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Lighting the populational impact of COVID-19 vaccines in Brazil

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Abstract

This paper examines the populational impact of the COVID-19 vaccinations for Brazil. Therefore, our analysis takes into account the time series of the daily number of deaths related to COVID-19 from March 17$^{\text{th}}$, 2020 until October 19$^{\text{th}}$ 2021 with 582 observations. Specifically, we apply the permutation entropy (H_s), statistical complexity (C_s) and Fisher information measure (F_s) to investigate the predictability of the daily deaths for COVID-19 considering two pandemic scenarios (until and after the extreme day). Based on these complexity measures, we construct the Complexity-Entropy causality plane (CECP) and Shannon-Fisher causality plane (SFCP), which allows us to assess the disorder and estimate randomness inherent to the time series of the daily deaths for COVID-19 concerning these two pandemic scenarios. Our empirical results indicate that after the extreme day, the increase in the vaccinated population contingent led to a lower entropy, higher predictability, and lower death cases. Given this, we conclude that the COVID-19 vaccines in Brazil were a highly effective public health action. In the most extreme situation, Brazil had 4249 records of daily deaths on April 08$^{\text{th}}$ 2021, approximately 3.5 months after the first dose of the vaccine. After this extreme situation on April 09$^{\text{th}}$ 2021, the daily records of deaths decrease to a minimum of 130 deaths on October 19$^{\text{th}}$, 2021. Thus, there is a percentage variation of -96.44% in records of daily deaths. To the best of our knowledge, this work is the first to provide empirical evidence for the populational impact related to COVID-19 vaccines.

Keywords:
COVID-19
Death records
Information theory quantifiers
Vaccines
Populational impacts

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1. Introduction

In December 2019, the first clinical report related to the cluster of idiopathic pneumonia case [1, 2] was released at Wuhan, Hubei Province, China [3]. To clarify this complex situation, researchers used the metagenomic next-generation sequencing technology [4]. This technology makes it possible the diagnosis the cause associated with a novel coronavirus labelled as Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), and its respective disease, COVID-19 [5].

Some past works present the COVID-19 as a single, positive-stranded RNA virus enveloped in a lipid bilayer [4, 6, 7]. COVID-19 belongs to the Coronaviridae Family that includes six other viruses, such as severe acute respiratory syndrome coronavirus (SARS-CoV) and Middle East respiratory syndrome coronavirus (MERS-CoV) [8]. The genome sequence of SARS-CoV-2 identified an 82% similarity with the severe acute respiratory syndrome coronavirus (SARS-CoV) [7].

The main transmission vector of SARS-CoV-2 is through respiratory droplets, which are expelled during distinct expiratory events such as breath, cough, sneeze, exhale, or talk [9]. Another, virus spread is via fomites [10]. As a result, SARS-CoV-2 has rapidly worldwide spread [11, 12] taking into account the daily number of real-time reverse transcription-polymerase chain reaction positive cases [13] and the daily number of death cases.

Given this, the World Health Organization (WHO) announced the COVID-19 crisis as a public health emergency of international concern (PHEIC), more specifically COVID-19 pandemic [14]. In this sense, the WHO recommended measures to mitigate the impact of COVID-19 as wearing masks, staying at home, social distancing, hygiene measures, and lockdown [15, 16, 17, 18].

Regardless of the country, COVID-19 had very similar propagation dynamics, with contagion starting in metropolis characterized by many international connections, many highways, a high number of people and intense tourist flow, followed by the internalized transmission phase (from metropolis to cities minors) [19]. Due to the widespread dissemination of COVID-19, the Unified Health System (UHS) and the private health system collapsed. In general, Brazil had an occupancy rate in intensive care units close to 100%.

This paper aims to provide empirical evidence associated with the populational impact related to COVID-19 vaccines in significantly reducing Brazil's mortality. Given this, we have investigated the time series of daily death cases for COVID-19 using information theory quantifiers. We verify that the COVID-19 vaccines positively impact a gradual decrease in the disorder inherent to the time series of daily death cases, leading to higher predictability and lower death cases. This paper contributed to the literature in several aspects:

(i) it draws an alternative way to check the populational impact for the COVID-19 vaccines via information theory quantifiers;

(ii) it combats fake news related to the inefficacy of the COVID-19's vaccines, which implies improving people's confidence in immunization;

(iii) it favours greater adherence to preventive public health policies;

(iv) it provides reliable information to support the design of more efficient public policies that reach a more significant number of people;

(v) it indicates that a higher number of people vaccinated leads to fewer death cases.

The rest of this paper is organized as follows. Section 2, presents the data that we have analyzed in this research. Section 3, explain the methods used in this work. Section 4, exposes and discusses our empirical results. Section 5, formalizes our conclusions.

2. Data

We collect the data at COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University,https://covid19.who.int/. Based on the terms of use, this data is public and can be used for academic, educational, public health, and research purpose.

3. Methods

3.1. Permutation entropy

Permutation entropy [20] is a robust complexity measure introduced for designating any type of time series [21]. Based on a public health perspectives the permutation entropy (H_s) has been applied to examine the predictability of infectious diseases [22, 23, 24, 25].

Specifically, (H_s) considering an association of symbolic sequences to the segments of the time series under analysis considering the existence of temporal causality within time series and the presence of ordinal patterns by comparing amplitude of neighboring values of the original series and uses the probability distribution function (PDF) related to these symbols to evaluate the complexity quantifier [17, 26, 27, 28, 29, 30, 31].

Thus, taking into account a time series $y_a, a = 1, ..., A$, the $A' \equiv A - (d-1)$ overlapping segments $Y_b = (y_b, y_{b+1}, ..., y_{b+(d-1)})$, $b = 1, ..., A'$ of length $d > 1$ are identified (d is the embedding dimension). Within each world the values are sorted in increasing order, yielding the set of indices $s_0, s_1, ..., s_{(d-1)}$ such that $y_{a+s_0} \leq y_a + s_1 \leq ... \leq y_{a+s_{(d-1)}}$. The corresponding vectors $\pi = s_0, s_1, ..., s_{(d-1)}$ may assume any of the $d!$ possible permutations of the set $\{0, 1, ..., d-1\}$ and symbolically represent the original words. Thus, permutation entropy (order $d \geq 2$) is:

$$H(d) = -\sum_{\pi} p(\pi) \log p(\pi) \tag{1}$$

where $\{\pi\}$ represents the summation over all the $d!$ possible permutations of order d and $p(\pi)$ comprises the relative frequency of occurrences of the permutation π.

It is widely be know that the optimal d is related with the underlying stochastic process [32, 33]. However, the literature indicates choosing a maximum of d to satisfy $n > 5d!$ to promote a better statistical fit [34].

3.2. Complexity-entropy causality plane (CECP)

The CECP was proposed by Rosso et.al [35] to differentiate between stochastic noise and deterministic chaotic behaviour. It is as a complexity space, which the horizontal axes represent (H_s) and the vertical reflects the statistical complexity measure (C_s). The statistical complexity measure is defined as

$$C\left[P\right] = -\frac{J\left[P,U\right]}{J_{max}} H_S\left[P\right] \tag{2}$$

where $H_S\left[P\right] = \frac{H[P]}{\log d!}$ is normalized permutation entropy, $J\left[P,U\right]$ is the Jensen-Shannon divergence

$$J\left[P,U\right] = \left\{ H\left(\frac{P+U}{2}\right) - \frac{H[P]}{2} - \frac{H[U]}{2} \right\} \tag{3}$$

It is applied to quantify the difference between the BPM probability distribution of ordinal patterns P and the uniform distribution U. The maximum possible value of $J\left[P,U\right]$ is obtained when one of the components of P is equal to one, and all the others are equal to zero.

$$J_{max} = -\frac{1}{2}\left[\frac{d!+1}{d!}\log\left(d!+1\right) - 2\log(2d!) + \log\left(d!\right)\right] \tag{4}$$

For each value of the normalized permutation entropy $H_s[P] \in [0,1]$ there is a range of possibilities for $C\left[P\right]$, forming the lower and upper bound envelopes in the CECP [36].

3.3. Fisher information measure

Fisher information measure (FIM) is a powerful approach to evaluate complexity considering a physical system [37]. Given this, it has been used in many research areas of science such as, Econophysics [36], Physics [38], Quantitative Biology [17] and others [39, 40, 41]. FIM is a flexible statistical measure of indeterminacy, which can apply in three distinct possibilities [17]: First, it is an adequate measure for estimating a parameter. Second, it is a qualitative measure associated with the amount of information extracted from a data set. Third, it is a measure that reveals the state of disorder of a system or phenomenon. The discrete normalized form of Fisher information measure ($0 \leq F \leq 1$), is given by

$$F\left[P\right] = F_0 \sum_{i=1}^{N-1} \left(\sqrt{p_{i+1}} - \sqrt{p_i}\right)^2 \tag{5}$$

where p_i and $p_i + 1$ are consecutive probabilities from discrete distribution P and F_0 is a normalization constant ($F_0 = 1$ if $p_1 = 1$ or $p_N = 1$, and $F_0 = 1/2$ otherwise).

Then, we execute the lexicographic ordering, which is a total ordering on vectors, to effectively evidence the distinct dynamics in 2D-plane (H_s x F_s). Therefore, taking into consideration a vector of dimension $d = 3$, words $x_{t+r_0} \leq x_{t+r_1} \leq x_{t+r_2}$ is mapped into the index vector $\pi = r_0, r_1, r_2$, with indices r_i consider values from the set $0, 1, 2$, and the six possible patterns are ordered as $\pi_1 = 0, 1, 2$, $\pi_2 = 0, 2, 1$, $\pi_3 = 1, 0, 2$, $\pi_4 = 1, 2, 0$, $\pi_5 = 2, 0, 1$, and $\pi_6 = 2, 1, 0$.

Vignat and Bercher [42] proposed the Shannon-Fisher causality plane (SFCP) to quantify information content and the historical data disorder underlying. The SFCP builds up a mathematical space in which the abscissa axis is H_s and the ordinate axis is F_s.

3.4. Sliding window approach

We employ the sliding window approach to provide a time-dependent analysis of the information theory quantifiers. The Sliding window approach is based on the following sequence. Considering a time series $y_1, ..., y_N$, we construct the sliding windows $k_t y_{1+t\Delta}, ..., y_{w+t\Delta}$, $t = 0, 1, ... \left[\frac{N-w}{\Delta}\right]$. The term $w \leq N$ is the window size, $\Delta \leq w$ is the sliding step, and $[\cdot]$ corresponds to taking the integer part of the argument. The values inherent of the time series in each window k_t are used to calculate permutation entropy, complexity measure and Fisher information measure, yielding the time evolution of window position in the CECP and SFCP.

4. Empirical results

Our analysis started with studying the temporal evolution of the daily number of deaths related to COVID-19. Fig. 1 presents the plot of the timeline of the daily number of deaths associated with COVID-19 from March 17$^{\text{th}}$, 2020 until October 19$^{\text{th}}$ 2021.

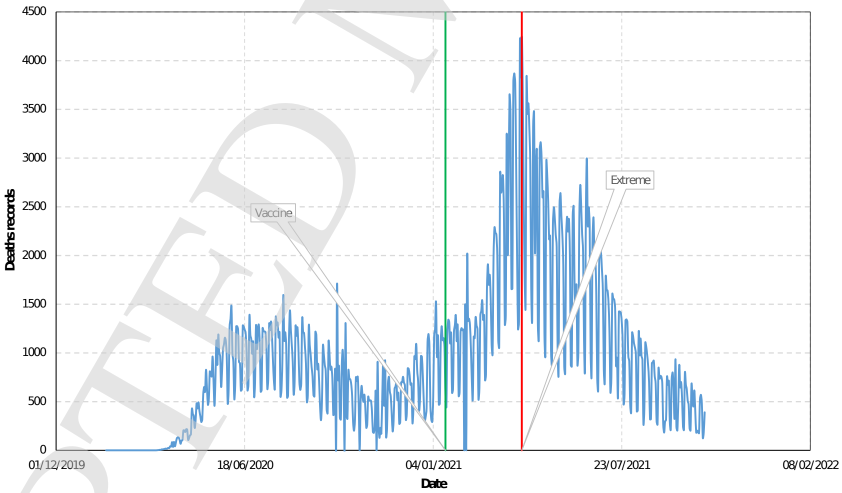

Figure 1: The timeline of the daily number of deaths related to COVID-19 from March 17$^{\text{th}}$, 2020 until October 19$^{\text{th}}$ 2021. The green bar presents the beginning of COVID-19 immunization in Brazil on January 17$^{\text{th}}$, 2021. While, the red bar shows the "extreme day" April 08$^{\text{th}}$, 2021, which is the day that Brazil had the highest number of deaths, totalling 4,249 deaths by COVID-19.

Note that after the start of immunization in Brazil, the daily number of deaths from COVID-19 continued to increase. It took 81 days for a decrease in the death cases. Some factors contributed to this situation, such as using only a single vaccine called CoronaVac manufactured by Sinovac (China) and Butantan Institute (Brazil), insufficient vaccines were given to the Brazilian population and turbulence in the political scenario.

The first doses of AstraZeneca/Oxford arrived in Brazil on January 22^{nd}, 2021. While, the first doses of Pfizer/BioNTech arrived in Brazil on April 29^{th}, 2021. In Fig. 1, it is clear that after April 09^{th}, 2021, there is a gradual decrease in the COVID-19 mortality. It suggests that from the moment there was an increase in the speed of immunization of the Brazilian population and diversification of vaccines, there was an inversion in the behaviour of the mortality curve.

We employ the information theory quantifiers to understand the predictability of this viral mortality considering two distinct scenarios (until and after the extreme day). Therefore, we perform the Bandt & Pompe method to quantify these complexity measures. Thus, we choose embedding dimension $d = 4$ to satisfy the condition $T > 5d!$ to estimate the permutation entropy, statistical complexity, and Fisher information.

We construct the CECP (H_s X C_s) to map these two scenarios (until and after the extreme day), and their respective locations are analyzed along this 2D plane. In this sense, we also examine the behaviour of these shuffled time series. Given this, we apply the CECP on these series, considering the shuffling procedure with 1000 x N transpositions on each time series. Fig. 2 depicts the phenomenology inherent to these two scenarios (Until and after the extreme day) varies widely along the CECP.

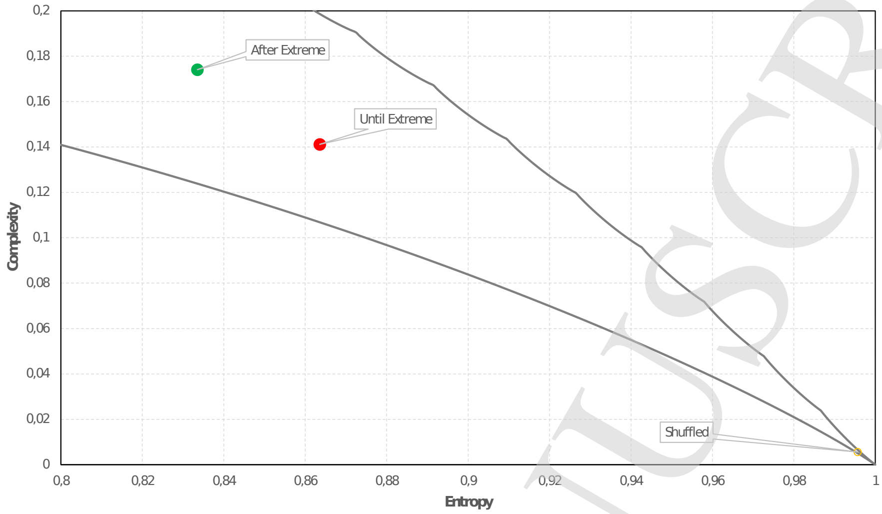

Figure 2: Red dot denotes the period until extreme day (from March 17th, 2020 until April 08th, 2021). The green dot represents the period after the extreme day (from April 09th to October 19th, 2021). Yellow dot reveals the random ideal position ($H_s = 1$, $C_s = 0$). The period until the extreme day is located at the lower-right region of the CECP (high entropy and low complexity). The period after the extreme day is located in the middle region of the CECP, which is characterized by low entropy and more complexity.

Then, we build up the SFCP (H_s X F_s) to assess the disorder and appraise randomness inherent for the time series of the daily number of deaths for COVID-19 time series considering both scenarios. Fig. 3 displays SFCP taking into account these two scenarios (until and after the extreme day).

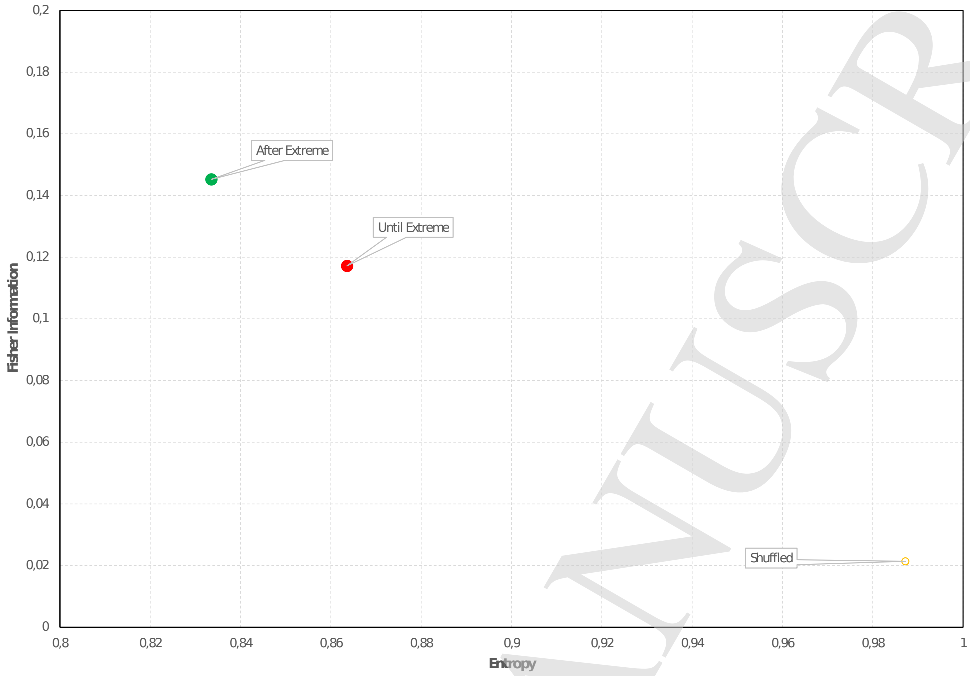

Figure 3: Red dot shows the period until extreme day (from March 17th, 2020 until April 08th, 2021). The green dot presents the period after the extreme day (from April 09th, 2021 to October 19th, 2021). Yellow dot reflects the random ideal position ($H_s = 1$, $F_s = 0$). Note that the period until the extreme day is marked by low distance to the random ideal position, which indicates a pandemic scenario characterized by high entropy and low predictability. After the extreme day, it is possible to observe a favourable pandemic scenario characterized by a high distance to the random ideal position (low disorder and high predictability).

We can draw some parallels to better understand our findings. First, the vaccination is focused on the risk group, which encompasses the elderly, people with comorbidities and health professionals. Second, in the beginning, the number of vaccines was somewhat restricted, considering the discrepant difference between the supply of the vaccine and the demand for it. It explains the gap of approximately 40 days between the first dose of the vaccine applied in England on December 08th, 2020 and the first dose used in Brazil on January 17th, 2021. Third, although Brazil had international partnerships to develop vaccines, more specifically Sinovac (China) and AstraZeneca (Oxford), the demand for vaccines was worldwide.

It implies a shortage of basic supplies and vaccines. Fourth, 320,004,887 vaccines have already been distributed. With the first dose, 153,640,236 Brazilians were already immunized, and with the second dose or a single dose, 115,489,350 Brazilians were vaccinated. In total, 269,129,590 doses of vaccines have already been applied. Fifth, the investment in the acquisition of vaccines was R$ 197.7 billion, which is equivalent to approximately 35.6 billion USD dollars (considering the exchange rate for the day October 25th, 2021. Currently, Brazil ranks fourth in the world ranking in the application of vaccine doses, second only to China (1.10 billion vaccines), India (717.68 million vaccines) and the USA (220.35 million vaccines).

Our results suggest a significant reduction in the number of deaths from COVID-19 as there was a gradual increase in the number of vaccines distributed. Based on our experience, we know that there is an inverse mathematical relationship between H_s and F_s [25, 17, 18]. Thus, we conclude that the COVID-19's vaccines significantly reduce disorder (entropy), which implies higher predictability and a better understanding of the dynamics of COVID-19 mortality related to more information extracted from this viral disease. In addition, the increase in the distance to the random ideal position ($H_s = 1$, $F_s = 0$) ratifies a public health scenario designated by low disorder (less entropy) and high predictability (high FIM). In this sense, our findings indicate that COVID-19 vaccination in Brazil was a highly effective public health action. Currently, Brazil has 54.3 % of the population fully vaccinated.

We consider the sliding window technique to perform a dynamical analysis concerning these two pandemic scenarios until and after the extreme day. Thus, we employ the CECP and SFCP concerning an embedding dimension $d = 4$, window size = 180 days (6 months), and sliding step $\Delta = 30$ days (1 month). Fig. 4 exhibits the dynamical analysis for the CECP and SFCP by sliding window considering these two pandemic scenarios.

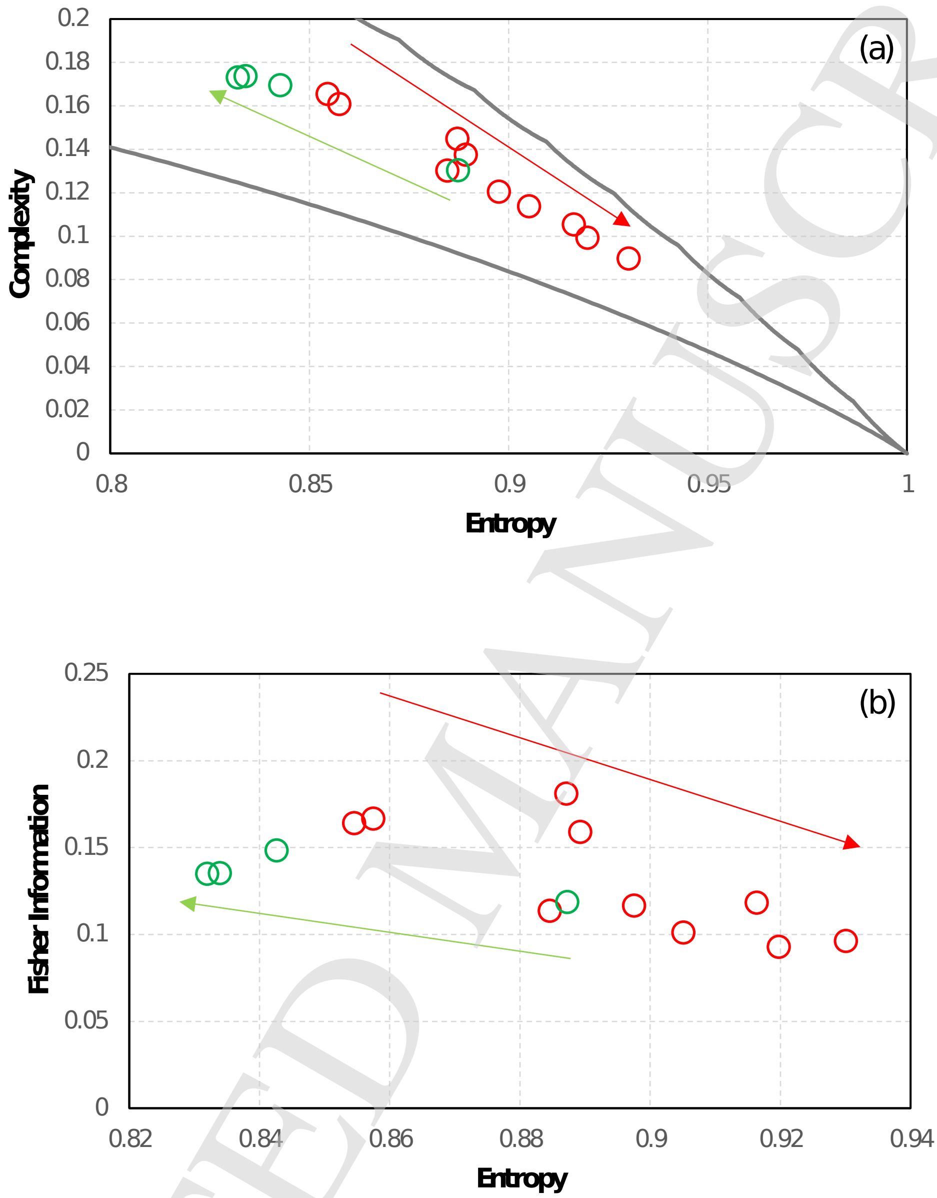

Figure 4: For both 2D-planes the red dot shows the period until extreme day (from March 17$^{\text{th}}$, 2020 until April 08$^{\text{th}}$, 2021). The green dot presents the period after the extreme day (from April 09$^{\text{th}}$, 2021 to October 19$^{\text{th}}$, 2021). (a) It presents the dynamical analysis considering the CECP by sliding window. (b) It displays the dynamical analysis bearing in mind the SFCP via the sliding window.

After that, we execute the sliding window technique to explore the dynamical interplay between the information theory quantifiers concerning the distance from the vertex $(1, 0)$ bearing in mind an embedding dimension $d = 4$, window size = 180 days (6 months), and sliding step Δ = 30 days (1 month) reflecting these two pandemic scenarios (until and after extreme day). Fig. 5 exposes the dynamical interplay between the information theory quantifiers for both pandemic scenarios.

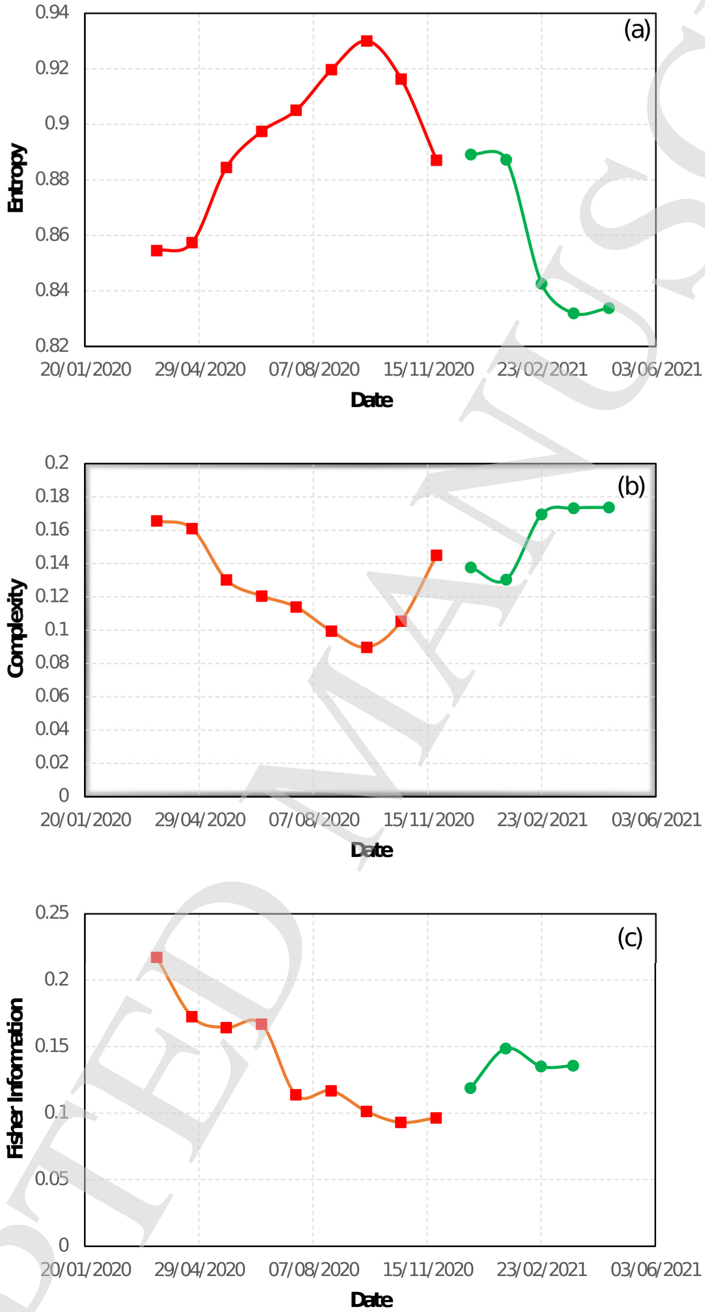

Figure 5: (a) It presents the dynamical analysis for the permutation entropy concerning until and after extreme day. (b) It shows the dynamical analysis for the statistical complexity taking into account until and after extreme day. (c) It depicts the dynamical analysis for the Fisher information measure considering until and after extreme day.

An overview of the permutation entropy, our "gold measure", allows us to check that the gradual increase in vaccinated people has reduced the time series disorder of deaths from COVID-19. Thus, our findings indicate the effectiveness of vaccines in creating antibodies, reducing the number of severe cases of the disease and, consequently, the number of deaths.

5. Conclusion

Humanity has been fighting an uphill battle against SARS-CoV-2. According to the World Health Organization's COVID-19 death dashboard, Brazil is in the second position in the ranking of deaths by COVID-19 with a total of 606,246 cases behind only the USA with a total of 734,447 cases.

Factors that aggravated the situation in Brazil were the disbelief of many people concerning the effectiveness of COVID-19 vaccines [43], and the dismantling of Brazilian Science [44]. Thus, the summation of these factors provided a social distortion scenario related to the decrease of the trust inherent to the immunization capacity of vaccines and in a pseudo belief in the existence of early treatment of COVID-19 [45].

Our research shed novel light on the efficacy of vaccines using information theory quantifiers. Specifically, we examine the time series of daily death cases for COVID-19 using information theory quantifiers concerning two pandemic scenarios (until and after extreme day). In this way, we evaluate the permutation entropy, complexity measure, and Fisher information measure. Considering these complexity measures, we build the Complexity-Entropy causality plane (CECP) and Shannon-Fisher causality plane (SFCP), which allows us to assess the disorder and estimate randomness inherent to the time series of the daily deaths for COVID-19 concerning these two pandemic scenarios.

Our results indicate that COVID-19 vaccines effectively promoted the gradual decrease of the disorder inherent in the daily records of death, leading to greater predictability and fewer deaths. Given this, Thus, we humbly suggest that this research be widely publicized to resolve existing doubts about the effectiveness of COVID-19 vaccines. Moreover, we can apply it in an advertisement that provides greater adherence to the immunization campaign.

6. Conflict of interest

The authors declare that this work has no conflicting personal or financial influences.

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