Probable Relationship between COVID-19, Pollutants and Meteorology: A Case Study at Santiago, Chile

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Special Issue:

Special Issue on COVID-19 Aerosol Drivers, Impacts and Mitigation (XIII)

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ABSTRACT

We present here a study about the possible spread of covid-19 pandemic between human's beings through aerosols contained in urban air polluted by respirable particulate matter and tropospheric ozone, as well as the incidence of local meteorology in an area with orographic basin characteristics and in a certain period of time. Hourly time-series data of three meteorological variables—temperature, relative humidity, wind speed—and three pollutants—PM₁₀, PM_{2.5} and O₃—were considered together with hourly data from the highest number accumulated sick's in seven communes—chosen at random—in Santiago, Chile, studying a probable link between them. From the epidemic perspective, the infected patients number was linked to the hourly time-series of meteorological and pollutant variables, generating new time-series. Nonlinear analysis and the chaos theory formalism was applied to these new time-series, obtaining the largest Lyapunov exponent, correlation dimension, Kolmogorov entropy, Hurst exponent and the Lempel-Ziv complexity. Our preliminary results show meteorological and air pollution variables can be part of the elements fraction that give sustainability to the accumulated growth of infected patients and favor the pandemic spread, making the accumulated sick's curve chaotic and complex. In addition, environmental pollution could worsen disease conditions like coronavirus (*COVID-19*) infection. For all time-series, the Lempel-Ziv complexity turned out to be between 0 and 1 which is indicative of connectivity and chaos. The largest Lyapunov exponent as well as the Kolmogorov entropy were positive which also exhibits chaos. The Hurst exponent was found to be greater than 0.5 and less than 1 for all time-series, indicating positive long-term autocorrelation. Finally, the correlation dimension was less than 5, revealing that new time-series constructed are not random.

Keywords: Coronavirus, Air pollution, Entropy, Chaos, SARS-CoV-2

OPEN ACCESS

Received: July 23, 2020

Revised: December 9, 2020

Accepted: January 14, 2021

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Publisher:

Taiwan Association for Aerosol Research

ISSN: 1680-8584 print

ISSN: 2071-1409 online

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1 INTRODUCTION

1.1 Coronavirus-types

The current pandemic that is ravaging the planet (COVID-19) is a variant of coronavirus with a RNA envelope that causes respiratory diseases of varying severity, from the common cold to fatal pneumonia. Various coronaviruses, such as the one discovered in the 1930s in poultry, caused respiratory, gastrointestinal, liver and neurological diseases in animals. Only 7 disease-causing coronaviruses are known in human beings. Most time, 4 of the 7 coronaviruses cause symptoms of the common cold. Types 229E and OC43 are responsible for the common cold; Serotypes NL63 and HUK1 were discovered, which were also associated with the common cold. Rarely, serious respiratory tract infections, including pneumonia, can occur, especially in infants, the elderly,

and immunocompromised persons. Three of the 7 coronaviruses cause respiratory infections in humans much more severe and even more fatal than the other coronaviruses and are the cause of pneumonia major outbreaks, fatal to humans, in the 21st century (Wilks *et al.*, 2003).

SARS-CoV was identified in 2002 as the cause of major severe acute respiratory syndrome outbreaks (SARS). MERS-CoV was identified in 2012 as the cause of Middle East respiratory syndrome (MERS). SARS-CoV-2 is a new coronavirus identified as the cause of 2019 coronavirus disease (COVID-19) that started in Wuhan, China in late 2019 and has spread throughout the world. These coronaviruses, which cause severe respiratory infections, are zoonotic pathogens, which start in infected animals and spread from animals to people. COVID-19 is an acute, sometimes severe, respiratory disease caused by a novel SARS-CoV-2 coronavirus (CDC, 2020b). The transmission mechanism is still being investigated, and to date it is observed that it is equivalent to influenza (Xu *et al.*, 2020), although it seems more transmissible than SARS.

Situations with a high risk of transmission include institutions such as nursing homes, long-term care centers, prisons, boats and, in general, where many people are concentrated. These situations involve high population density and often lead to difficulties in maintaining safety precautions. Through quarantine and isolation measures, attempts are made to limit the local, regional and global spread of this outbreak. Strict compliance with these measures has given satisfactory results in controlling the infection spread, in selected areas, in countries that have followed the suggestions and warnings given by the WHO (maintain social distance, wear face masks or masks and handwashing). SARS is much more severe than other coronavirus infections, and includes surfaces. Tests on stainless steel and plastic showed that a percentage of the virus survived and retained its infectious capacity for up to three days. These findings suggest that the virus could remain this amount of time on laminated or laminated door handles, countertops (or seats) and other hard surfaces (Kampf *et al.*, 2020). SARS is a flu-like illness that sometimes culminates in severe progressive respiratory failure (CDC, 2020a, b; JHMI, 2020).

1.2 PM_{2.5} and PM₁₀ Particulate Matter

Particulate matter is found in dust, ash, soot, metal particles, cement, or pollen. Other sources are coal industrial and domestic combustion from industrial processes fires, wind erosion and volcanic eruptions, buildings, demolitions and so on (Zereini and Wiseman, 2010; Fuzzi *et al.*, 2015; Đorđević *et al.*, 2020). The main effects on human health range from irritation to the respiratory tract, deposition in the lungs causing diseases such as silicosis and asbestosis, as well as worsening asthma and cardiovascular disease (Fishman and Crutzen, 1978; Schwartz *et al.*, 2002; Cakman *et al.*, 2007; Brook *et al.*, 2010; Cassee *et al.*, 2011; Lee *et al.*, 2014). All kinds of surfaces (houses, public sculptures, etc.) also experience deterioration. They affect vegetation by interfering with photosynthesis. In the environment, they decrease visibility and induce cloud formation (Iwasaka *et al.*, 1983). Its effects are also manifested in height (Salini and Medina, 2017), as well as in medium-sized cities (Salini, 2018).

The World Health Organization (WHO, 2013) recommends as a limit for coarse particulate matter (PM₁₀) 20 $\mu\text{g m}^{-3}$, for annual average; and 50 $\mu\text{g m}^{-3}$ for average in 24 h. For fine particulate matter (PM_{2.5}), 10 $\mu\text{g m}^{-3}$ of annual average, and 25 $\mu\text{g m}^{-3}$ for average in 24 h.

1.3 Tropospheric Ozone (O₃)

This is a powerful oxidant that produces adverse effects on human health (Walker, 1978; Grewe, 2006; Saliba and Massoud, 2011). Short-term studies show that O₃ concentrations (especially in the summer) have adverse effects on respiratory function, causing lung inflammation, respiratory failure, asthma, and other bronchopulmonary diseases. Several European investigations have shown that daily mortality rises with increasing exposure to ozone. There is also new evidence linking long-term exposure to ozone with greater effects than previously thought in terms of impaired reproductive health and mortality. Since 2005, several cohort analyzes have been published on long-term ozone exposure and respiratory mortality. Furthermore, there is evidence in cohort and mortality studies among people with previous diseases (chronic obstructive pulmonary disease (COPD) or chronic obstructive pulmonary disease (COPD), diabetes, heart failure, heart attack, etc.). In addition to its impacts on human health, vegetation and crops, ozone is currently considered the third most important greenhouse gas (after carbon dioxide and

methane). According to the WHO (2006, 2013), the eight daily average hours of concentration for tropospheric ozone is $100 \mu\text{g m}^{-3}$ (51 ppb).

2 METHODOLOGY

2.1 The Data

The data from seven PM₁₀/PM_{2.5} and tropospheric ozone (O₃) monitoring station in Santiago is analyzed in this study, where their locations are shown in Fig. 1 and they report 1-hour averages. Meteorological data like temperature (T), wind speed (VV), and relative humidity (HR) are also measured in these stations. The data were obtained from National Air Quality Information System (SINCA in Spanish, dependent on MMA). These data make up time series for 2.5 months (March 30–June 15). Accumulated sick's data were obtained from Chile's Health Ministry (MINSAL), which summarizes Table 1 and shows the communes present on study with their inhabitants (Census, 2017).

Three pollutants selection—especially O₃—is based on the fact that they have an adverse effect on the human being's respiratory tract, generating a picture of pre-existing diseases before the pandemic advent. There is a connected urban meteorology that arises from urban heat islands and urban canyons, apart from the basin geography of the area. A large number of local climatic zones are present depending on the size and city complexity; thus, sectors can be recognized according to their predominant socio-ecological characteristics. These sectors make up socio-climates or socially constructed climates based on the socioeconomic levels of their inhabitants

Fig. 1. Map of Metropolitan Area of Santiago, Chile.

Table 1. Study communes and inhabitants (Census, 2017).

Commune	Population (2017)	Accumulated sick's by study communes (2020)
Santiago	404 495	9412
Independencia	100 281	4300
Las Condes	294 838	3623
Puente Alto	568 106	12212
El Bosque	162 505	3176
La Florida	366 916	7633
Pudahuel	230 293	4848
Total	2127434	451196

and can be highly connected to indoor and /or outdoor, which favors the disease spread (Byass, 2020).

2.2 Meteorological Variables

In this study, nonlinear time series analysis tools were applied to local meteorological variables, such as temperature (T), relative humidity (RH) and wind speed magnitude (WS). These parameters vary both spatially and temporally, allowing the description of various atmospheric and thermodynamic processes associated with it (Iqbal, 2020).

In the case of the Metropolitan Region (MR) communes from Santiago city, there is also an orographic influence due to the area geographical basin nature, see Fig. 2. At the 2017 census, the Metropolitan Region had 7,037,000 inhabitants, the population of these seven selected communes represents approximately 30% of the entire population (by 2020, Metropolitan Region inhabitant's projection is 7,987,723 inhabitants). Column 3 of Table 1 shows the population infected amount with COVID-19 for the period under study.

2.3 Irreversible Processes

From a historical point of view, thermodynamics has focused on the study of equilibrium processes in which determinism works correctly. Reversibility and order define these processes. However, Prigogine observes that far from the equilibrium situation, new types of structures appear spontaneously (Eckert *et al.*, 1998). Out of the chaos, ordered structures arise that require a contribution of energy to conserve themselves, but do not maintain linear relationships, and cannot be predicted precisely due to their non-linear nature. Close to the point where dissipative

Fig. 2. Communal map of the Metropolitan Area and its thermal island (winter) with directions of temperature flow. Landsat 8 Image. 2015–2018 Images. Bands 4.5 and 10. (<https://earthexplorer.usgs.gov/>)

Fig. 3. Dynamics of dissipative structures (Manríquez, 1987).

structures are organized, large fluctuations are observed. Instead of being damped, they can spread throughout the system, leading to new situations that are qualitatively very different from those that are close to equilibrium. Thermodynamics shows how systems capable of moving away from determinism have to be placed far from equilibrium. We must distinguish between equilibrium conditions, non-equilibrium conditions, a process that leads from one to another and a threshold that separates them both. This situation is shown in Fig. 3, whose interpretation is the following: at the beginning, there are equilibrium conditions—whatever they are—in which fluctuations occur with respect to these conditions, attenuating with time. If energy is added to the system, the fluctuations begin to increase. However, the system still manages to dampen them. Until a certain instant is reached when a certain threshold, U , is exceeded. In this case, the fluctuations are no longer dampened, stabilizing in a state far from the equilibrium that it originally possessed but equally stable, while energy continues entering to the system. At this point, the system has formed a dissipative structure (Manríquez, 1987).

2.4 Nonlinear Time Series Analysis and Chaos Theory

Chaos theory is applied to the indicated data in order to analyze the possible relationships between them and their connection with general thermodynamic properties, such as entropy (Pacheco *et al.*, 2019). The Lyapunov exponent (λ) is defined as (Hilborn, 2000):

$$\lambda = \frac{1}{n} \ln \frac{d_N}{d_0} \quad (1)$$

where N is the iterations number. That is, if two points of an orbit are very close initially, this exponent for large N is calculated. If the points are separated after N iterations, there will be a possible chaos indication in that system. A positive value of the maximum Lyapunov exponent is chaos indication (Sprott, 2003). For a given time-series, the sum of all positive Lyapunov exponents defines its S_K entropy and its reciprocal the mean predictability time, (Salini and Pérez, 2015; Chen *et al.*, 2017):

$$T_p = \frac{1}{S_K} \quad (2)$$

In practice, the Lyapunov exponent is obtained from this equation at the large N limit, for which saturation is evident. For the same reason, and due to stability conditions in its calculation, ideally over 5,000 data should be kept and the largest Lyapunov exponents for all-time-series are calculated using the algorithm proposed by Wolf *et al.* (1985).

On the other hand, correlation entropy (Sprott, 2003) is defined as:

$$K_2 = \lim_{m \rightarrow \infty} \lim_{T \rightarrow \infty} \lim_{N \rightarrow \infty} \log \frac{C(m, r)}{C(m+1, r)} \sim S_K \quad (3)$$

where S_K is the Kolmogorov entropy; $C(m, r)$ is the correlation integral of the reconstructed trajectory of a time series; m is the embedding dimension and r is the circle radius whose center

is on an object that is discrete points made up (in dimensions greater than two, the circles become-hyperspheres). K_2 is zero, positive, or infinity for regular, chaotic, or random data, respectively. A method to estimate K_2 for experimental data is based on Grassberger and Procaccia (1983). These relationships are part of the numerical calculation procedure applied to each time-series (both pollutants and meteorological variables), each of 1,872 data, since they do not present missing data.

The Hurst exponent is a measure of the degree to which the data can be represented by a random walk. Here, the root-mean-square displacement is calculated as a time function, where each point in the time-series is taken as an initial condition. The curve slope obtained is the Hurst exponent. For ordinary Brownian motion the exponent is 0.5. Values between 0.5 and 1 indicate deterministic behavior and persistence. Hurst exponent significantly less than 0.5 is typical for deterministic behavior and anti-persistence (Kantz and Schreiber, 2005).

If the COVID-19 pandemic enters the human organism through the respiratory tract, then a connected urban meteorology that promotes sustainability and the pollutants diffusion makes its actions more effective, favoring the infection, cultivation and spread of diseases. To demonstrate this hypothesis, chaos theory is applied, considering the system as a dissipative structure. Virus effect is quantified from the patients accumulated over time together with meteorological variables and pollutants through the entropy that indicates diffusive capacity. Entropy also accounts for the natural evolution of the system towards states of higher probability.

3 RESULTS AND DISCUSSION

The time-series chaotic analysis was carried out using the Chaos Data Analyzer software (CDA, Sprott, 1995). The parameters that were studied were the Lyapunov exponent (λ), Correlation Dimension (Dc), Correlation entropy (SK), Hurst (H) exponent. These indices confirmed the chaotic nature of the six-time-series belonging to each of the seven communes under study. With these same time-series, the new hourly ratios were constructed: $X = AS/T$; $Y = AS/WS$; $Z = AS/RH$; $W = AS/PM_{10}$; $U = AS/PM_{2.5}$ and $V = AS/O_3$. A new time-series family (42 in total) was originated, each one with 1,872 hourly data. AS is for the accumulated sick's per hour, and for each commune (data extracted from MINSAL). This process can be interpreted as a "transfer" of chaos—or entropy—from the meteorological and polluting variables to the accumulated sick's curve according to each commune. These new series are processed through the same software, with a total of 78624 data, all of which are chaotic, confirming the hypothesis of this research that meteorology and pollutants can dissipate a pandemic, increasing its complexity. The Iterated Function Systems (IFS) fragmentation test also suggests an analysis method of the data under study. The symbolic dynamics use (Horna *et al*, 2016) allows calculating the Lempel-Ziv (LZ) complexity relative to white noise. When the data is chaotic they are distributed forming, on a surface, localized groups. It is true for the 42 series since $0 < LZ < 1$, for chaotic data, which is shown in Table 2.

According to the data on period studied—and showed at Table 2—, the Hurst's exponent for each time-series is persistent ($0.5 < H < 1.0$). This is interpreted as "the following results strongly depend on the previous ones within a certain time period" having less entropy or predisposition to disorder and staying in time. For each commune, there is a decline in entropy as persistence increases, which favors the virus spread within each social urban "island". As the time-series under study—according to communes—, arise from the quotient between hourly accumulated sick's, with meteorological variables and hourly pollutants, it is shown that this relationship strengthens them and gives them strength supporting the study hypothesis: the meteorological variables and pollutants can form part of the elements fraction giving sustainability to the accumulated growth of the patients infected and the pandemic spread. This is shown in Fig. 4. The entropy growth is accompanied, with an asymptotic tendency, by growth of persistence loss, represented in Fig. 5 (both figures referred to Table 2).

From Table 3, (columns 5 and 6) and Table 4 (columns 6 and 7) it is observed that the environmental entropies (meteorological variables) are less than the anthropic ones (tropospheric pollutants), generating a mechanism of high connectivity that cooperates in the spread and pandemic persistence (Figs. 4 and 5).

Fig. 6 reveals that the entropy contribution from meteorological variables could cooperate in disease spread, of the characteristics of COVID-19, promoting the increase in infected rate.

Fig. 7 indicates that the pollutants entropy emitted into the atmosphere can act cooperatively with meteorological variables, further increasing the sustainability and spread of a virus, accentuating the trend of Fig. 6.

Table 2. Chaotic indicators (by commune) for the time series under study.

Communes	λ [bits/h]	D_c	S_k [bits/h]	H	LZ
Las Condes (LC)					
X	0.675 ± 0.061	1.626 ± 0.306	0.294	0.8980994	0.01585
Y	0.317 ± 0.055	4.166 ± 0.545	0.330	0.8320369	0.51153
Z	0.131 ± 0.036	3.480 ± 0.616	0.254	0.8699403	0.42337
W	0.786 ± 0.064	1.669 ± 0.545	0.564	0.8443708	0.48764
U	0.378 ± 0.063	1.462 ± 0.037	0.272	0.7711021	0.67889
V	0.396 ± 0.074	1.440 ± 0.053	0.640	0.7754118	0.73784
Santiago (SANT)					
X	0.558 ± 0.056	1.768 ± 0.185	0.389	0.8923760	0.01585
Y	0.073 ± 0.054	2.960 ± 0.558	0.505	0.6921257	0.51612
Z	0.241 ± 0.048	3.616 ± 0.662	0.240	0.8567320	0.38544
W	0.691 ± 0.058	2.353 ± 0.407	0.518	0.8544294	0.46023
U	0.319 ± 0.061	2.046 ± 0.419	0.534	0.7858549	0.63312
V	0.288 ± 0.067	1.353 ± 0.545	0.458	0.7661108	0.69328
Independencia (IND)					
X	0.500 ± 0.056	1.630 ± 0.206	0.378	0.8917318	0.01902
Y	0.198 ± 0.063	3.772 ± 1.026	0.443	0.7387629	0.39725
Z	0.272 ± 0.046	4.348 ± 0.962	0.155	0.8550301	0.28933
W	0.770 ± 0.060	1.713 ± 0.107	0.543	0.8635525	0.35081
U	0.640 ± 0.071	1.451 ± 0.664	0.480	0.8446618	0.57034
V	0.424 ± 0.081	1.260 ± 0.711	0.386	0.8192579	0.70688
La Florida (LF)					
X	0.536 ± 0.052	1.740 ± 0.188	0.354	0.8969514	0.02536
Y	0.196 ± 0.055	3.485 ± 0.423	0.377	0.7752033	0.46990
Z	0.198 ± 0.046	3.397 ± 0.593	0.244	0.8350216	0.39771
W	0.840 ± 0.059	2.278 ± 0.260	0.316	0.8521985	0.48625
U	0.546 ± 0.071	3.291 ± 0.051	0.440	0.8307689	0.70660
V	0.380 ± 0.078	2.081 ± 0.070	0.518	0.8031664	0.71715
Puente Alto (PA)					
X	0.560 ± 0.056	1.786 ± 0.186	0.384	0.8908278	0.02536
Y	0.194 ± 0.056	3.379 ± 0.880	0.414	0.8017714	0.42913
Z	0.174 ± 0.042	3.958 ± 0.764	0.251	0.8972083	0.31780
W	0.666 ± 0.061	2.356 ± 0.152	0.477	0.8486598	0.48340
U	0.387 ± 0.068	2.078 ± 0.520	0.353	0.8243979	0.65894
V	0.440 ± 0.076	1.496 ± 0.204	0.469	0.7889941	0.73108
El Bosque (EB)					
X	0.639 ± 0.057	1.739 ± 0.208	0.315	0.8943638	0.01585
Y	0.157 ± 0.053	3.347 ± 0.758	0.413	0.6864654	0.42515
Z	0.206 ± 0.042	3.697 ± 0.677	0.230	0.8456352	0.27907
W	0.960 ± 0.059	1.719 ± 0.212	0.487	0.8590738	0.33455
U	0.810 ± 0.070	1.646 ± 0.223	0.414	0.8304427	0.50682
V	0.358 ± 0.089	1.106 ± 0.168	0.385	0.7820740	0.64869
Pudahuel(P)					
X	0.582 ± 0.055	1.719 ± 0.264	0.306	0.8980994	0.02853
Y	0.237 ± 0.059	3.181 ± 0.595	0.508	0.7464291	0.43271
Z	0.240 ± 0.047	3.579 ± 0.542	0.254	0.8414325	0.34681
W	0.919 ± 0.062	1.533 ± 0.262	0.403	0.8616340	0.32561
U	0.067 ± 0.061	1.722 ± 0.307	0.283	0.8412599	0.26013
V	0.560 ± 0.090	2.541 ± 0.250	0.474	0.8060385	0.70741

Fig. 4. Total entropies by commune versus persistence. The symbology of localities according to the series of data representation is indicated in Table 2.

Fig. 5. Total entropies by commune versus Persistence loss percentage.

Table 3. Summary of the sum of entropies (S_k) X, Y and Z by commune ordered from highest to lowest according to entropy with accumulated sick's of the period under study.

Commune	S_{XYZ} [bits/h]	AS*
Santiago	1.134	9412
Pudahuel	1.068	4840
Puente Alto	1.049	12212
Independencia	0.976	4300
La Florida	0.975	7633
El Bosque	0.958	3176
Las Condes	0.878	3623

* The third column is the number of sick accumulated by commune (From MINSAL (2020)). AS is for accumulated sick's.

Table 4. Entropies of $S_{K.W}$, $S_{K.U}$ and $S_{K.V}$ and their sum by commune. (The seventh column is the accumulated number of sick by commune for the study period).

	Commune	$S_{K.W}$ [bits/h]	$S_{K.U}$ [bits/h]	$S_{K.V}$ [bits/h]	$S_{K.W} + S_{K.U} + S_{K.V}$ [bits/h]	AS
1	Santiago	0.518	0.534	0.458	1.510	9412
2	Pudahuel	0.403	0.283	0.474	1.160	4840
3	Puente Alto	0.477	0.353	0.469	1.300	12212
4	Independencia	0.543	0.480	0.386	1.409	4300
5	La Florida	0.316	0.440	0.518	1.274	7633
6	El Bosque	0.487	0.414	0.385	1.286	3176
7	Las Condes	0.564	0.272	0.640	1.476	3623

Fig. 6. Growth of sick accumulated by commune (in the study period) versus total entropy that adds the effect on sick accumulated by hour and by commune, of each hourly meteorological variable of the study.

A possible interpretation of Figs. 6 and 7 is as follows. Entropy can be considered as a random distribution measure for a system (consisting of time-series for each of the system representative variables: pollutants, meteorological variables and accumulated sick's). According to thermodynamics, the randomness degree or disorder in a system is called entropy. This is because a system in an unlikely condition will naturally tend to reorganize into a more likely condition. This reorganization will give rise to entropy increase, reaching a maximum when the system approaches equilibrium; thus, achieving a configuration with the highest probability or stability (Ruelle, 2003; Coccia, 2020). At the time of this study, the pandemic has not yet reached that state.

From an applied point of view and following the indicators provided up to mid-June 2020, Puente Alto, Peñalolén, La Florida, Santiago, Maipú, La Granja, San Bernardo are the municipalities with the highest number of active sick's and in decreasing order, La Pintana, Recoleta and Quilicura, corresponding to the low- and middle-income sectors. In Figs. 4 and 5 it can be seen that they are correctly incorporated in their trend. In many communes of the Santiago MR that is evaluated—based on the pieces number used exclusively as rooms and the inhabitants number of

Fig. 7. Total entropy versus accumulated sick. A gradual increase in entropy and patients by commune is shown corresponding to Table 5.

Table 5. Total entropy that associates the accumulated sick by commune with the meteorological and pollutants variables.

Commune	$S = S_{XYZ} + S_W + S_U + S_V$	Accumulated Sick's by study communes
Santiago	1.84	9412
Independencia	1.70	4300
Las Condes	1.67	3623
Puente Alto	1.60	12212
El Bosque	1.56	3176
La Florida	1.52	7633
Pudahuel	1.47	4848

a dwelling, the greatest overcrowding affects the virus spread. When this ratio exceeds 2.4 people per room, it is considered overcrowding, according to the Mapcity study (Camhi, Betancourt, 2020). Thus, the overcrowding rate by commune: Independence: 13.1%; Cerro Navia: 12.1%; La Pintana: 12.0%; San Ramón: 11.7%; Recoleta: 11.6%; Maipo Island: 11.6%; Lo Espejo: 10.9%; Central Station: 10.7%; Renca: 10.3%; Conchalí: 10.2%. From the land uses point of view, design and construction materials used in streets and buildings, long-term studies (Rossi-Espagnet, 1983; Mouchet, 1997; Neiderud, 2015), show that they favor the formation of urban canyons, thermal islands, etc., elements recognized for not promoting the health of the population in cities (Acuto, 2020). It is shown that they rather favor the pandemic spread.

The parameters values calculated for all seven stations, including the largest Lyapunov exponent, is shown in Table 2, confirming that time-series under study are chaotic.

4 CONCLUSIONS

Weather and air pollution variables can be part of the elements fraction that give sustainability to the accumulated growth of infected patients, favoring the pandemic spread, making the accumulated sick's curve chaotic and increasing its complexity. Even more, environmental pollution could make diseases like the covid-19 coronavirus worse.

For all time-series, the Lempel-Ziv complexity turned out to be between 0 and 1 which is indicative of connectivity and chaos. The largest Lyapunov exponent as well as the Kolmogorov entropy were positive which also exhibits chaos. The Hurst exponent was found to be greater than 0.5 and less than 1 for all time-series, indicating positive long-term autocorrelation. Finally, the correlation dimension was less than 5, revealing that new time-series constructed are not random.

From our chaotic study applied to the six time-series representing the meteorology-pollutant-accumulated sick's interactive system, we were able to verify our hypothesis: a system made up of a connected urban meteorology that promotes sustainability and the pollutants spread, favors infection, cultivation and a coronavirus-type disease spread. This is due to system entropy, calculated for each studying commune, was greater than zero, revealing a trend towards a new equilibrium of the virus + meteorology + pollutants system, according to communes.

The population statistics overcrowding and active sick's, until mid-June 2020 and for our study communes, show agreement with this trend. Said scheme (Official Data COVID-19) indicates that the majority of these overcrowded communes are concentrated in the Chile central zone—including the communes considered in our study—with a greater number of active sick's.

We believe that our study will allow us to review the public health policies applied to the population. The chaotic analysis points to the weaknesses shown in the pandemic first stage in Chile. Learning stage for the authorities and the population, as in other parts of the world, which favored the accumulated sick's curve growth. Trend beginning to decrease in late June and early July, when the measures imposed by the authority—understood as necessary by the population—such as sanitation and public places cleaning, population confinement that caused a sharp decline in transport land—main responsible for air pollution in Santiago de Chile—, social distancing, health residences for infected, permanent hand hygiene, masks use, interregional health cords (with police and military control), permits granting through the internet for consumer goods purchases and regional travel. As a deterrent, very high fines were implemented for offenders. In addition, in Chile there was the natural seasonal transition from winter to spring (August–September) that manifests itself as a change in local meteorology (temperature, wind speed, relative humidity, among other climatic variables).

ACKNOWLEDGMENTS

The support from Dirección de Investigación and Facultad de Ingeniería, Universidad Católica de la Sma. Concepción, is gratefully acknowledged. We also appreciate the support provided from Dirección de Investigación and Departamento de Física, Universidad Tecnológica Metropolitana.

DISCLAIMER

The authors declare no conflict of interests.

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