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Transboundary and Emerging Diseases

Complex dynamics related to death cases of COVID-19 from Brazil

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The SARS-CoV-2 pandemic has radically changed the status quo of the global society. The fast spread of the new coronavirus is governed by nonlinear dynamics. The purpose of this paper is to investigate the complex dynamics inherent by the dissemination of COVID-19 into 27 Brazilian States. Because of this, we have investigated the time series of daily death caused by COVID-19. Our analysis taking into account the Bandt & Pompe method (BPM) to estimate the Information Theory quantifiers, the Permutation entropy (H_s), and the Fisher information measure (F_s). Based on the Information Theory quantifiers we build up the Shannon-Fisher causality plane, which made it possible to study the temporal evolution inherent of the phenomenology associated with the number of daily deaths by COVID-19, as well as their respective locations along the SFCP were mapped. Our results show that the number of death cases due to COVID-19 for Brazilian States present a dynamical behavior that tends to have their starting positions close to the lower-right region at the 2-D plane (H_s x F_s). Thus, the Brazilian States located in this region or its surroundings show high entropy and lowest disorder (highest efficiency). While the Brazilian States located in the

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middle region of the 2-D plane (H_s x F_s) or its surroundings are depicted by a less entropic and highest disorder (lowest efficiency). We also employed the Permutation entropy and the Fisher information measure to rank the conjuncture of the Brazilian States considering the number of daily death due to COVID-19 based on the complexity hierarchy. From a mathematical point of view, we found an inverse relationship between the Permutation entropy and Fisher information measure. Given this, we concluded that the higher value of the permutation entropy (H_s)the lower value related to the Fisher information measure (F_s).

KEYWORDS
SARS-CoV-2, *COVID-19*, Nonlinear dynamics, Information Theory quantifiers, Shannon-Fisher causality plane, Complexity hierarchy

1 | INTRODUCTION

The coronavirus disease-2019 (COVID-19) Z. Wu and McGoogan, 2020, is a respiratory infectious with most commonly reported clinical symptoms being fever, dry cough, fatigue, dyspnoea, anosmia, ageusia or some combination of these symptoms Guan et al., 2020, other less common symptoms include runny nose, nausea, vomiting, and diarrhea, and complications can lead to severe infections, such as pneumonia (infection of the lungs), kidney failure, and death Huang et al., 2020.The COVID-19 can varies from a asymptomatic stage with or without detectable virusto subsequent symptomatic stages with crescent detectable viral load Shi et al., 2020.

The COVID-19 is caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), a single-stranded positive-sense RNA virus that belongs to the Betacoronavirus genus, Coronaviridae family. This viral family contains six other human coronavirus (OC43, 229E, NL63, and HKU1), and other two zoonotic viruses, the severe acute respiratory syndrome coronavirus (SARS-CoV) and the Middle East respiratory syndrome coronavirus (MERS-CoV), which have caused an epidemic outbreak in the past, leading to high pathogenicity and mortality in humansA. Wu et al., 2020. COVID-19 is now causing a pandemic disease with huge impacts on countries around the world.

The SARS-CoV-2 was first described in Wuhan city, Hubei province, China, at the end of 2019. In just a month later, the SARS-CoV-2 had already spread to several countries in Asia and Europe and in the US, and the epicenter of new cases of COVID-19 has been changing among countries since then. Much evidence supports the cases of Covid-19 are growing exponential and many epidemiologists have suggested using social distancing, quarantine, and isolation to flatten the upcoming curve for slowing down its quick spread Adam, 2020.

It is estimated that SARS-CoV-2 started to spread in Brazil in early February 2020 Delatorre et al., 2020. The first confirmed case of COVID-19 in Brazil occurred on 26 February 2020, in the São Paulo metropolis through travelers mainly from Italy. Later, other Brazilian cities also received viral strains from travelers like, Porto Alegre, Salvador, Curitiba, Belo Horizonte, Recife, Vitória e Florianópolis, featuring multiple entries of the virus into the countryCandido et al., 2020. More than 100 international introductions of SARS-CoV-2 were identified in Brazilda Silva Candido et al., 2020.

During this first phase of the epidemic establishment of SARS-CoV-2 in Brazil, the virus spread mostly locally and within-state borders da Silva Candido et al., 2020. Currently, Brazil has reported the largest number of cases in Latin America (n = 891.556 cases and 44.568 deaths, as of 15 June 2020) and SARS-CoV-2 has been now detected in all of the 27 Federal States.

This paper used the Informational Theory quantifiers, more specifically, the Permutation Entropy (PE) and Fisher Information measure (FIM) Fisher, 1922, both measures estimated by the Bandt & Pompe method (BPM) Bandt and Pompe, 2002 to investigate the temporal evolution inherent to the spread of SARS-CoV-2 into 27 Brazilian States. In a previous study, we applied this methodology to investigate the temporal evolution of SARS-CoV-2 spreading in 15 diverse countries, including Brazil Fernandes et al., 2020.This study revealed distinct pattern of temporal evolution of SARS-CoV-2 spread among the countries, showing a complex dynamics of virus spread around the world.

Futhermore, we carry out a systematic study based on PE and FIM to understand the phenomenology associated with the disordered state of Brazilian States implies by the spread of COVID-19 considering the time series of daily death related to this viral disease.

For each Brazilian State the higher values related to PE and the lower values inherent to FIM means that less is the disordered state, that is, the Brazilian State is less impacted taking into account the number of daily death due to COVID-19. Otherwise, the lower values related to PE and higher values of FIM means that more is the disordered state (chaotic state), that is, the Brazilian State is higher impacted considering the number of daily death resulting from COVID-19.

Also, we employed the Shannon-Fisher Causality plane (SFCP) Vignat and Bercher, 2003 to map the complex dynamics to the spread of COVID-19 based on the number of daily death and their respective locations along this two-dimensional complexity plane for the 27 Brazilian States. Moreover, we also applied PE and FIM to rank the Brazilian States according to the complexity hierarchy.

The scientific progress related to the applications of Informational Theory quantifiers is associated to the possibility to study the spread of viral diseases, in this specific case, COVID-19 as a complex system instead of using classical statistical approaches that can induce bias.

This paper contributes to the literature in several aspects. We can highlight: First, it extends the literature of Virology, Epidemiology, and Biophysics applications based on Information Theory. Second, it shows a general theoretical framework that provides explanations inherent to the Information Theory models. Third, it builds up the SFCP, which allowed us to map the complex dynamics to the spread of COVID-19 based on the number of daily death and their respective locations along this two-dimensional plane (H_s x F_s). Fourth, it shows the rank of the conjuncture of the Brazilian States considering the number of daily death due to COVID-19 based on the complexity hierarchy Finally, it draws news perspectives to analyze the complex dynamics of viral diseases.

The remainder of this paper is organized as follows. Section 2, explains the theoretical framework of the Information Theory methods. Section 3, details the database used in this research. Section 4 shows the empirical results and discusses our empirical findings. Section 5, draws our conclusions and some concluding remarks.

2 | METHOD

This section has been segregated into 2 distinct subsections in which we present the theoretical framework of the methods applied in this research. We employed the Bandt & Pompe method (BPM), to estimate the Information Theory quantifiers, more specifically the Permutation entropy (H_s) and Fisher information measure (F_s). Based on these Information Theory quantifiers we build-up the Shannon-Fisher causality plane and we also ranking the real

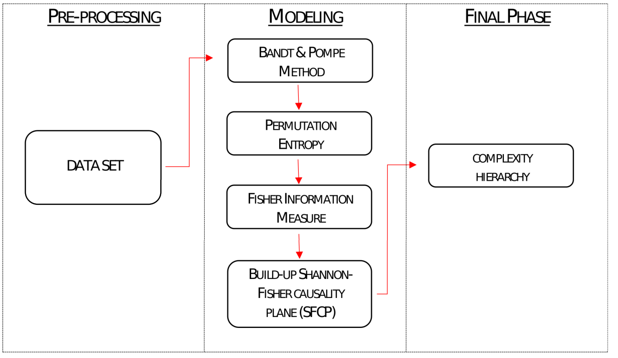

FIGURE 1 The flowchart of the theoretical framework of the procedures adopted in this research. Pre-processing corresponds to the analysis of the data set. Modeling reflects the methods highlighted here and the final phase show the hierarchical complexity.

situation of the Brazilian States considering the number of daily death due to COVID-19 through the complexity hierarchy. Fig. 1 depicts the flowchart related to the theoretical framework used in this research.

2.1 | Bandt & Pompe method

The focus of Bandt & Pompe method (BPM) consists in to define Bandt and Pompe, 2002 a basic quantity measure that can be employed to investigate any type of time series such as regular, chaotic, noisy or reality-based Ribeiro et al., 2012.

Therefore, the BPM considers an association of symbolic sequences to the segments of the time series under analysis, based on the existence of ordinal patterns by comparing neighboring values of the original series and employs the probability distribution function (PDF) related to these symbols, to evaluate the complexity quantifier Fernandes and Araújo, 2020. In this way, the working mechanics associated with the construction of Bandt & Pompe permutation entropy necessarily considering the temporal causality within the time series.

Given this, let a time series denoted by $x_t, t = 1, ..., T$ and regard $T - (d - 1)$ overlapping segments $X_t = (x_t, x_{t+1}, ..., x_{t+d-1})$ of length d. Within each segment, the ranking of the values are carried out based in increasing order to find the indices $r_0, r_1, ..., r_{d-1}$ such that $x_{t+r_0} \le x_{t+r_1} \le ...x_{t+r_{d-1}}$. The respective d-tuples (or words) $\pi = (r_0, r_1, ..., r_{d-1})$ are symbolic corresponding the original segments, and can be assumed any of the $d!$ possible permutations of the set $\{0, 1, ..., d-1\}$. Thus, the Bandt & Pompe permutation entropy of order $d \ge 2$ can be defined as

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

where $\{\pi\}$ represents the summation over all the $d!$ possible permutations of order d, and $p(\pi)$ denotes the relative frequency of occurrences of the permutation π. The better fit promoted by d strongly is related with the phenomenology of each event investigated, but in order to provide a goodness statistics criteria as a rule of thumb it is typically recommended Ribeiro et al., 2012 to choose maximum d such that $T > 5d!$.

It is important to mention that Bandt & Pompe permutation entropy has been successfully applied in distinct research areas such climatology Saco et al., 2010, geophysical Li and Zuntao, 2014, biomedical and econophysics applications Zanin et al., 2012 and many others Amigó and Keller, 2013; Bandt, 2016; Traversaro and Redelico, 2018.

2.2 | Fisher Information measures

The historical exhibition of the last few years allows verifying a relevant increase in the scope and variety of physical applications of Fisher's information measure (FIM) Casas et al., 2002; Martin et al., 2001; Stein et al., 2014, mainly in applications related to time series analysis Liu et al., 2020; Telesca and Lovallo, 2017.

The Fisher information is a very flexible statistical measure of indeterminacy, it can be noted 3 associated possibilities to understanding this approach such as a measure of the ability to estimate a parameter, as the amount of information that can be extracted from a set of measures (the "quality" of the measurements), and as the disorder state measure of a system or phenomenon for more details see Frieden, 2004; Mayer et al., 2006 being its most important property is the so-called the Cramer-Rao Bound (CRB) for nonlinear parameter estimation Dehesa et al., 2007; Rosso et al., 2010. The discrete normalized form of the Fisher information measure $(0 \leq F \leq 1)$, is given by

$$F[P] = F_0 \sum_{i=1}^{M} \left(\sqrt{P_{i+1}} - \sqrt{P_i} \right)^2 \tag{2}$$

where the normalization constant F_0 is defined by

$$F_0 = \begin{cases} 1, \text{ if } P_i = 1 \text{ for } i* = 1 or i* = M \text{ and } P_i = 0 \forall i \neq i*, \\ 1/2 \text{ otherwise.} \end{cases} \tag{3}$$

We also employed the lexicographic ordering (or Lehmer coding), which was presented to well differentiate different dynamics in the Shannon-Fisher causality plane (H_s x F_s). In this way, considering 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 take 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 $\pi_6 = 2, 1, 0$.

The Shannon-Fisher causality plane representation space was proposed by Vignat and Bercher Vignat and Bercher, 2003. This method builds up a 2-D plane which Shannon entropy is the horizontal axes and Fisher information measure is the vertical axes. This approach has been successfully applied in distinct research areas such Physiology studies Baravalle et al., 2018; Montani et al., 2014, Chaotic systems Olivares et al., 2012; Olivares et al., 2019 and Econophysics Bariviera et al., 2015; Gonçalves et al., 2019.

3 | DATA

We have analyzed the complex dynamics exhibit by the spread of SARS-CoV-2 into 27 Brazil States. Therefore, the data used in this analysis is the time series of daily death related to COVID-19. For each Brazilian State, the periods cover 120 days from March 12nd, 2020 until July 09th 2020 with 120 observations. The data were obtained via public service on the internet at Transparency Portal,https://transparencia.registrocivil.org.br/especial-covid. A list of States taking into account in this analysis with State name, abbreviations, and the respectively total death number is presented in Table 1.

4 | EMPIRICAL RESULTS

For each Brazilian State, the time series of daily death related to COVID-19 presents a complex dynamics related to characteristics such as non-linear dynamics, noisy and chaotic characteristics. The time series of the temporal evolution of daily death for COVID-19 are shown in Fig. 2.

TABLE 1 Details of State, abbreviations and total death number for each Brazilian State

i	State	Abbreviation	Total death
1	Acre	AC	372
2	Alagoas	AL	1274
3	Amapá	AP	395
4	Amazonas	AM	1598
5	Bahia	BA	2523
6	Ceará	CE	6120
7	Distrito Federal	DF	926
8	Espírito Santo	ES	1873
9	Goiás	GO	905
10	Maranhão	MA	1460
11	Mato Grosso	MT	162
12	Mato Grosso do Sul	MS	121
13	Minas Gerais	MG	1489
14	Pará	PA	2800
15	Paraíba	PB	1235
16	Paraná	PR	1511
17	Pernambuco	PE	3687
18	Piauí	PI	308
19	Rio de Janeiro	RJ	13215
20	Rio Grande do Norte	RN	888
21	Rio Grande do Sul	RS	1062
22	Rondônia	RO	436
23	Roraima	RR	233
24	Santa Catarina	SC	523
25	São Paulo	SP	19329
26	Sergipe	SE	629
27	Tocantins	TO	130

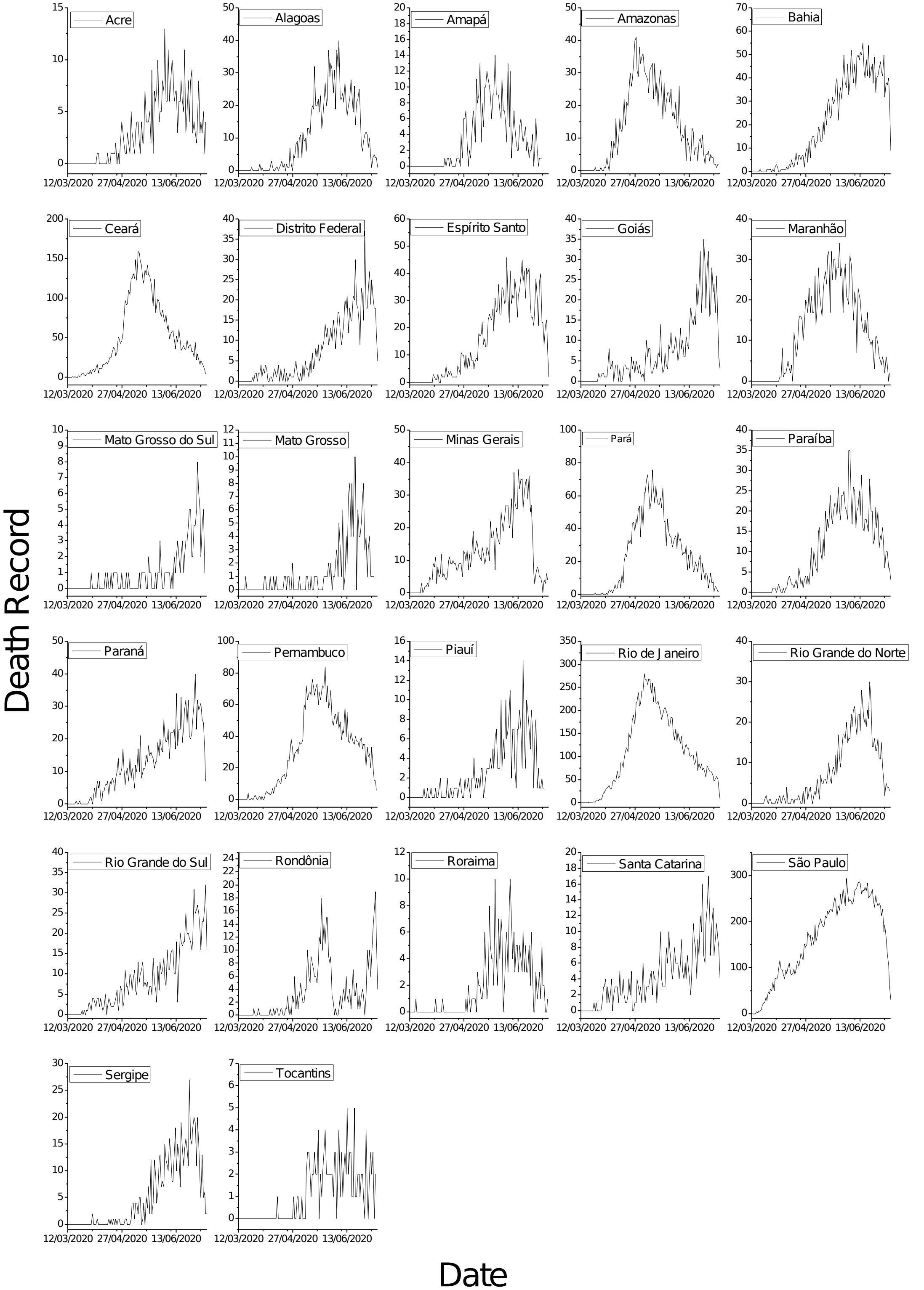

FIGURE 2 For each Brazilian States, the time line of daily death number related to COVID-19 from March 12nd, 2020 until July 09th 2020 with 120 observations.

An overview covering the number of deaths due to COVID-19 depicts that some Brazilian States such as CE, PE, RJ, AL, and PA are in a phase of decay. On the other hand, DF, MG, PI, RO, RR, RS, SC, SP, and TO present an evolutionary dynamics in the number of deaths resulting from COVID-19 so unpredictable and complex that it portrays a very different scenario alternating days between peaks cases and decays cases.

The complex behavior exhibit by DF, MG, PI, RR, RS, SC, SP, and TO related to COVID-19 deaths is the worst possible because they reflect the high level of disorder in the analyzed time series.

Our findings reveal that RO exhibit anomalous dynamics in the number of deaths due to the COVID-19. Specifically, this State was in the decay phase and there was an inflection in the curve that made the death toll rise again. This inflection may be due to a loosening in relation to protective measures such as testing symptomatic and asymptomatic carriers, social distancing, lockdown, stay-at-home orders, and hygienic measures Helmy et al., 2020; Jacobson et al., 2020. The number inherent to daily death related to the COVID-19 at SE is in the exponential growth phase.

Some key factors such as demographic characteristic like high population density Feng et al., 2020, international connections Kucharski et al., 2020; Rodriguez-Morales et al., 2020, basic sanitation Kluge et al., 2020; Lancet, 2020, political attitude Lancet, 2020 and Carnival festivities Ebrahim and Memish, 2020 have effectively contributed to a relevant discrepancy between the Brazilian States considering the number of deaths due to COVID-19. Thus, it would be very unlikely that the 27 States of Brazil would have the same behavior in relation to the number of deaths resulting from COVID-19.

We apply the causality Shannon-Fisher plane (SFCP) which carries out a systematic investigation based on the global and local characteristics of the Bandt Pompe's probability density function (PDF). Thus, the SFCP which allowed us to map the complex dynamics to the spread of COVID-19 based on the number of daily death and their respective locations along this two-dimensional plane (H_s x F_s) the normalized permutation entropy and Fisher information measure are calculated considering $d = 4$ to satisfy the common condition $T > 5d!$.

We also studied the behavior dynamics of the shuffled time series of daily death related to COVID-19. Therefore, we used the SFCP in these series, where the shuffling procedure with 1000 x N transpositions on each series. Fig. 3 shows the trajectory of COVID-19 dissemination in the SFCP of Brazilain States taking into account the daily number of deaths from March 12nd, 2020 until July 09th 2020 for embedding dimension $d = 4$ as well the shuffled series.

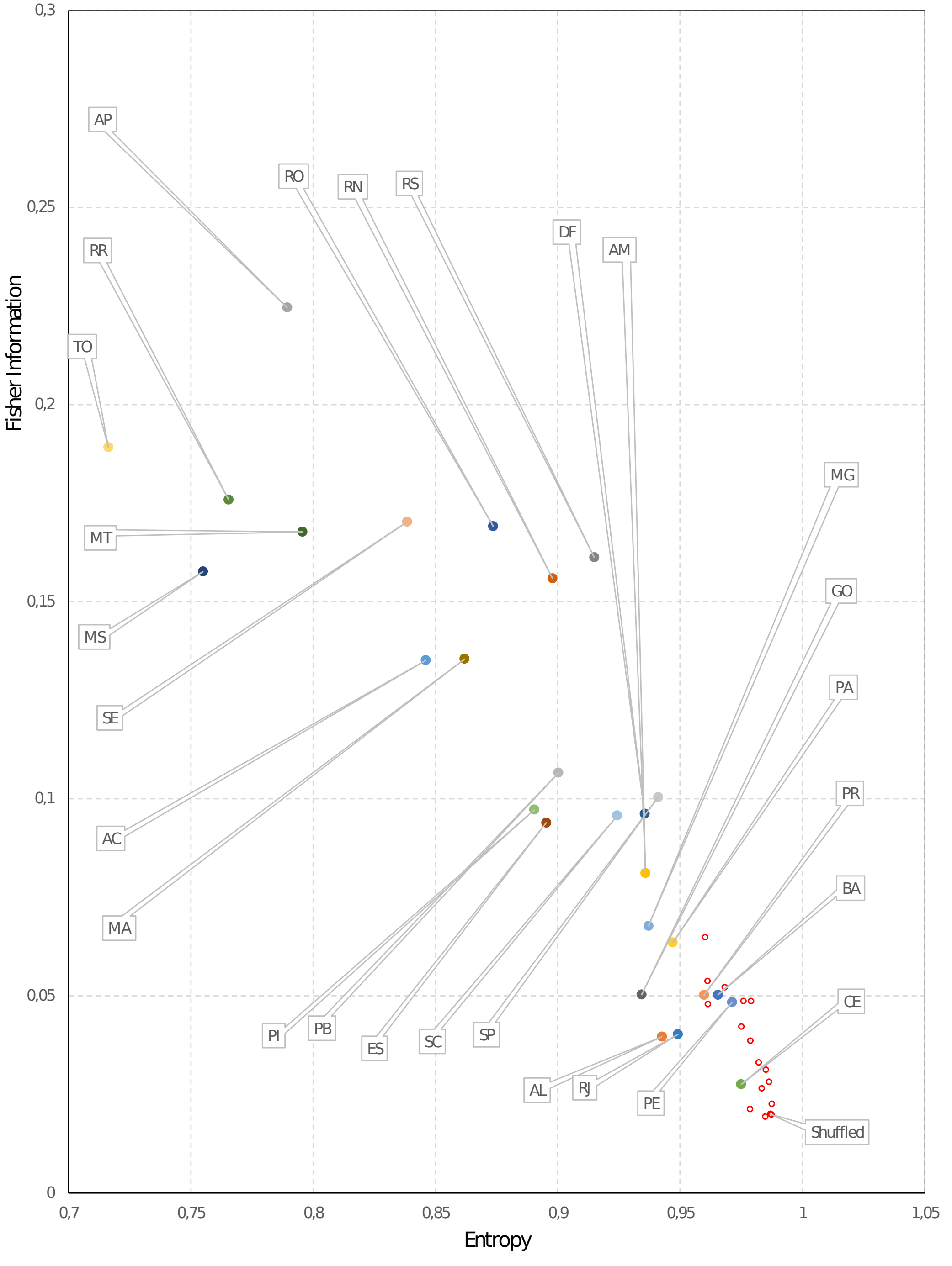

FIGURE 3 Position in the SFCP plane of the original and randomized time series of daily death related to COVID-19 for embedding dimension $d = 4$.

The spread of COVID-19 which implies in the death cases for the Brazilian States tends to have their starting positions close to the lower-right region at the causality Shannon-Fisher causality plane. The Brazilian States located in this region or in its surroundings are characterized by high entropy and lowest disorder (highest efficiency). Thus, these Brazilian States have a higher level of efficiency in reducing the number of daily deaths due to the COVID-19.

While the Brazilian States located in the middle region of the two-dimensional plane (H_s x F_s) or in its surroundings are characterized by a less entropic and highest disorder (lowest efficiency). So, these Brazilian states have a lower level of efficiency in reducing the number of daily deaths due to COVID-19.

It is important to mention that some factors such as quantity and qualification of health professionals, accessibility to specific equipment necessary to reduce lethality such as respirators and financial resources directly impact efficiency in reducing the daily number of deaths due to the COVID-19. The Table 2 shows the classification of Brazilian States based on the complexity hierarchy (H_s x F_s).

There is a trend in behavior related to the number of deaths due to COVID-19 considering the Brazilian States. From a mathematical point of view, there is an inverse relationship between Permutation entropy and Fisher information. Thus, it is noted that the higher value of the permutation entropy (H_s), the lower value related to the fisher information (F_s).

Making a relationship between the data of the temporal evolution of daily death for COVID-19 Fig. 2. and the ranking of the Brazilian Federal States Table 2, we can observe that the top seven in the ranking, with the exception of Paraná, are clearly in the process of decreasing the number of deaths from COVID-19. Considering the 3 best placed states in this ranking, some factors may have contributed to these positions, such as the early onset of COVID-19 cases, climatic factors - the virus arrived during the summer in these states, and probably in their capitals, and later, when it spread to cities in the interior of these states, the semi-arid climate of these cities, did not contribute to the spread of the virus, despite the change of season. In addition, Ceará, the highest ranked state, was one of those that most tested the population for COVID-19.

The state of Paraná, which occupies the 4th position in the ranking, despite not being clearly in a phase of decline in the number of deaths due to COVID-19, showed a very slow growth in the increase in the number of deaths over time, possibly due to good social conditions, among other factors. Unlike Paraná, Amazonas and Pará states experienced a very abrupt increase in the number of deaths cases at the beginning of the SARS-CoV-2 epidemic, which may have influenced their positions in the ranking, causing them to occupy the 7th and 10th positions despite being in a phase of clear decrease in the number of deaths. The arrival of the virus in the rainy season in these states, and also the genetic composition of the same with great indigenous influence may have influenced the great number of initial death experienced by the two states.

The internalization of the virus in the states and in Brazil as a whole during the autumn and winter period can help explain the growing moment in the number of deaths / plateau phase and placement in the ranking of states such as GO, MG, DF, SP, SC and ES.

Besides, we validated our results based on statistical analysis. Therefore, we perform a comparison between the Kernel distribution and Normal distribution considering the time series of daily death related to COVID-19. This analysis allowed us to verify the most critical moments, that is, they are not governed by a Normal distribution, so they are extreme events. Fig. 4 depicts statistical behavior considering the daily number of deaths related to COVID-19 from March 12^{nd}, 2020 until July 09^{th} 2020 for the eight best Brazilian states shown in Table 2

TABLE 2 Ranking of the Brazilian States, values of permutation entropy (H_s), Fisher Information measure (F_s) and distance from vertex $(1,0)$ considering $d = 4$

Ranking	Brazilian States	Entropy (H_s)	FIM (F_s)	Dist to $(1,0)$
1	CE	0.97498	0.02753	0.037201
2	PE	0.97126	0.04839	0.056283
3	BA	0.96543	0.05024	0.060981
4	PR	0.95978	0.05019	0.064315
5	RJ	0.94914	0.04025	0.06486
6	AL	0.9426	0.03964	0.069754
7	PA	0.94704	0.06353	0.082712
8	GO	0.93426	0.05031	0.082781
9	MG	0.93706	0.06775	0.092472
10	AM	0.93586	0.08111	0.103401
11	DF	0.9355	0.09617	0.115795
12	SP	0.94104	0.10039	0.116428
13	SC	0.92431	0.09569	0.122008
14	ES	0.89527	0.09393	0.140679
15	PB	0.90031	0.10657	0.145932
16	PI	0.89037	0.09717	0.146498
17	RS	0.91493	0.16122	0.182285
18	RN	0.89789	0.15586	0.186327
19	MA	0.86192	0.13544	0.193415
20	AC	0.84611	0.13512	0.204792
21	RO	0.87364	0.16909	0.211092
22	SE	0.83839	0.17023	0.234729
23	MT	0.79563	0.16769	0.264362
24	MS	0.75497	0.15763	0.291353
25	RR	0.76551	0.17585	0.293101
26	AP	0.78946	0.22455	0.307818
27	TO	0.71633	0.18912	0.340935

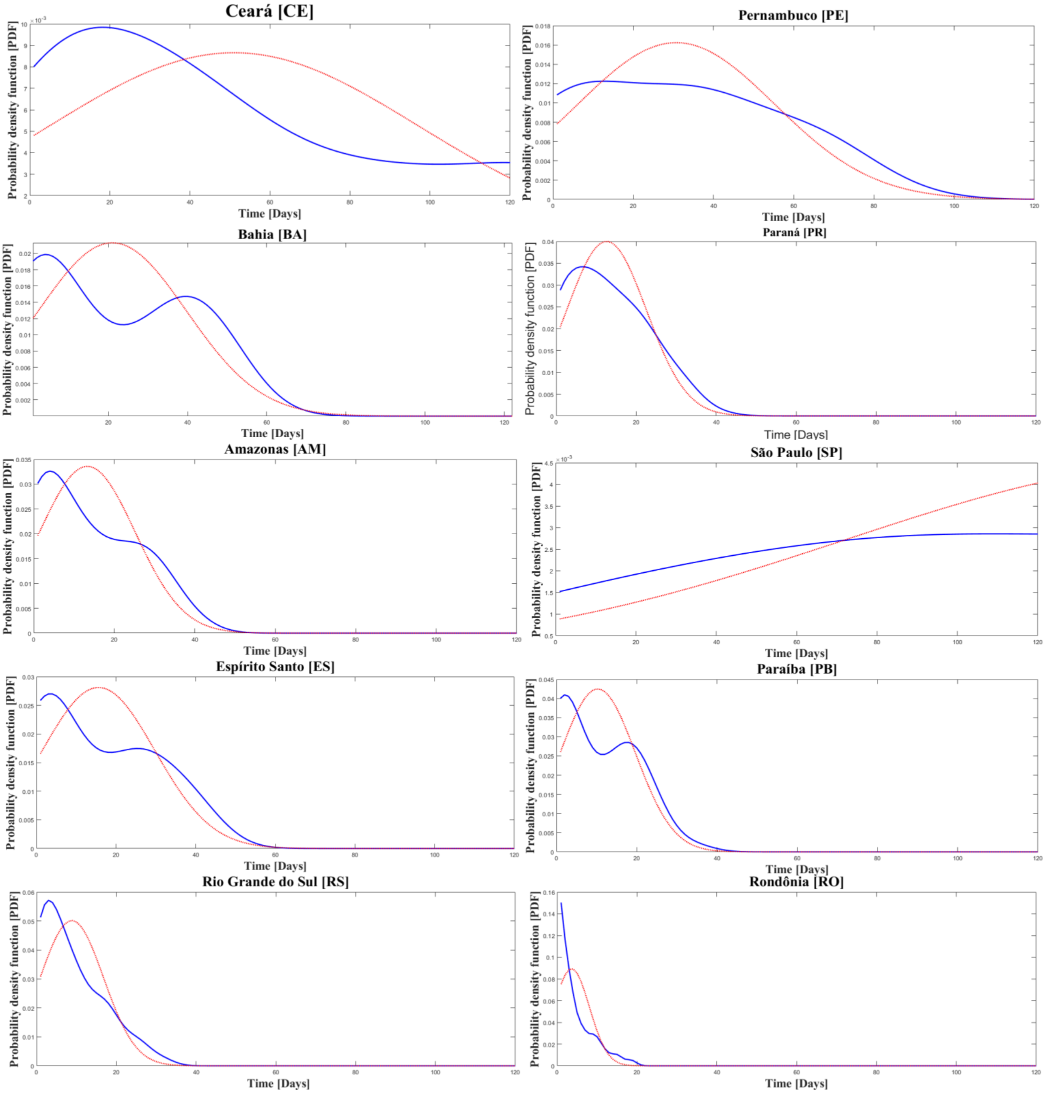

FIGURE 4 The statistical behavior considering the daily number of deaths related to COVID-19 based on the complexity hierarchy rank. The blue line is the Kernel distribution and the red dots is the Normal Distribution.

The periods of time in which the Kernel distribution exceeds Normal distribution reflect the most complicated periods in terms of mortality related to COVID-19, whereas the periods of time in which the Kernel distribution is below the Normal distribution indicate lower mortality related to COVID-19 in the final phase, it appears that the statistical behavior of mortality comparing Kernel distribution and Normal distribution tend to converge asymptotically.

CE until the fortieth day presented a leptokurtic curve, but gradually there was a flattening of the curve, which implies a drop in the number of deaths due to COVID-19. In the final phase, it is clear that there was stabilization in the number of deaths, this may be occurring, because although the number of deaths is in decline in the metropolitan region, COVID-19 has been spreading in relation to the interior of this State.

PE presented a high lethality, but much lower than the CE and, from the fifteenth day on, there is a flattening of the lethality curve. On the sixtieth day, there is an increase in lethality, but in the final phase, there is asymptotic convergence between Kernel distribution and Normal distribution.

SP showed an exponentially increasing lethality up to the seventieth day, but from that date, it entered the Plateau phase. PR is the Brazilian state with the highest human development index (HDI), it showed a lethality in growth until the tenth day, however there was a gradual reduction in lethality on the thirtieth day, it showed an increase in lethality, however 15 days later it appears that there was an asymptotic convergence between the Kernel distribution and Normal distribution.

For the other States (BA, ES, PB, RS, and RO), there is at least the incidence of 2 peaks of lethality resulting from COVID-19. We emphasize that unfortunately the underreporting of deaths from COVID-19 is a phenomenon common to all 27 Brazilian states.

5 | CONCLUSIONS

As Brazil is a country with continental dimensions, it is expected that the diverse Brazilian States are in different phases of confrontation with COVID-19. This reality is demonstrated in our results. Added to this, due to internal political issues, each Brazilian State had the freedom to adopt their own strategies to combat the COVID-19 epidemic Lancet, 2020.

In addition, we observed different dynamics of the dissemination of COVID-19 among the Brazilian States. These dynamics were revealed through the relationship between the entropy and FIM values.

All of these differences can be influenced by factors like quantity and qualification of health professionals, accessibility to specific equipment necessary to reduce lethality, respirators and personal protective equipment (ppe), and financial resources directly impact efficiency in reducing the daily number of deaths due to the COVID-19.

Moreover, these differences between the Brazilian States inherent to viral dynamics influenced by several factors may have implications for making predictions for the SARS-CoV-2 epidemic.

We found an inverse relationship between Permutation entropy (H_s) and Fisher information measure (F_s). Thus, we concluded that the higher value of the Permutation entropy (H_s) implies in the lower value related to the Fisher information measure (F_s).

Based on the Information Theory quantifiers, our results revealed the higher level of the degree of accuracy of the estimated parameters, taking into account the quantity and quality information extracted from the time series of COVID-19 death cases and the disorder inherent into the temporal evolution of these time series.

Currently, Brazil together with the United States of America are the countries that present the highest cases of lethality resulting from the new Coronavirus (COVID-19). This article can collaborate so that public health policymakers can allocate resources more efficiently in the fight against COVID-19 since it is presenting empirical evidence concerning the Brazilian States' reality.

conflict of interest

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

6 | ETHICS STATEMENT

The authors confirm that the ethical policies of the journal, as noted on the journal's author guidelines page, have been adhered to.

7 | DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in Transparency Portal at https://transparencia.registrocivil.org.br/covid.

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