wind speed, and the population density effects on daily COVID-19 infection evolution; consequently, in our estimated model, the number of daily susceptible people and infections has slightly decreased compared to the presented S-I-R model.

Author Contributions: Conceptualization, R.L. and L.L.; Data curation, R.L. and L.L.; Formal analysis, R.L. and L.L.; investigation, A.D. and A.K.; Project administration, R.L. and L.L.; Supervision, A.D. and A.K. All authors have read and agreed to the published version of the manuscript.

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Appendix A

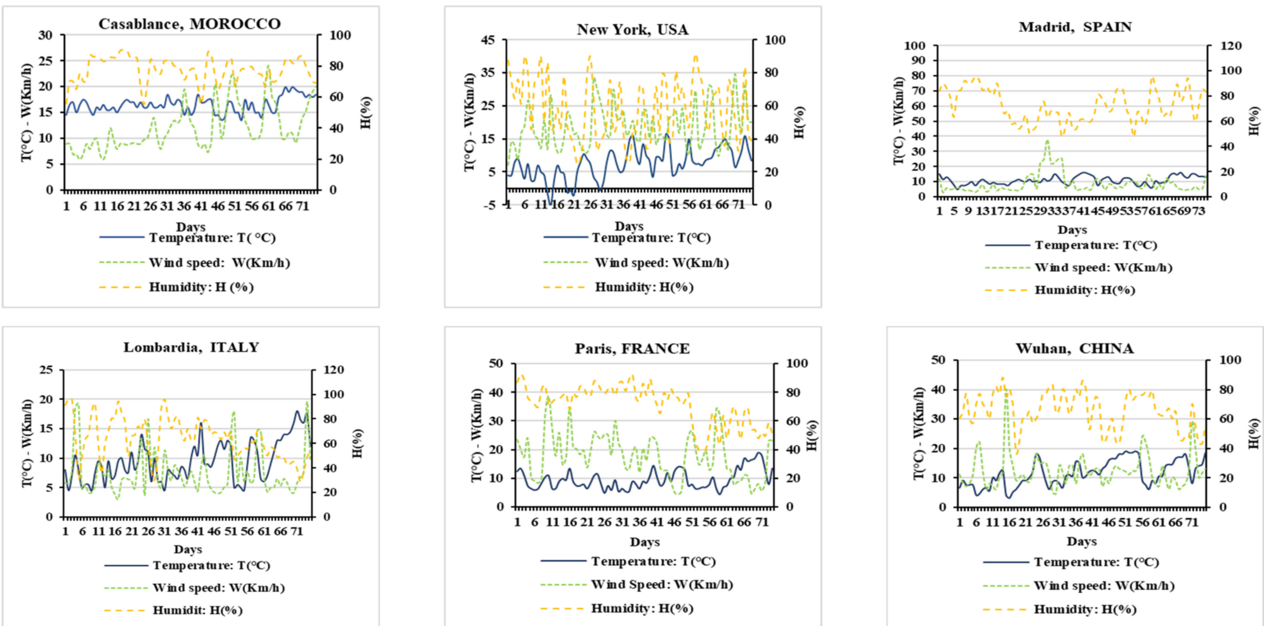

Figure A1. Climate condition changes across the studied cities between 23 January and 25 April 2020.

Table A1. Table A1. Climate data of the sixth cities under study.

	Average Temperature		Average Humidity		Average Wind Speed	
	Minimal	**Maximal**	**Minimal**	**Maximal**	**Minimal**	**Maximal**
Casablanca	13.5 °C	20 °C	55%	90.5%	6 km/h	25 km/h
New York	−0.5 °C	16.5 °C	24.5%	91.8%	11.2 km/h	55.7 km/h
Madrid	5 °C	16.3 °C	47.5%	95.3%	4.5 km/h	60.8 km/h
Lombardy-Milan	4.5 °C	19.3 °C	28.7%	96%	4.96 km/h	32 km/h
Paris	4.5 °C	19 °C	40%	93%	6.88 km/h	55 km/h
Wuhan	3 °C	19 °C	37%	87%	6 km/h	29 km/h

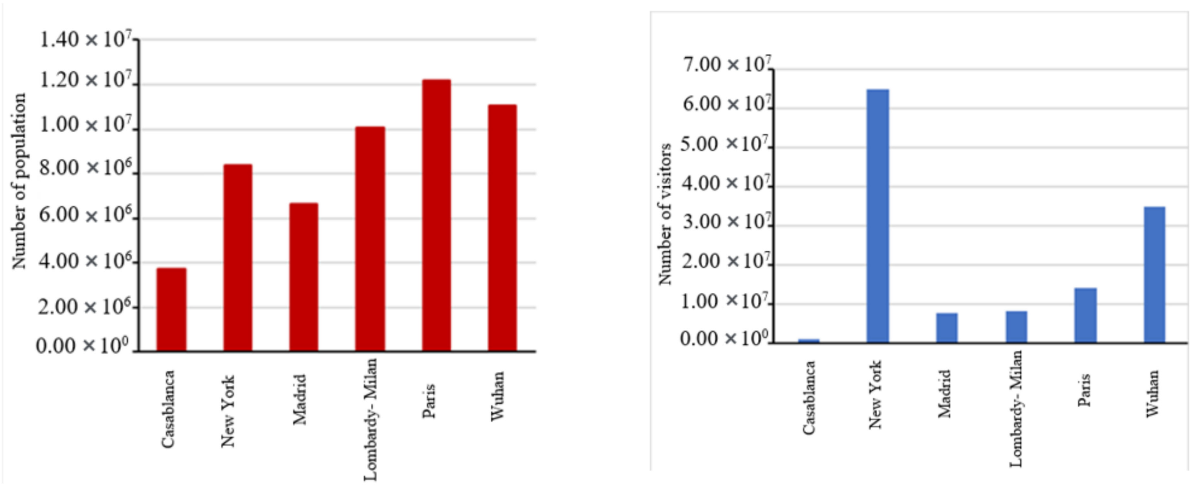

Figure A2. Average annual population density and visitors across the six cities under study [16].

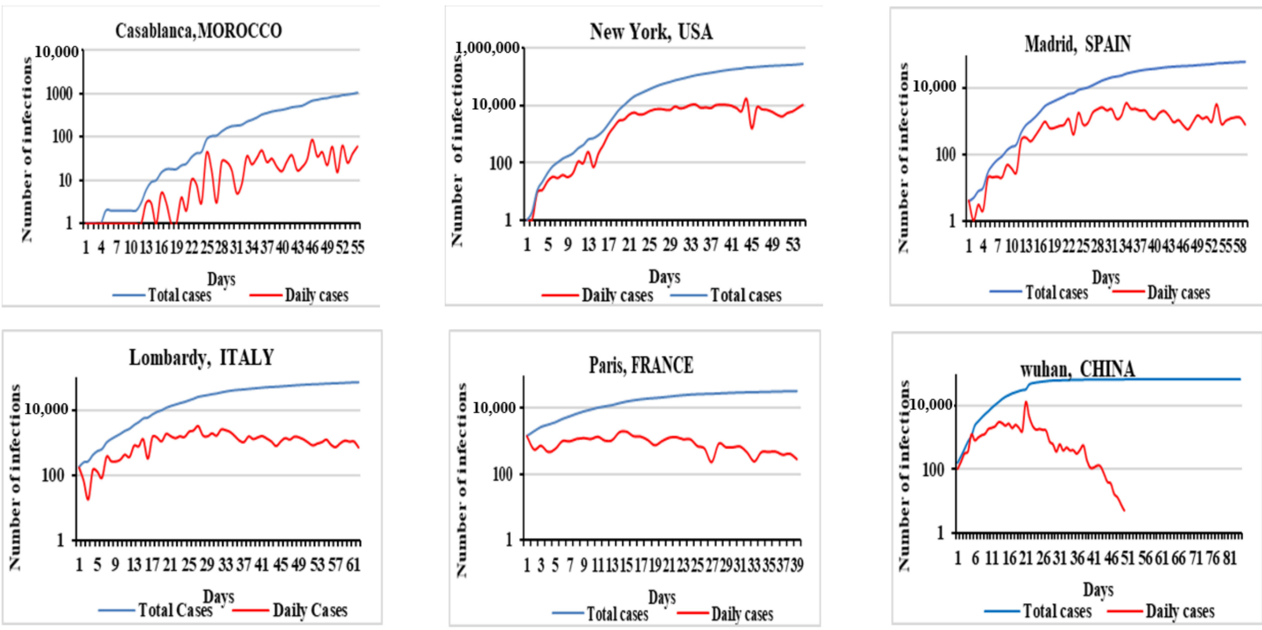

Figure A3. Evolution of daily and total COVID-19 infections over time (days) with a logarithmic scale [17–22].

Appendix B

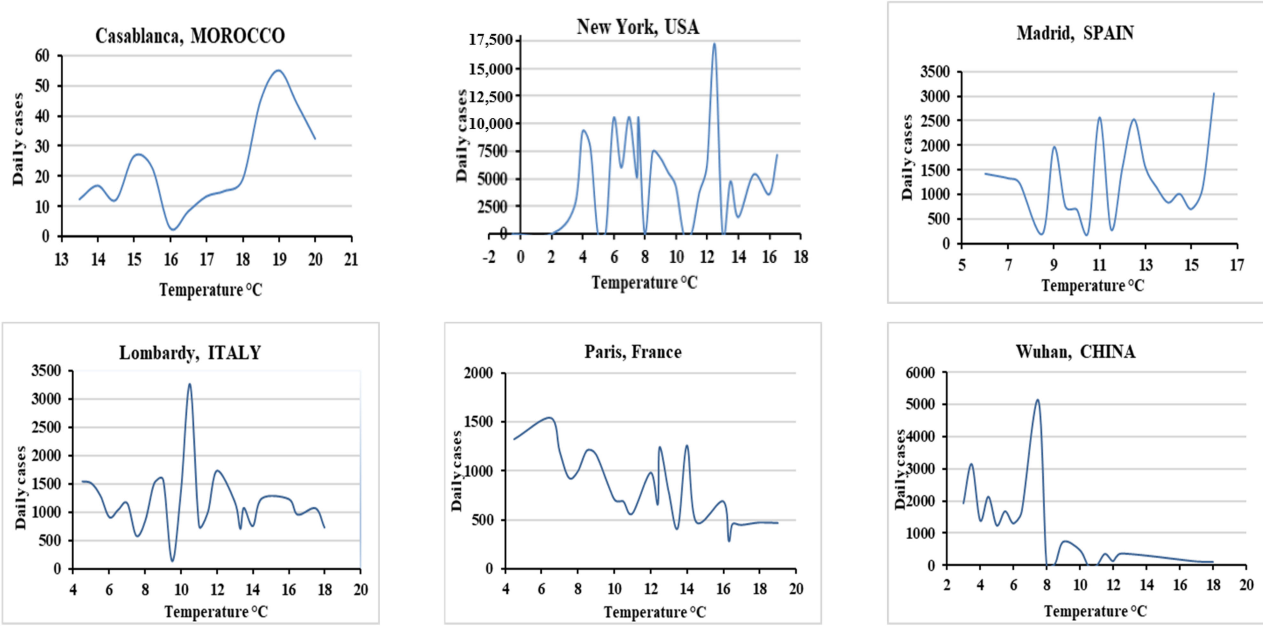

Figure A4. Influence of temperature on the daily number of COVID-19 infected cases.

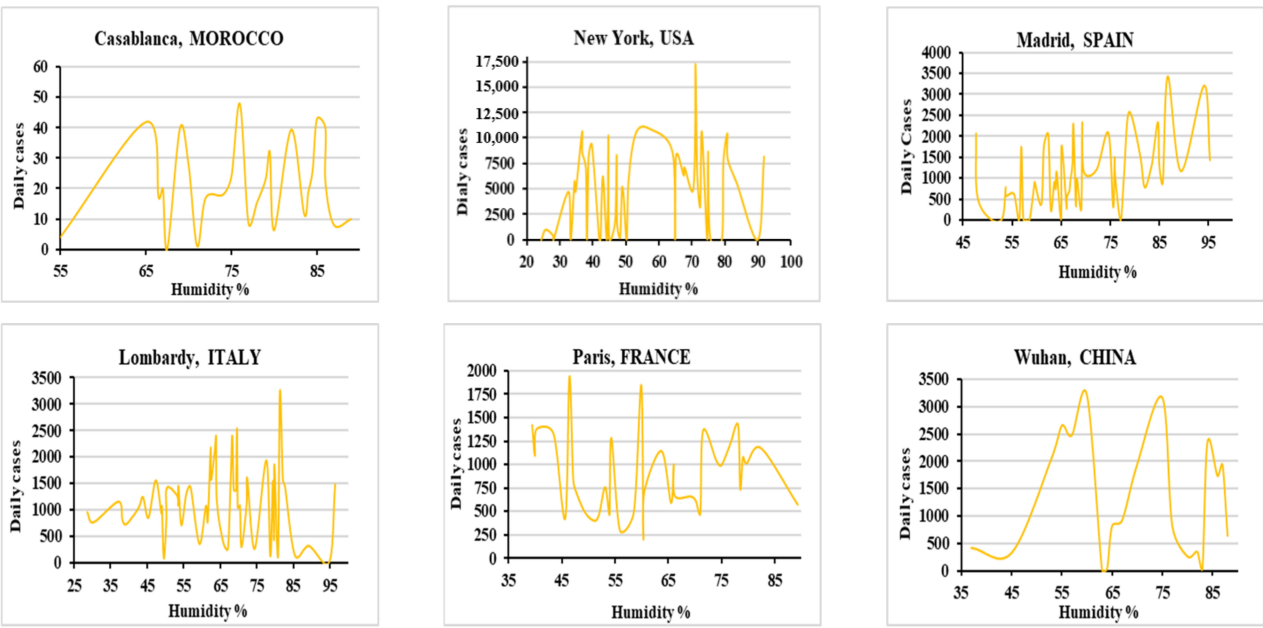

Figure A5. Average humidity impact on the daily number of COVID-19 infections.

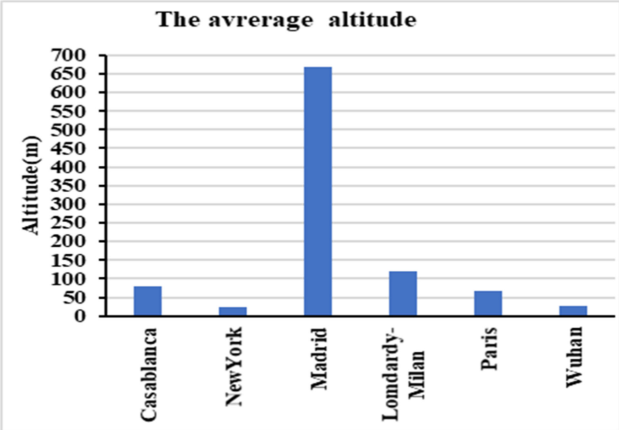

Figure A6. Average altitude of the studied cities [23].

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