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Influence of meteorological patterns on the 2020 COVID-19 pandemic in the Mexico City region

Alejandro Salcido\textsuperscript{a,}\textsuperscript{b}, Telma Castro\textsuperscript{b}

\textsuperscript{a} Departamento de Física, Universidad Autónoma Metropolitana-Iztapalapa, San Rafael Atlixco 186, Ciudad de México 09340, Mexico
\textsuperscript{b} Instituto de Ciencias de la Atmosfera y Cambio Climático, Universidad Nacional Autónoma de México. Circuito exterior, Ciudad Universitaria, 04510, Coyocacán, Ciudad de México, Mexico

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\textbf{ABSTRACT}

Meteorology is a critical factor affecting respiratory infectious diseases such as MERS, SARS, and influenza, but its effect on the spread of the COVID-19 disease remains controversial. Nevertheless, since the infected people cough-jets produce plumes of droplets and aerosols that can travel for several meters in the atmosphere, the possible influence of wind circulation and atmospheric turbulence on the infectious plume’s fate cannot be ignored. This paper applied cluster analysis for identifying the near surface wind circulation patterns and associated temperature and humidity distributions in the Mexico City Metropolitan Area (MCMA), then their influence on the spread of the COVID-19 disease during the 2020 pandemic was discussed. Meteorology data and daily numbers of confirmed COVID-19 infections were obtained from public sources. An intense infection activity occurred from October to December 2020, and notable spreading of the disease toward the southwest and south MCMA was observed. In the same period, temperature and humidity conditions that could favor the virus stability and replication were detected in the same sectors, besides 60% of the wind observations revealed considerable northerly components. These findings suggested the existence of correlations between both phenomena. For assessing the possible relationship, the Pearson coefficients between the daily confirmed infections and the temperature and inward flux were estimated, and values from -0.32 to -0.55 and 0.62 to 0.70 were obtained. Correlation was negligible for relative humidity. Multilinear regression for the daily infections in response to the meteorological variables produced coefficients of determination from 0.3839 to 0.6138. Because of its implications for public health, this topic deserves a more in-depth investigation.

\section{1. Introduction}

The COVID-19 disease is transmitted human-to-human due to close contact with an infected person, exposed to coughing, sneezing, respiratory droplets or aerosols, which can penetrate the human body through the nose or mouth (Chan et al., 2020; Shereen et al., 2020). There is significant potential for inhalation exposure to viruses in microscopic respiratory droplets (microdroplets) at short to medium distances (up to several meters, or room-scale), which indicates a route of airborne transmission (Bhaganagar and Bhimireddy, 2020; Morawska and Cao, 2020; Morawska and Milton, 2020; Zhang et al., 2020). Coughing, singing, speaking, and even breathing produce a mixture of droplets and aerosols in a wide range of sizes, and these secretions can travel together for up to 9 m indoor. It is feasible for SARS-CoV-2 to remain suspended in the air and viable for hours (Bourouiba, 2020; Klompas et al., 2020).

The risk of virus transmission in outdoor locations has been hypothesized to be lower than in indoor spaces. Outdoor spaces generally allow for more physical distancing, which mitigates the virus transmission through larger respiratory droplets. Outdoor spaces allow for airflow, ventilation, and lack of recycled air, which all may reduce the risk of aerosol transmission through smaller respiratory droplets. Existing evidence (Bulfone et al., 2021) supports the wide-held belief that risk of SARS-CoV-2 transmission is lower outdoors but there are significant gaps in our understanding of specific pathways and distance ranges. Therefore, it is important to note that infections are possible outdoors and the advantage may be overtaken by relaxed mitigation efforts. SARS-CoV-2 RNA on aerosols was identified by measurements in Wuhan’s hospitals (Liu et al., 2020) and outdoor in northern Italy (Setti
et al., 2020), unraveling the likelihood of indoor and outdoor airborne transmission (Zhang et al., 2020). The work of (Setti et al., 2020) provides evidence that SARS-CoV-2 RNA can be present on outdoor particulate matter (PM), suggesting that, in conditions of atmospheric stability and high concentrations of PM, SARS-CoV-2 could create clusters with outdoor PM$_{10}$ and PM$_{2.5}$ and enhance the persistence of the virus in the atmosphere.

Viruses may be adsorbed through coagulation onto PM and remain airborne for hours or days (Martelletti and Martelletti, 2020), thereby increasing inhaled concentrations of virus via PM in the lungs. Therefore, PM may provide a possible platform to carry the SARS-CoV-2 during atmospheric processes of transport and dispersion. Thus, PM containing SARS-CoV-2 could be a direct transmission model in a highly polluted area (Tung et al., 2021).

The meteorological factors must be considered as reliable indicators of the outdoor viability, transmission, and range of virus spread (Rendana, 2020). Specifically, wind circulation and turbulence determine atmospheric transport and dispersion. These factors play an essential role in measuring air pollutants such as biological ones, including bacteria and viruses (Calderon-Ezquerro et al., 2021).

Numerous studies carried out statistical analysis to investigate the correlation between the local meteorology and the COVID-19 pandemic in various world regions (Auler et al., 2020; Coccia, 2020; Mecenas et al., 2020; Pan et al., 2021; Pramanik et al., 2020; Rodrigues et al., 2020; Shi et al., 2020; Srivastava, 2021). These studies considered, in general, air temperature, humidity, pollution levels, and seasonal temperature as the main factors for the disease spreading. However, as the infected people cough-jets constitute numerous plumes of infected viral aerosols in the atmosphere, the atmospheric conditions will determine their flow paths (Bhaganagar and Bhimireddy, 2020). Of course, that the infectious aerosol plumes raise to heights beyond the canopy layer or the surface layer, reaching the mixed layer under unstable conditions, will depend on the size of the aerosols microdroplets (Finlayson-Pitts and Pitts, 2000) and the time the viruses can remain active outdoor. This last issue, however, is still under study for SARS-CoV-2 (Martelletti and Martelletti, 2020; Rendana, 2020; Tung et al., 2021).

Bhaganagar and Bhimireddy (2020) investigated the scales of mixing (or diluting) of the virion in terms of the atmospheric characteristics, such as atmospheric stability, wind conditions (wind shear, wind speed and wind direction), air turbulence, air/ground temperature and moisture content in the air. They analyzed the length and time scales of the horizontal transport of SARS-CoV-2 virions using high-resolution simulations to understand the meteorological factors influencing the transport and mixing processes. They found that atmospheric weakly convective conditions that result in low wind speeds, low level turbulence and cool moist ground conditions favor the transmission of the disease, being the wind direction an important factor that dictates the direction of the transport. This study made an important contribution demonstrating the role of local meteorological conditions in spreading the coronavirus, and the results demonstrated that, from the initial time of release, the virus can spread up to 30 min in the air, covering a 200 m radius region at a time and moving to 1–2 km from the original source.

The transmission route in outdoor environments is complicated to understand and assess due to the combination of the factors that contribute to a favorable spread of the infection. The airborne transmission accelerates the spread of the disease when the transport is towards a densely populated region. Then, depending on the combination of factors in the environment, the airborne transmission of the SARS-CoV-2 virions is highly possible, and winds can drive a long-range spread of the disease.

On other hand, it is interesting to observe that, as it was demonstrated by Biasin et al. (2021), UVC radiation has a potential for inactivation and complete inhibition of all viral concentrations. However, it should be noted that as the sunlight passed through the atmosphere all UVC is absorbed by ozone, water vapor, oxygen and CO$_2$. Therefore, although some evidence shows that sunlight may rapidly inactivate SARS-CoV-2 on surfaces (Ratnesar-Shumate et al., 2020), the natural sunlight may not have the affinity to deactivate the virus in the air.

Atmospheric turbulence constitutes the dispersion mechanism of air pollutants (gases and particulate matter), and the local wind circulation dictates the trajectory and extent of pollutants impact in the atmosphere (Garrat, 1994; Stull, 1988). Indoor deposition studies under air calm conditions provide a rough estimation of the distances traveled by the infectious excretions. Some studies (Coccia, 2021, 2020) attributed to meteorological conditions such as lower average wind speeds and low ambient temperatures the disease’s accelerated outdoor spread in Northern Italy compared to the other regions till April 2020. The number of infections was higher in polluted cities than in cleaner cities (Coccia, 2020).

In the MCMA, the free troposphere is above 3000 m and the mixed layer depth ranges between 100 and 3000 m, depending on the time of year (de Foy et al., 2005). This favors the rapid transport of air parcels. Among other properties, the half-life of atmospheric particles depends on their size. In urban areas, particles with diameters of 0.03 to 3 µm can remain in the atmosphere for 2 to 5 days (Finlayson-Pitts and Pitts, 2000) and be carried by the wind to places far from the emission site.

Different studies report that the sizes of the viruses range from 0.003 to 0.100 µm. In the case of the SARS COV2 virus, Laue et al. (2021) report that this virus has sizes between 0.045 and 0.250 µm depending on the place of collection (Italy and Germany, in their study).

The atmospheric stability regimes in the MCMA correspond to weakly convective conditions, very frequently throughout the year. Fig. 1 shows the mean diurnal behavior of the Monin–Obukhov length ($L$) and the stability parameter ($\lambda = u_*/L$) detected in the MCMA during 2001. These parameters were estimated from surface measurements carried out with an ultrasonic anemometer (Salcido et al., 2003).
at three urban sites in Mexico City (Texcoco, Azcapotzalco and Xochimilco). According to this Figure and the Arya definition of the stability classes (Arya, 1981), the MCMA atmospheric stability regimes in the afternoon were weakly unstable conditions on average over 2001, going from moderately unstable to near neutral unstable.

Moreover, light winds from north and northeast are observed predominantly in the MCMA during daylight hours. For the period 2001-2006, Carreón-Sierra et al. (2015) reported the general average characteristics of Mexico City winds as follows: 9% were calm, 65% light air, 52% of the wind observations, indicating a very slight predominance of winds with a westerly flow component; and the south–north wind component was negative for 66% of the observations, revealing clear predominance of winds with a northerly flow component.

In this paper, we discussed the possible influence of the wind conditions on the spread of SARS-CoV-2 in the Mexico City Metropolitan Area (MCMA) during the 2020 pandemic. The spreading patterns of the COVID-19 disease show the southwest and south MCMA sectors as the more affected from October to December 2020. In the same period 60% of the wind observations, indicating a very slight predominance of winds with a westerly flow component; and the south–north wind component was negative for 66% of the observations, revealing clear predominance of winds with a northerly flow component.

Table 1

| Name               | ID    | Entity | Population | Area [km²] | Mean Density [hab/Km²] |
|--------------------|-------|--------|------------|------------|------------------------|
| Cuauhtémoc         | 9015  | CDMX   | 548,606    | 32.5       | 16,880.2               |
| Gustavo A. Madero  | 9005  | CDMX   | 1,176,967  | 87.9       | 13,389.8               |
| Venustiano         | 9017  | CDMX   | 433,231    | 33.9       | 12,779.7               |
| Carranza           | 9002  | CDMX   | 408,441    | 33.5       | 12,192.3               |
| Miguel Hidalgo     | 9016  | CDMX   | 379,624    | 46.4       | 8,181.6                |
| Iztapalapa         | 9006  | CDMX   | 393,821    | 23.1       | 17,048.5               |
| Milpa Alta         | 9007  | CDMX   | 1,815,551  | 113.2      | 16,038.4               |
| Tlahuac            | 9011  | CDMX   | 366,586    | 85.8       | 4,272.6                |
| Xochimilco         | 9013  | CDMX   | 418,060    | 114.1      | 3,664.9                |
| Álvaro Obregón     | 9010  | CDMX   | 755,537    | 95.9       | 7,878.4                |
| Benito Juárez      | 9014  | CDMX   | 433,708    | 26.7       | 16,243.7               |
| Coyoaquán          | 9003  | EDOMEX | 621,952    | 53.9       | 11,539.0               |
| La Magdalena       | 9008  | CDMX   | 245,147    | 63.4       | 3,866.7                |
| Conterras          | 9004  | EDOMEX | 199,809    | 71.5       | 2,794.5                |
| Tláhuac            | 9012  | CDMX   | 682,234    | 314.5      | 2,169.3                |
| Tultitlán          | 15109 | EDOMEX | 556,493    | 70.8       | 7,860.1                |
| Coacalco de        | 15020 | EDOMEX | 310,743    | 35         | 8,878.4                |
| Berriozabal        | 15024 | EDOMEX | 175,004    | 40.8       | 4,289.3                |
| Cubautitlán        | 15033 | EDOMEX | 1,707,754  | 156.2      | 10,933.1               |
| Ecatepec de         | 15081 | EDOMEX | 500,585    | 156.9      | 3,190.5                |
| Morelos            | 15099 | EDOMEX | 262,015    | 428.1      | 612.0                  |
| Tecamach           | 15103 | EDOMEX | 557,108    | 92.9       | 5,996.9                |
| Zaragoza           | 15121 | EDOMEX | 577,190    | 110.1      | 5,242.4                |
| Naucalpan de        | 15057 | EDOMEX | 910,187    | 157.9      | 5,764.3                |
| Juárez             | 15060 | EDOMEX | 441,064    | 232.6      | 1,896.2                |
| Tlalnepantla de     | 15104 | EDOMEX | 756,537    | 80.4       | 9,409.7                |
| Morelos            | 15025 | EDOMEX | 397,344    | 225.2      | 1,764.4                |
| Chichinaapan        | 15029 | EDOMEX | 226,911    | 42.1       | 5,389.8                |
| Chimalhuacan        | 15031 | EDOMEX | 720,207    | 54.5       | 13,214.8               |
| Ixtapaluca          | 15039 | EDOMEX | 551,034    | 32.4       | 1,700.7                |
| La Paz             | 15070 | EDOMEX | 309,596    | 36.6       | 8,458.9                |
| Nezahualcóyotl      | 15058 | EDOMEX | 1,135,786  | 63.3       | 17,942.9               |
| Valle de Chalco     | 15122 | EDOMEX | 419,700    | 46.6       | 9,006.4                |
| Solidaridad         | 15037 | EDOMEX | 290,231    | 140.9      | 2,059.8                |

| Total              |       |        |            | 19,824,134 | 5,989.4                |

one of the largest and most rapidly growing urban agglomerations in the world (INEGI, 2020, 2018). CDMX is divided into 16 boroughs (alcaldías). The MCMA has a mean altitude of 2240 meters above sea level (masl) and is surrounded by mountains and volcanoes on three sides, with an opening to the Mexican Plateau to the north and a mountain gap to the south east. In this work, we considered a region smaller than CDMX (which, however, we will still call CDMX hereafter) that contains CDMX and the 19 nearest and next-nearest EDOMEX municipalities that surround it (Fig. 2 and Table 1). This region contains 90% of the actual MCMA population (19,824,134 inhabitants) distributed over an area of 3989 km²; so, the mean population density in the region is 4,969 inhabitants per square kilometer. In the world, some big cities with similar population density are Beijing, Madrid, Tokyo, and Buenos Aires (Global Change Data Lab, 2014). Specifically, we considered a 3000 km² rectangular domain (50 km South-North and 60 km West-East), which comprises the offices of the mayors of the CDMX boroughs and EDOMEX municipalities. This region (blue rectangle in Fig. 2) locates between the 19.173° and 19.713° North latitude and the 99.384° and 98.904° West longitude. This domain has
its center at the Cuauhtémoc borough. We divided it as a 9-cell lattice, with the cells labeled as C, NE, N, NW, W, SW, S, SE, and E. The cell label indicates the cell cardinal sector relative to the center cell (C), as illustrated in Fig. 2. The area of each cell is 335 km$^2$ approximately.

In Fig. 2, the grayed region corresponds to the boroughs of CDMX, and the rest are municipalities of EDOMEX. Table 1 lists the boroughs and municipalities, including ID, population, area, and mean population density.

Table 2 lists the MCMA lattice cells, the cell members (CDMX boroughs and EDOMEX municipalities that the cell contains), and the cell mean population density.

| Cell | Cell Members | Cell Mean Population Density [hab/Km$^2$] |
|------|--------------|------------------------------------------|
| 0 SW | 9006, 9004, 9012, 9010, 15037 | 3144 |
| 1 S  | 9009, 9013, 9007,9003, 9012, 9010 | 6065 |
| 2 SE | 9007, 9009, 9011,9013, 15025, 15122, 15059 | 7040 |
| 3 W  | 9016, 9010, 9004, 15057, 15037 | 4157 |
| 4 C  | 9015, 9017, 9002, 9006, 9014, 9005, 9016, 9007, 9010 | 11860 |
| 5 E  | 9007, 15099, 15029, 15031, 15070, 15058 | 9253 |
| 6 NW | 15013, 15121, 15060 | 3659 |
| 7 N  | 9005, 15109, 15020, 15024, 15033, 15121, 15104 | 8956 |
| 8 NE | 15033, 15081 | 4879 |

2.2. COVID-19 confirmed infected data

In Mexico, the information reported by 475 viral respiratory disease monitoring units throughout the country regarding cases associated with COVID-19 is available to the general population through an official web site (Secretaría-de-Salud, 2021).

To contain the spread of the virus in the Mexican population, the epidemiological surveillance of viral respiratory disease has been focused primarily on the immediate detection of cases that meet the operational definition of suspects (person of any age who has presented at least one of the following symptoms in the last 10 days: cough, dyspnea, fever or headache, accompanied by at least one of the following signs or symptoms: myalgia, arthralgia, odynophagia, shaking chills, chest pain, rhinorrhea, polyypnea, anosmia, dysgeusia, and conjunctivitis). A SARS CoV-2 confirmed infected was defined as a person who meets the definition of suspected and has a laboratory confirmed diagnosis by RT-PCR or a positive rapid antigenic test for SARS-CoV-2 using a certified commercial kit, or has been in close contact (within a distance < 1 m) for more than 15 continuous or accumulated minutes) with a case confirmed by laboratory or rapid antigenic test, from 2 to 14 days before the onset of symptoms (Dirección-General-de-Epidemiología, 2021).

We obtained the MCMA data of the daily confirmed infected by SARS CoV-2 in the period February-December 2020, through the website (CONACYT et al., 2020). As underlined in Salcido (2021), the fast Fourier transform of the time series of the daily number of COVID-19 confirmed infections in MCMA displays a 7-day periodicity reflecting incomplete data recording on weekend days. To address this problem, the data for these days were considered outliers and substituted using a Lagrange interpolation procedure to estimate the missing numbers. The same interpolation procedure was used for the official holidays of September 16, November 2, November 16, and December 25 of 2020, and for January 1 of 2021.

2.3. Meteorological data

In this study, we used the meteorological data (wind speed, wind direction, temperature, and relative humidity) measured at the stations of the official meteorological network (REDMET) of the MCMA. The REDMET reports hourly mean values on a public domain database (SEDEMA-CDMX, 2020). The meteorological measurements (wind speed, wind direction, temperature, and relative humidity) are performed in the REDMET according to national and international standards and guidelines. Performance audits are carried out regularly by international institutions (SEDEMA-CDMX, 2021). No atmospheric
turbulence information is available at the REDMET. Moreover, no turbulence measurements are carried out systematically in Mexico.

The REDMET has 28 stations spatially distributed over the MCMA (see Fig. 4 and Table 3). Table 3 provided the station name, ID, entity of location, altitude, and data availability for each station of REDMET. The mean altitude of the REDMET stations is 2360 m and the median altitude is 2264 m. 79% of the stations have altitudes with a mean deviation of 30 m from the median. Despite the terrain complexity, all meteorological data obtained from REDMET were assumed as measured at a representant station altitude given by the median. The measuring frequency of the meteorological variables at the REDMET stations is 0.017 Hz (one measurement per minute) and 1-hour arithmetic averages are calculated and reported. We collected the 1-hour averages of wind speed, wind direction, temperature, and relative humidity reported by each station of REDMET. The mean number of daily confirmed infected in the MCMA cells throughout 2020 and January 2021, as follows:

c = 0, 1, 2, 3, 4, 5, 6, 7, 8 = SW, S, SE, W, E, NE, N, NE.

In these equations, $u_i(t)$, $v_i(t)$, $T_i(t)$, and $\phi_i(t)$ denote the west-east and south-north wind components, temperature, and relative humidity, respectively.

We applied a cluster analysis procedure described in (Carreón-Sierra et al., 2015; Salcido et al., 2019) for organizing the set of wind observations into six clusters (wind patterns). We considered the set $S$ as the data matrix (8784 × 18), where the attributes were the wind velocity components at the nine cells of the lattice. The maximum wind speed normalized these 18 velocity components in the period. Then, we applied Ward’s algorithm of hierarchical cluster analysis (Romberg, 2004) with a Euclidean distance as a similarity criterion. We used the software Epina DataLab (Lohninger, 2021) to carry out the cluster analysis. For each wind pattern, we built the associated spatial distributions of temperature and relative humidity.

3. Results

3.1. Spreading of the COVID-19 disease in the MCMA

The mean number of daily confirmed infections (dci) at each cell of the lattice domain (Fig. 5) was estimated using the dci data reported in (CONACYT et al., 2020) for the CDMX and EDOMEX municipalities listed in Table 1. For each cell $c$ with population $P_c$ and confirmed infected $N_c(d)$ the day $d$, the mean number of daily confirmed infected every million (dcipm) inhabitants is calculated as follows

$$n_i(d) = \frac{N_i(d)}{P_i} \times 10^6 = \frac{\sum A_{ci} N_i(d)}{\sum A_{ci} P_i} \times 10^6 ,$$  

Here, $A_{ci}$ ($i = 1, 2, ..., m$) denotes the fraction of the i-member effectively contained cell c, $P_i$ denotes the population of the i-member and $N_i(d)$ represents its number of daily confirmed infected. The sums run over the number $m$ of the members that belong to cell c. We assumed that $P_i$ and $N_i$ are uniformly distributed in the region occupied by the i-member. We considered the fraction $A_{ci}$ as the quotient of the area of the
The estimations of these fractions were carried out numerically using a Monte Carlo procedure (Fishman, 1996; McCloskey and Braithwaite, 1995).

The curves reported in Fig. 5 for the COVID-19 dcipm reveal different growing trends in the different cells of the MCMA. These trends become more differentiated during the second semester of the year. In decreasing order of magnitude, we detected in this Figure that the most active infection spreading occurred in the cells SW, S, and C, followed by the cells SE, W, E, N, NE, and NW.

In Fig. 6, we presented the number of COVID-19 confirmed infected persons (every million inhabitants) at the MCMA lattice cells for the days of March 31, April 30, May 31, June 30, July 31, August 31, September 30, October 31, November 20 and 30, and December 30 of 2020, and January 19, 2021. The date is indicated under each graph as YYYYMMDD, where YYYY denotes the year, MM the month, and DD the day.

Fig. 6. Number of COVID-19 confirmed infected persons (every million inhabitants) at the MCMA lattice cells for the days of March 31, April 30, May 31, June 30, July 31, August 31, September 30, October 31, November 20 and 30, and December 30 of 2020, and January 19, 2021. The date is indicated under each graph as YYYYMMDD, where YYYY denotes the year, MM the month, and DD the day.

### Table 4
Averages of the meteorological conditions in the MCMA cells over the year 2020

| CELL  | W-E Wind Comp (m/s) | S-N Wind Comp (m/s) | Temperature (°C) | Relative Humidity (%) |
|-------|----------------------|----------------------|------------------|-----------------------|
|       | MIN      | AVG     | MAX     | MIN      | AVG     | MAX     | MIN      | AVG     | MAX     | MIN      | AVG     | MAX     |
| 0 (SW)| -4.49    | 0.15    | 4.54    | -4.94    | 0.06    | 6.91    | 2.17     | 12.99   | 25.59   | 4.17     | 60.07   | 95.08   |
| 1 (S) | -4.50    | 0.12    | 4.59    | -5.84    | 0.05    | 8.08    | 4.09     | 15.76   | 28.04   | 3.68     | 53.07   | 92.35   |
| 2 (SE)| -5.40    | 0.02    | 4.24    | -6.59    | 0.08    | 6.86    | 3.83     | 17.07   | 29.92   | 3.68     | 50.91   | 87.85   |
| 3 (W) | -4.17    | 0.27    | 4.49    | -5.20    | -0.64   | 3.52    | 2.52     | 15.75   | 29.41   | 3.49     | 55.07   | 90.36   |
| 4 (C) | -4.43    | 0.05    | 4.52    | -5.88    | -0.79   | 4.80    | 5.30     | 18.33   | 30.77   | 4.62     | 50.59   | 90.27   |
| 5 (E) | -5.38    | -0.41   | 4.12    | -7.51    | -0.29   | 7.74    | 3.33     | 18.06   | 30.23   | 5.84     | 52.17   | 90.87   |
| 6 (NW)| -3.86    | 0.36    | 4.55    | -4.84    | -1.14   | 4.38    | 1.62     | 16.04   | 30.84   | 2.72     | 56.82   | 94.73   |
| 7 (N) | -4.73    | 0.18    | 3.90    | -5.36    | -1.26   | 4.60    | 3.29     | 17.50   | 31.02   | 5.75     | 53.68   | 90.76   |
| 8 (NE)| -5.43    | 0.02    | 4.19    | -6.97    | -0.78   | 7.68    | 2.35     | 17.63   | 30.52   | 4.92     | 54.72   | 94.06   |

In Table 4, we observed that, on average over the year, the SW cell had the lowest temperature (13°C) and the highest relative humidity (60%), while cell C had the highest temperature (18°C) and the lowest temperatures. The behavior detected from October on is striking. It seems incompatible with the MCMA population density distribution (see Fig. 3). The graphs of Fig. 6 show an infection-spreading with the larger intensities at the cells SW, S, SE and C, but Fig. 3 shows the larger population densities at the cells C, N, E, and SE. It is especially striking that it was in cells SW and S where the highest values of dcipm were detected.

### 3.2. The MCMA meteorology during the 2020 pandemic

Table 4 summarizes the meteorological conditions that prevailed in the MCMA cells throughout the 2020 pandemic. Here, we included minimum, average, and maximum values of the wind components (m/s), temperature (°C), and relative humidity (%) for each lattice cell. In Fig. 7, we presented the frequency distribution of the mean wind speed in the city in 2020. In Fig. 8, we presented the frequency distributions of the wind components at the MCMA cells from January to December 2020.
relative humidity (51%). We also observed that the West-East wind component was tiny in all the MCMA cells, the South-North wind component was negligible in the SW, S, and SE cells, and reflected the predominance of northerly winds in the W, C, E, NW, N, and NE cells. In Fig. 7, we observe that weak winds prevailed in the MCMA during 2020.

Fig. 7. Frequency distribution of the MCMA mean wind speed (m/s) in 2020.

Fig. 8 shows the frequency distributions of the hourly values of the northerly and southerly wind components for the year 2020. The curves reflect a predominance of north blowing winds in the MCMA cells during the 2020 pandemic, especially in the NW, N, NE, W, C, and E cells.

On the other hand, Fig. 9 shows the clusters (or patterns) in which the wind events resulted organized by the application of the Ward algorithm of cluster analysis (Lohninger, 2021; Romesburg, 2004) to the data set given by the Equation (2) and with previous results (Carreón-Sierra et al., 2015; Salcido et al., 2019). Our physical motivation was as follows: the mean diurnal behavior of solar radiation, temperature, and wind speed at the MCMA evidences that the meteorological conditions comprised in the six local time-periods 0–4, 4–8, 8–12, 12–16, 16–20, and 20–24 h, are quite different from each other. The periods 0–4 and 20–24 h show the cooling phase of the atmosphere during the night. In the period 4–8 h, we observe the sunrise occurrence, and temperature and wind speed reach their minimum values. The period 8–12 h shows the growing phases of solar radiation, temperature, and wind speed, with solar radiation reaching its maximum. The period 12–16 h depicts the temperature reaching its maximum, while wind speed keeps growing, and solar radiation starts to decrease. Finally, the period 16–20 h shows the sunset occurrence, the wind speed reaching its maximum, and temperature decreasing.

We denoted the wind patterns as WP₁, WP₂, ..., WP₆, which we presented in the Fig. 9 as an array of graphs with 3 columns and 6 rows. Each row is associated with one of the wind patterns and contains the mean wind velocities (left column) at the cells of the MCMA, the hourly frequencies (center), and the monthly frequencies (right column) of the pattern.

For a given wind pattern WPₖ, the mean wind velocity \((u_{c_k}, v_{c_k})\) presented at a given cell \(c\) was obtained by averaging the wind velocities \((u_{ci}, v_{ci})\) at the cell over the number \(N_k\) of the wind observations contained in the wind pattern:

\[
(u_{c_k}, v_{c_k}) = \frac{1}{N_k} \sum_{i=1}^{N_k} (u_{ci}, v_{ci})
\]

The mean temperature and mean relative humidity distributions associated with a given wind pattern were obtained in a similar way. Here, we detected that the patterns WP₂ and WP₆ occurred (mainly) during the night hours and have their maximum frequencies at hour 21 (i.e., on average, over 21:00 and 22:00 LST) and hour 6, respectively. Both patterns correspond to highly convergent winds, WP₂ towards cell C and WP₆ towards cell E. These patterns represent the nocturnal downslope winds from the surrounding mountains. The pattern WP₁ represents winds blowing mainly from the south cells towards north cells of MCMA during the afternoon hours, with its maximum at hour 18. The other three patterns (WP₃, WP₄, and WP₅) are very interesting as they describe winds blowing (mainly) from north to south during the daylight hours. The patterns WP₃ and WP₄ correspond to the northerly winds of midday and midafternoon, respectively. The pattern WP₅ is associated with the trade winds from NE, which occurred mainly during the morning hours. All these patterns were already recognized by Carreón-Sierra et al., 2015.

Fig. 8. Frequency distributions of the hourly values of wind components observed at the MCMA cells during 2020.
In Table 5, we present the frequencies of the wind patterns for each season. We calculated the frequency of a pattern as the fraction of its wind events during a given period to the total data set of wind observations. Then, now we can observe that the patterns WP_3, WP_4, and WP_5, which represent the northerly winds, include 60% of the 2020 MCMA wind events, with frequencies more significant during the second semester (32%) of the year than during the first semester (28%). This observation implies that North to South is a preferred direction for the transport phenomena driven by the wind circulation. In particular, WP_5 provides a key contribution to the high ozone levels observed in the sector SW of MCMA (Peralta et al., 2021; Salcido et al., 2019, 2015; Zavala et al., 2020).

Figs. 10 and 11 show the mean temperature and the mean relative humidity distributions associated with the 2020 MCMA wind patterns.
For each cell and wind pattern, we averaged the temperature and relative humidity of the set of meteorological observations \(\{(u, v, T, \phi)\}\), where \((u, v)\) belongs to the given wind pattern, using the analogs of Equation (4) for these parameters. The distributions presented in these Figures, show that the lowest temperature and the most considerable relative humidity occurred at the cell SW for all the patterns WP\(_g\)-T and WP\(_g\)-RH (with \(g = 1, \ldots, 6\)). Otherwise, the highest temperature and lowest relative humidity were detected at the cell C. The average values over the year 2020 were presented in Table 4.

Qualitatively, the comparison of the spatial distribution of the daily confirmed COVID-19 infected persons (every million inhabitants), as illustrated by Fig. 6, and the MCMA meteorology conditions (wind circulation (Fig. 9), temperature (Fig. 10), and relative humidity (Fig. 11) patterns) suggests the existence of correlations between both phenomena. However, we know that correlation is a necessary but not a sufficient condition for causality, and we recognize that conclusive results require a more complete epidemiological basis in the analysis, where crucial information and social aspects such as mobility patterns, transport means, health resources or access to hospitals and health centers, among other factors that influence the spatial distribution of the disease, are considered. Unfortunately, no such detailed information is available in Mexico, even in the case of the MCMA. Moreover, although a dispersion modeling study would be appropriate to assess the atmospheric dispersion of the infection plume, no atmospheric turbulence or radiosonde data are available systematically in Mexico to determine the characteristic parameters, such as Monin-Obukhov length, friction velocity, roughness length, sensible heat flux and mixing height, that even in the simple models are required as input.

### 3.3. Influence of winds on the disease spreading

We carried out a more in-depth investigation of the MCMA COVID-19 infection-spreading response to the meteorological conditions, emphasizing the wind circulation.

The rate of change of the concentration of infectious aerosols in each region is basically the result of two processes: the exchange of aerosols between the region and its surroundings, and the production of the virus within the region (replication and deactivation). The main exchange processes involve, at least, person-to-person spread by physical contact, transport by mobility of infectious people, and transport by wind (advection). In this approximation, the balance equation for the virions is

\[
\frac{d}{dt} \int_R \mu dV = \int_R [\sigma + \gamma] dV - \oint_S [\Lambda + \mu v] \cdot n dA
\]

where \(\mu\) is the concentration of infectious aerosols, \(\sigma\) is the production rate of the virus (replication/deactivation), \(\gamma\) is the person-to-person infection rate by physical contact, \(\Lambda\) is the transport of the disease by mobility of infectious people, and \(\mu v\) is the transport of infectious aerosols by wind advection.

The relevance of the terms \((\sigma, \gamma, \Lambda, \mu v)\) is object of studies of the epidemiological dynamics of the SARS-CoV2 virus. In this work, we were only concerned with the assessment of the relevance of the advective transport (by the wind) of the virus. Specifically, we studied the correlation between the concentration of the virus in a region and the transport by wind of infectious aerosols into this region through its boundary. In the balance equation, the term

\[
\Phi_R = -\oint_S \mu v \cdot n dA
\]

represents the exchange of virions (by wind advection) between the region \(R\) and its immediate surroundings through the boundary surface \(S\), which implies a nearest neighbor interaction between the region and

#### Table 5
Frequencies (%) of the 2020 MCMA wind patterns.

| Season       | WP\(_1\)   | WP\(_2\)   | WP\(_3\)   | WP\(_4\)   | WP\(_5\)   | WP\(_6\)   |
|--------------|------------|------------|------------|------------|------------|------------|
| Winter (Jan-Mar) | 6.648     | 1.639     | 4.656      | 2.823      | 6.375      | 2.721      |
| Spring (Apr-Jun)  | 5.806     | 2.345     | 5.897      | 3.632      | 4.724      | 2.459      |
| Summer (Jul-Sep)   | 3.358     | 2.823     | 7.400      | 3.472      | 4.702      | 3.381      |
| Autumn (Oct-Dec)   | 3.347     | 1.947     | 7.935      | 2.801      | 5.647      | 3.461      |
| Total            | 19.160    | 8.755     | 25.888     | 12.728     | 21.448     | 12.022     |

![Fig. 10. Temperature distribution in the MCMA cells associated with the wind patterns.](image-url)
adjacent regions. This process does not assume that infectious aerosols are transported from long distances, what matters is that in the adjacent regions the infectious aerosol concentrations are positive, and the wind velocities non-zero.

We defined the mean virion concentration in a region $R$ as

$$\mu_R = \frac{1}{V} \int_R \mu dV \quad (7)$$

and the virion inward flux to this region as

$$\Phi^+_R = -\oint_S \left[ 1 - H(v_n) \right] \mu_v dA \quad (8)$$

where $v_n = v \cdot n$, and $H(x)$ is the Heaviside function

$$H(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (9)$$

Then, under this framework, we investigated the correlation between the mean virion concentration in a region $R$ and the virion inward flux to $R$, that is, $\langle \mu_R \| \Phi^+_R \rangle$.

From an operational standpoint, we divided the MCMA region in a number $N$ of regular cells identified as $(i, j)$ with $i, j = 1, 2 \ldots N$. At each cell, the mean virion concentration $\overline{\mu}(i, j)$ was assumed proportional to the dcipm (mean number of daily confirmed infected every million inhabitants), and the components of the virion flow vector $j = \mu v$ were estimated as

$$j_{WE}(i, j) = \overline{\mu}(i, j) u(i, j), \ j_{SN}(i, j) = \overline{\mu}(i, j) v(i, j) \quad (10)$$

where $(u, v)$ denotes the mean wind velocity components at the cell. Then, the inward flux to cell $(i, j)$ was estimated as (see Fig. 12)

$$\Phi(i, j) = j_{WE}(i-1, j)[1 - H(j_{WE}(i-1, j))] + j_{WE}(i+1, j)[1 - H(j_{WE}(i+1, j))] + j_{SN}(i, j-1)[1 - H(j_{SN}(i, j-1))] + j_{SN}(i, j+1)[1 - H(j_{SN}(i, j+1))]$$

or, equivalently,

$$\Phi(i, j) = |j_{WE}^>(i-1, j)| + |j_{WE}^<(i+1, j)| + |j_{SN}^>(i, j-1)| + |j_{SN}^<(i, j+1)| \quad (12)$$

Here, the super-index $>0 (<0)$ indicates a positive (negative) flux component.

We underline that $\Phi(i, j)$ is not defined in terms of the concentration in the cell $(i, j)$, but in terms of the products of the concentrations and...
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## 4. Discussions

The compartmental epidemiological models, such as SIR, SEIR, and extensions, consider the time-rate of the number of infected (I) persons proportional to the number of susceptible (S) individuals or proportional to the number of exposed people (E), which has a time-rate proportional to the number of susceptible (Godfrey, 1983; Kermack and McKendrick, 1991, 1927). Therefore, during the MCMA 2020 pandemic, we would expect, in principle, to see a greater number of infected people in regions with higher population densities than in regions with lower population densities. However, a comparison of Figs. 6 and 3 shows that the infection’s intensity was smaller in the cells N and E (with higher population densities) than in the SW and S cells (with lower population densities).

Moreover, the graphs of Fig. 6 reveal a COVID-19 infection-spread with a striking behavior that seems to reflect a preferred propagation direction towards the SW cell. However, the compartmental epidemiological models cannot explain this behavior because it could be due to driving factors that these models do not consider, such as the people mobility in the MCMA and, possibly, the wind circulation in the region. To our knowledge, no database of detailed people-mobility data is available for the MCMA, neither other crucial information on population data (mobility patterns, transport means, health resources or access to hospitals and health centers) that could influence the spatial distribution of the disease. Therefore, in this work, we did not assess their contributions to the striking asymmetric spatial distribution of the COVID-19 confirmed infected.

Nevertheless, for meteorology and air quality, the MCMA has an excellent and reliable historical database with hourly data for more than 30 years. The official meteorological network (REDMET) consists of almost 30 stations spatially distributed over the MCMA (Table 3 and Fig. 4) where reliable measurements of wind speed, wind direction, temperature, and relative humidity are performed systematically. Unfortunately, no measurements of atmospheric turbulence are carried out in the REDMET. The data availability of REDMET allowed us to carry out a meteorological analysis of the 2020 year to identify the main (near surface) wind circulation patterns in the region. Among these patterns, we recognized WP<sub>3</sub>, WP<sub>2</sub>, and WP<sub>1</sub>, which show that 60% of the 2020 meteorological events were associated with winds with a considerable velocity component from north to south. Interestingly, these three patterns had larger frequencies during the second semester (32%) of the year than during the first semester (28%).

COVID-19 pandemic gained strength in MCMA from October to December, and the dcipm increased from almost 150 to 442, 634, and 538 in the C, SW, and S cells. It is striking because the C, SW, and S cells constitute the most polluted part of the MCMA, especially for the largest ozone surface concentrations (Peralta et al., 2021; Salcido et al., 2019; Zavala et al., 2020). The researchers frequently associate this phenomenon with the MCMA wind circulation.

Interestingly, the cell (SW) with the largest infection spreading was also the MCMA cell with the lowest temperature (13°C) and the highest (but moderate) relative humidity (60%) during the 2020 pandemic. These conditions are considered favorable for SARS-CoV-2 stability and velocities in the nearest neighbor cells that have a component pointing toward cell (i, j). Then, it is clear that the inward flux Φ(i,j) is not proportional to the concentration p(i,j), and that a correlation (p(i,j)/Φ(i,j)) ≠ 0 is not obvious.

Specifically, we calculated the Pearson correlation coefficients among the dcipm time series and each time series of the daily averages (calculated over the sunlight hours) of temperature, relative humidity, and inward flux. To carry out the estimations, we assumed p proportional to the dcipm at each cell: 

$$\mu = k \cdot \text{dcipm}.$$ 

The value of k is assumed to be constant and therefore is not relevant for the calculation of the correlation coefficients.

In Table 6, we summarized the results obtained for the Pearson correlation coefficients. In this Table we denoted by DCI[c] the dcipm time series given by Equation (3) for the cells c = 0, 1, ..., 8.

Table 6 exhibits a moderated negative correlation of the dcipm with temperature (-0.50, on average), a small negative correlation with relative humidity, and a moderate positive correlation (0.62, on average) with the inward flux.

Finally, for assessing the response of the dcipm to the temperature, relative humidity, and inward flux, we performed a multilinear regression (MLR) procedure with

$$\text{MLR}(c,t,k) = A_0(c) + A_1 T(c,t) + A_2 \Phi(c,t) + A_3 \frac{1}{k} \text{dcipm}(c,t),$$

(13)

where, A<sub>0</sub>, A<sub>1</sub>, A<sub>2</sub>, and A<sub>3</sub> are constants determined by the MLR procedure for given k. In Table 7, we summarized the results for k = 1, including the determination coefficients R<sup>2</sup> and F-statistic. Here, we denoted by MLR[c] the time series given by Equation (13).

In Fig. 13, we presented comparisons between the MLR estimates (labeled as MLR) and the dcipm registered at the MCMA cells (labeled as DCI) during the 2020 pandemic. This Figure also included comparisons between the cumulative infections (labeled as CCI) and their MLR estimations (labeled as CMLR).

On average, the coefficient of determination between the number of daily infections and the estimations made with the MLR model was 0.545 (Table 7). For the cells SW, S, and C, we detected the most considerable values of R<sup>2</sup> and F-statistic. We noticed the smallest value at the cell NW.

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### Table 7

| MLR estimation of dcipm | A₀ | A₁ | A₂ | A₃ | R² | F-statistic | p-value |
|------------------------|----|----|----|----|----|-------------|---------|
| MLR[0]                 | 1105.83 | -47.78 | -3.56 | 0.4155 | 0.631 | 155 | < 10⁻⁶ |
| MLR[1]                 | 1103.49 | -41.55 | -4.00 | 0.2816 | 0.649 | 167 |        |
| MLR[2]                 | 510.95 | -17.23 | -2.26 | 0.383 | 0.494 | 88 |        |
| MLR[3]                 | 361.30 | -12.40 | -1.20 | 0.151 | 0.545 | 108 |        |
| MLR[4]                 | 1093.21 | -36.30 | -4.66 | 0.334 | 0.631 | 155 |        |
| MLR[5]                 | 241.68 | -7.34 | -1.07 | 0.214 | 0.489 | 86 |        |
| MLR[6]                 | 99.29 | -2.79 | -0.384 | 0.306 | 0.436 | 79 |        |
| MLR[7]                 | 213.25 | -6.81 | -0.846 | 0.350 | 0.572 | 121 |        |
| MLR[8]                 | 121.93 | -3.57 | -0.401 | 0.321 | 0.458 | 76 |        |
Fig. 13. Comparison of the daily (left) and cumulative (right) confirmed infected against the corresponding estimations using multilinear regression.
replication (Aboubakr et al., 2020; Auler et al., 2020; Mecenas et al., 2020). The existing scientific evidence indicates that warm and wet climates seem to reduce the spread of COVID-19, but these variables alone are not enough to explain most disease transmission variability. Although most studies acknowledge that factors like population susceptibility, behavior, and public health intervention are the primary influence on the infection spreading, many others found an association between factors like temperature, humidity, and air pollution (Mecenas et al., 2020).

Moreover, since viruses may be adsorbed through coagulation onto PM and can remain airborne for hours or days (Martelletti and Martelletti, 2020), PM can provide a platform to carry the SARS-CoV-2 during atmospheric processes of transport and dispersion. Then, PM containing SARS-CoV-2 can be a direct transmission model in a highly polluted area (Tung et al., 2021), as it was the case in northern Italy. Findings of Setti et al., 2020). The existing scientific evidence indicates that warm and wet conditions allow the survival and replicative potential of the SARS-CoV-2 in different environments (Setti et al., 2020).

MCMA is also a highly polluted area, with high concentrations of PM$_{10}$ and PM$_{2.5}$ for the period 2001-2010, important PM$_{10}$ flow patterns were detected in Mexico City, exhibiting flow vectors with intense northerly components, which convey PM$_{10}$ towards the south-west and south of the city (Salcido et al., 2019).

On the other hand, measurements carried out with ultrasonic anemometers at three urban sites of the MCMA throughout 2001 (Salcido et al., 2003), which allowed to estimate the Monin-Obukhov length and the Arya stability parameter (see Fig. 1), show that weakly convective conditions frequently prevail on average in MCMA. These atmospheric stability conditions and the persistence of weak winds in the MCMA during 2020 (Fig. 7), according to the simulations of Bhagnagar and Bhimireddy (Bhagnagar and Bhimireddy, 2020) the possibility of long-range airborne transmission of the SARS-CoV-2 by wind advection.

For assessing the response of the daily confirmed infected to the temperature, relative humidity, and inward flux in the MCMA, we carried out an estimation of the Pearson correlation coefficients between the time series of the dcipm and the meteorological parameters’ time series. On average, we found a moderated negative correlation of -0.50 for the dcipm with temperature and a moderate positive correlation of 0.62 with the inward flux. A negligible negative correlation of -0.04 with relative humidity was observed. A multilinear regression of dcipm as a function of temperature, relative humidity, and inward flux produced a coefficient of determination (R$^2$) of 0.545 and F-statistic of 114 (p-value $< 10^{-40}$), on average.

5. Conclusions

The possibility that the infectious aerosol plumes raise heights beyond the canopy layer or the surface layer, reaching the mixed layer under unstable conditions, depends on the size of the aerosols (Finlayson-Pitts and James N. Pitts, 2000) and the time the viruses can remain active outdoor, both of which are topics that remain under discussion by the scientific community. Even so, because of its implications for the public health derived from controlling the COVID-19 disease pandemic, the assessment of the meteorology scenarios that could favor the spread of the COVID-19 disease in a megacity like MCMA stays up essential. In a megacity like the MCMA, with numerous elevated buildings and highways, the infected cough-jets may constitute plumes of infected viral aerosols released in the atmosphere at different heights more extensive than the average human height. These infectious plumes, creating clusters with outdoor PM$_{10}$ and PM$_{2.5}$, and in the presence of some other phenomena such as resuspension and vertical dispersion, make highly plausible that the winds transport the virus over long distances.

We discussed, in this work, the influence of the wind conditions on the spread of SARS-CoV-2 in the Mexico City Metropolitan Area during the 2020 pandemic. We observed that the spreading patterns of the COVID-19 disease from October to December 2020 show the southwest and south as the more affected sectors of MCMA. In the same period 60% of the winds in this region had considerable northerly components. These observations suggested the existence of correlations between both phenomena. Our suspicion became stronger by the frequent occurrence of weakly unstable atmospheric conditions in the MCMA, and by the predominance of weak winds revealed by the mean wind speed frequency distribution in 2020. Using meteorology data and daily numbers of COVID-19 infections obtained from official public domain sources, we carried out an assessment of the correlation between the spatial distribution of the infected people and the virions flux by wind advection. On average, we found a moderated negative correlation of -0.50 for the dcipm with temperature and a moderate positive correlation of 0.62 with the inward flux.

We believe that our results suggest the convenience of conducting a more in-depth investigation of the MCMA COVID-19 infection-spreading response to the meteorological conditions, emphasizing the wind circulation and atmospheric stability conditions.

CRediT authorship contribution statement

Alejandro Salcido: Conceptualization, Methodology, Data curation, Software, Formal analysis, Investigation, Supervision, Writing – original draft, Writing – review & editing. Telma Castro: Formal analysis, Investigation, Writing – original draft, Writing – review & editing.

Declaration of Competing interest

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

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