Physica A 502 (2018) 619–628

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Self-affinity and self-organized criticality applied to the relationship between the economic arrangements and the dengue fever spread in Bahia

A.S. Nascimento Filho [a,*], M.L.V. Araújo [a,b], J.G.V. Miranda [d], T.B. Murari [a], H. Saba [c], M.A. Moret [a,d]

[a] SENAI – CIMATEC – Salvador, Bahia, Brazil
[b] Instituto Federal de Bahia - Salvador, BA, Brazil
[c] Universidade do Estado da Bahia, Salvador, BA, Brazil
[d] Universidade Federal da Bahia, Salvador, BA, Brazil

HIGHLIGHTS

- We studied dengue fever spread in the economic regions of Bahia-Brazil.
- We studied self-affinity in a disease diffusion process.
- We compare the spread disease for different regional arrangements.
- We finding two self-affinity behavior in the time series.
- We suggest that dengue fever behavior follow a complex adaptive system.

ARTICLE INFO

Article history:
Received 18 September 2017
Received in revised form 9 March 2018
Available online 20 March 2018

Keywords:
Dengue fever
Self-affinity process
Self-organized criticality

ABSTRACT

In this paper, we evaluate whether the diffusion of the dengue fever can be explained by differences among regional economies. We evaluate the dengue fever self-affinity behavior and self-organized critical behavior within the fifteen economic regions of State of Bahia, Brazil, between 2000 and 2009. The results showed two distinct behaviors for long-range correlation scaling: persistent for a month and subdiffusive for one year, according to DFA method. Furthermore, the dengue fever distribution presented power law behaviors for these data sets, according to SOC analysis. In this study, we concluded that this disease was not influenced by economic aspects or regional arrangement, and also suggest that the disease's vector (*Aedes aegypti* mosquito) has adapted to all the economic regions.

1. Introduction

The dengue fever is a systemic viral infection transmitted among humans by the bite of the *Aedes aegypti* [1]. It is the most common and widespread arbovirus in the world and especially highlighted among reemerging diseases [1,2]. The substantial vector control efforts have not stopped the rapid emergence and global spread of dengue fever; thereby, it has become an international public health problem, according to the World Health Organization (WHO) [2–4]. Brazil is one of the countries that compose the world's dengue fever risk area. In the State of Bahia-Brazil, the overall number increased from 160 cases per

* Corresponding author.
E-mail address: aloisio.nascimento@gmail.com (A.S.N. Filho).

https://doi.org/10.1016/j.physa.2018.03.024
0378-4371/

Table 1
Dengue fever record per economic regions in Bahia-Brazil between year 2000 and 2009.

Id	Symbol	Economic region	Quantity of cities	Cases
1	RMS	Região Metropolitana de Salvador	10	57,394
2	LTN	Litoral Norte	20	5658
3	NDE	Nordeste	46	32,942
4	PIE	Piemonte da Diamantina	24	24,812
5	PGU	Paraguaçu	42	36,821
6	REC	Recôncavo	33	10,444
7	LTS	Litoral Sul	53	57,645
8	EXS	Extremo Sul	21	14,196
9	SDE	Sudoeste	39	36,703
10	SGE	Serra Geral	29	10,609
11	CHP	Chapada Diamantina	33	8594
12	IRC	Irecê	19	26,567
13	BMF	Baixo Médio São Francisco	9	14,678
14	MSF	Médio São Francisco	16	4914
15	OST	Oeste	23	8676
	Total		417	350,653

100 thousand inhabitants in 2011 to 200.9 cases per 100 thousand inhabitants in 2012 [5]. Moreover, the silent transmission of dengue infections has been recognized, due the atypically symptomatic, even asymptomatic, in this way it is likely this disease can spread silently and remain in a community or region without being noticed [6].

The paradigm of complexity originates from studies in a wide range of physical, biological, and social phenomena, including diffusion problems and epidemiological spread [7]. Thus, increasing the understanding of how dengue fever spreads is mandatory going forward, the search must focus on discovering new ways of combating this disease, as proposed by [8] that assessed the spatial and temporal pattern of dengue incidence for two cities in Taiwan; in [9,7,10,11], where they verified the roles of transportation among cities in the dengue spread; in Ref. [12] the self affinity applied in multi-scale analysis; in Ref. [13], they measured the existence of a spatial correlation among socioeconomic, demographic and environmental variables in the incidence of dengue; in [14], they found that the incidence was strongly associated with the percentages of shop-houses, brick-made houses and houses with poor garbage disposal. Thereby, if the spatial and temporal factors for dengue cases clustering were better understood, we could prevent and control the transmission of dengue virus more efficiently [8,7].

The relationship between health and wealth seems to be well established, in such a way that, normally, wealthy areas or regions tend to have healthier populations than poor counterparts. At first glance that rule should be applicable for majorities of diseases, including dengue fever, once that one depends just on collective efforts (*e.g.*, coalition, education, communication, and sanitary conditions) to stop or minimize the risks of an outbreak. Thus, the aim of this study is to evaluate the occurrence of symmetries and correlations patterns for dengue cases in 417 cities in Bahia, Brazil, organized in fifteen economic regions, between 2000 and 2009. In addition, we verified whether the hypothesis of economic and social arrangement significantly influences the spread of dengue.

2. Materials and methods

In this section are presented the sets of data, climatic variables, the description of the scaling detrended fluctuation analysis method and the definition of the self organized criticality.

2.1. Data

The first step of this work was to collect the daily records of dengue fever cases in Bahia's cities between 2000 and 2009. The collected data is available at the Brazilian Diseases Notification System databases from the Brazilian health ministry. Additionally, these data were organized by clusters in the economic regions [15]. Table 1 shows the record of dengue fever cases per economic region. In Fig. 1 is shown the map of Bahia (total area 564.732 km^2), with 417 cities and their economic region identifications (Id). The sample of original time series of dengue fever daily cases is shown in Fig. 2, where their shapes suggest cycles of periodic outbreaks of dengue fever cases.

2.2. Climatic features

The climatic approach is normally associated with dengue fever problems. According to [1], high levels of precipitation and temperature suitability for dengue transmission are strongly associated with elevated dengue risk.

There are 29 meteorological stations in State of Bahia. It is a low number of stations, covering less than 7% of the its municipalities, that are not able to reach the economic region studied. This lack of data makes it difficult to analyze large areas in this region.

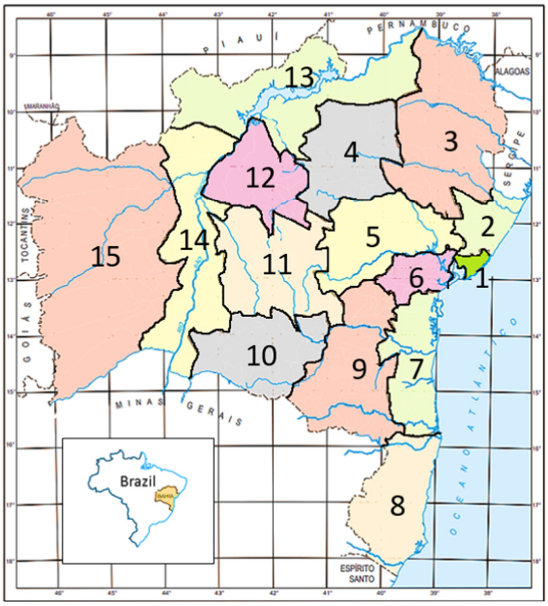

Fig. 1. Map of Bahia-Brazil (inset), economic regions division. The economic regions arrangement are characterized by diversities, e.g., in 1(RMS)- there is a petrochemical cluster and automotive pole; in 7(LTS), 8(EXS) and 11(CHP) adventure and ecological tourism; in 13(BMF)- fruit-culture and wine industry and; 15(OST)- agribusiness [15].

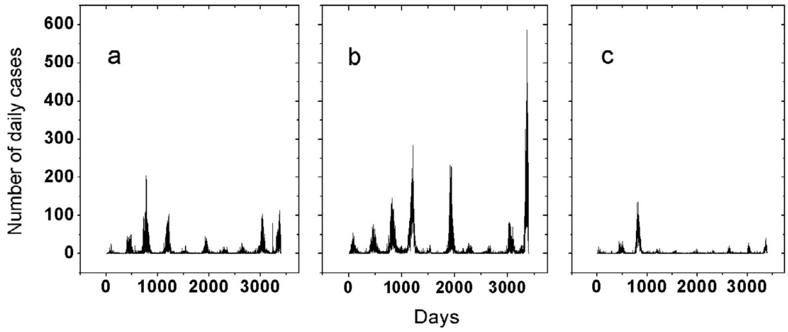

Fig. 2. Original time series of dengue fever daily cases from (a) PIE, (b) LTS and (c) REC.

It was collected daily precipitation measurements (mm) from fifteen meteorological stations inside the economic regions, between 2000 and 2008, as showed in Table 2. We decided do not use 2009 information because there is a lack of measurements on the data set. These data were provided by Meteorological Database for Teaching and Research (BDMEP) [16].

In Fig. 3, we organize the average precipitation by season and meteorological station. As we can see, the average result does not exceed 10 mm for any season of the year. Bahia is located in a Brazilian region that presents low precipitation when compared to the rest of the country. The annual total precipitation measured between 1976 and 2009 was mostly less than 1000 mm, according to U.S. department of commerce, through Physical Science Division at NOAA [17].

2.3. Detrended fluctuation analysis method

The Detrended Fluctuation Analysis method (DFA) [18] was used to assess the self-affinity properties of dengue fever cases. The DFA method avoid false detection of correlations that are artifacts of non-stationary time series and it has been applied to time series analyses in many areas, including the following: cloud structure analysis [19,20], fluctuation analyses of astrophysical systems [21], sunspot [22], protein energy [23], field of seismology [24,25], transport systems [26], efficiency in combustion processes [27], fluid dynamics [28], ion channel [29], finances [30], and blood pressure [31]. The following steps are used for the DFA method:

Table 2
The average precipitation by meteorological station for fifteen meteorological stations inside the economic regions between 2000 and 2008. The average precipitation is very low for all cities.

Station name (city)	Coordinates	Econ.Region	Average precipitation (mm)
Salvador	−12.974606, −38.511435	RMS	5.13
Alagoinhas	−12.137584, −38.424553	LTN	3.10
Serrinha	−11.657489, −39.006739	NDE	2.21
Senhor do Bonfim	−10.461947, −40.191283	PIE	2.08
Feira de Santana	−12.259114, −38.956272	PGU	2.05
Cruz das Almas	−12.673997, −39.102709	REC	3.20
Canavieiras	−15.672663, −38.954121	LTS	4.71
Caravelas	−17.733878, −39.265700	EXS	4.16
Vitória da Conquista	−14.849327, −40.837372	SDE	2.17
Caitité	−14.068791, −42.484159	SGE	1.75
Lençois	−12.563700, −41.391978	CHP	3.23
Irecê	−11.302874, −41.857971	IRC	1.70
Remanso	−9.625357, −42.080921	BMF	1.68
Barra	−11.091831, −43.144915	MSF	1.88
Barreiras	−12.148781, −44.993107	OST	2.68

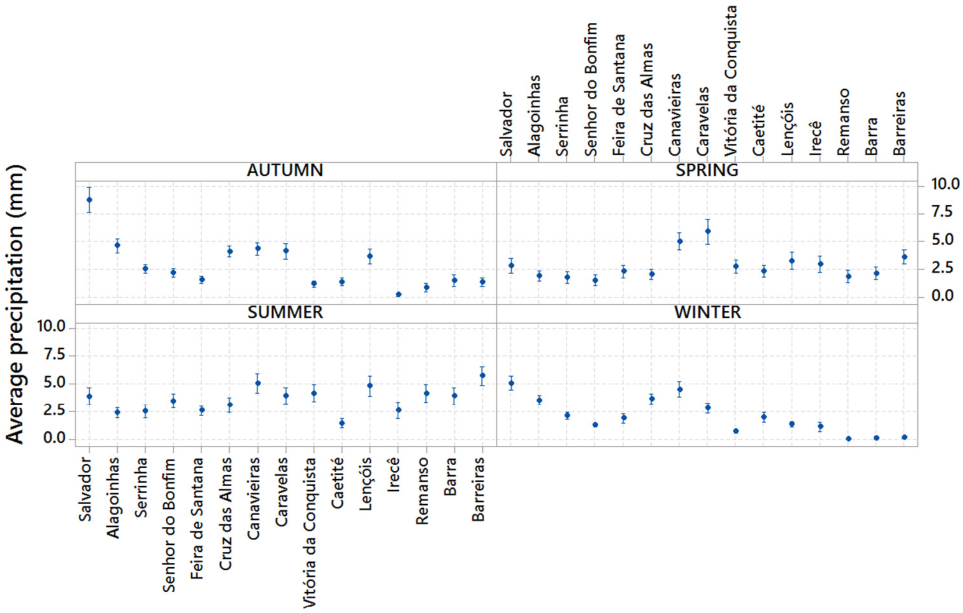

Fig. 3. The average precipitation by season and meteorological station for fifteen meteorological stations inside the economic regions between 2000 and 2008.

Consider an original time series r_i , where r_i is the number of cases of dengue fever at the ith day, with $i = 1, \ldots, N$, and N is the total number of days registered. The time series r_i is integrated to obtain

$$y(k) = \sum_{i=1}^{k} [r_i - \langle r \rangle], \tag{1}$$

where $\langle r \rangle$ is the average value of r_i. The integrated signal $y(k)$ is divided into non-overlapping boxes of equal length n; and for each $n - size$ box, $y(k)$ is fitted using a polynomial function, which represents the trend in the box. The coordinate of the fitting line in each box is denoted by $y_n(k)$ because a polynomial fitting of degree 1 is used and the algorithm DFA-l is denoted; the integrated signal $y(k)$ is detrended by subtracting the local trend $y_n(k)$ within each box (of length n);

For a given $n - size$ box , the root-mean-square fluctuation, $F(n)$, for the integrated and detrended signal is given as

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} [y(k) - y_n(k)]^2}, \tag{2}$$

The above computation is repeated for a broad range of scales ($n - sizedbox$) to provide a relationship between $F(n)$ and the box size n.

Table 3
Results of α exponent for fifteen economic regions, for one month and one year and power law γ distribution of dengue fever for each economic region. The σ represent the error of these results.

Symbol	DFA results				SOC results	
	α_{month}	σ_{month}	α_{year}	σ_{year}	γ	σ
RMS	1.01	0.08	1.36	0.07	−1.99	0.10
LTN	0.75	0.09	1.32	0.06	−1.89	0.11
NDE	0.68	0.03	1.40	0.04	−1.71	0.08
PIE	0.65	0.04	1.37	0.05	−1.72	0.07
PGU	0.73	0.07	1.29	0.04	−1.88	0.08
REC	0.76	0.09	1.41	0.05	−1.61	0.09
LTS	0.77	0.08	1.25	0.07	−1.77	0.09
EXS	0.66	0.04	1.21	0.06	−1.80	0.07
SDE	0.78	0.06	1.32	0.12	−1.72	0.09
SGE	0.70	0.03	1.36	0.05	−1.64	0.08
CHP	0.78	0.05	1.11	0.05	−1.82	0.07
IRC	0.68	0.07	1.37	0.06	−1.52	0.06
BMF	0.92	0.07	1.22	0.05	−1.72	0.09
MSF	0.66	0.04	1.13	0.03	−1.83	0.10
OST	0.81	0.03	1.11	0.04	−1.79	0.07

The scaling exponent α is defined whenever such a relationship is characterized by power law $F(n) \sim n^{\alpha}$. Therefore, the scaling exponent α is a self-affine parameter expressing the long-range power-law correlation properties.

Moreover, the scaling exponent α allows the assessment of how the long-range correlation influences the future behavior. The α exponent is classified as follows [27,28,22,31,32]:

1. $0.00 < \alpha < 0.50$ - anti-persistent signal;
2. $\alpha = 0.50$ - white noise with no memory;
3. $0.50 < \alpha < 1.00$ - persistent signal;
4. $\alpha = 1.00$ - the time series shows a noise type $1/f$;
5. $1.00 < \alpha < 1.50$, - subdiffusive process.

2.4. Self organized criticality

In the late 1980 Bak, Tang, and Wiesenfeld [33] introduced a sandpile model, in order to describe the so-called self organized critical (SOC) phenomena, where throughout a numerical simulation in geology of a dynamical system that imitated avalanches [34]. The authors suggested that there is a class of systems in nature that go into critical state throughout their own dynamic evolution, as an extension of fractal geometries to thermodynamic systems in the vicinities of instabilities [34,35].

For [34] a remarkable feature of their model is the ever-amplifying, self adjusting activation processes at all length and time scales, where the simplest model can capture the characteristics of a vast class of spatial and temporal evolution processes. The SOC approach is a critical state of a nonlinear energy dissipation system that is slowly and continuously driven toward a critical value of a system-wide instability threshold, producing scale-free, fractal diffusive, and intermittent avalanches with power law distributions [36].

3. Results

3.1. The power law analysis

In addition, the power law was obtained from dengue fever incidences frequency days as a function of the number of days into all economic regions, see Table 3. The power law behavior occurs in several complex systems related to many scientific fields and has significant consequences for understanding natural phenomena. Fig. 4 shows the distribution of dengue fever incidence frequency as function of number of dengue fever cases in a day. Piemonte da Diamantina (PIE) curve's shape suggests a behavior similar to the one observed in objects that follow a self organized criticality (SOC) [33,37].

The result of SOC analysis indicates that for small number of cases, an elevated frequency of days is observed, and the number of days with elevated number of cases are rare. This non exponential decreasing in the frequency of number of cases per day, suggests a correlated dynamic of its elements, typical of self-organized systems [33,37]. As example the log–log distribution observed to PIE presents Pearson 's correlation coefficient $R = -0.97$, $Fvalue = 562.35$ and $Prob > F \rightarrow 0$. Moreover, the dynamics underlying this type of distribution are equivalent to high cooperative evolutionary activities [38]. In the case of dengue fever, we hypothesized that the different characteristics of economic regions could alter the dynamics of disease diffusion in the epidemic process.

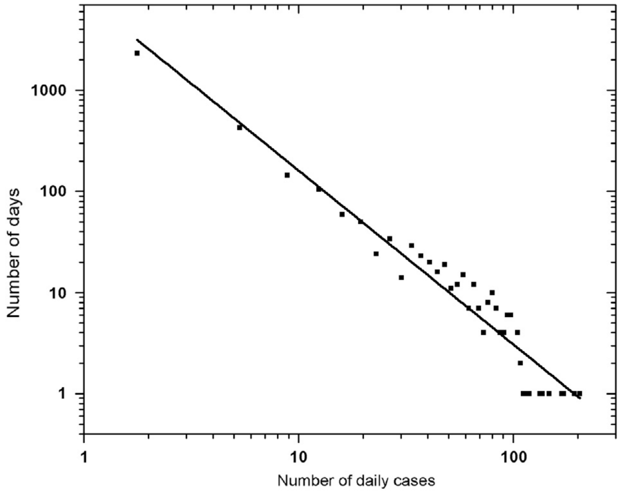

Fig. 4. Dengue fever daily incidence frequency in the economic region of Piemonte da Diamantina (PIE).

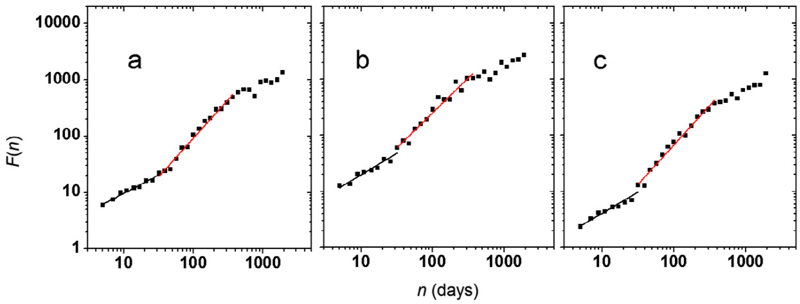

Fig. 5. Samples of self-affinity study applied in dengue fever daily cases in three economic regions (PIE, LTS and REC). We recall for two distinct behavior in the scale exponent α, the first one the α_{month} depicts the persistent behavior ($0.50 < \alpha_{month} < 1.00$) whereas the second, $1.00 < \alpha_{year} < 1.50$, represent a subdiffusive behavior.

3.2. Self-affinity analysis

The DFA method was applied in time series of dengue fever incidences in the fifteen economic regions of Bahia-Brazil to verify the self-affinity properties of these regions. Fig. 5 shows the relationship between root-mean-square fluctuation, $F(n)$, and the box size n, for three economic regions (PIE, LTS and REC). It was detected that for one month the result of α exponent is persistent for long-range correlations ($0.50 < \alpha_{month} < 1.00$), the large amount (small) of values that are likely followed by large amounts (small). For an annual period, the α exponent varies between $1.00 < \alpha_{year} < 1.50$, as a subdiffusive process (*i.e.*, the behavior tends to be seasonal, without presenting similar epidemics from year to year). That behavior is observed for all economic regions, as shown in Table 3.

3.3. The γ exponent distance verification

The γ exponent results is depicted in Fig. 6. The initial analysis does not allow distinguish the SOC behavior in economic regions. To better compare the obtained γ values with each other, we calculated the difference (D) between each value and that of RMS region which is the largest. Notable are the three groups of cluster ranges, as shown in Fig. 7. Where the first cluster is formed by eight economic regions, its range is ($0.00 < D < 0.05$); the second cluster is ($0.05 > D < 0.10$), which has four economic regions. We recall that the third range does not represent a cluster, scattered among ($0.10 < D < 0.23$). Accordingly, we did not recognize any relationship between the difference D and the economic region, since each cluster does not contain regions with similar economic conditions.

3.4. Randomization test analysis

Finally, the correlation properties between α exponent values and γ were verified for all 417 cities in order to verify a potential relationship between the SOC dynamic and the long term correlation in time described by the DFA method.

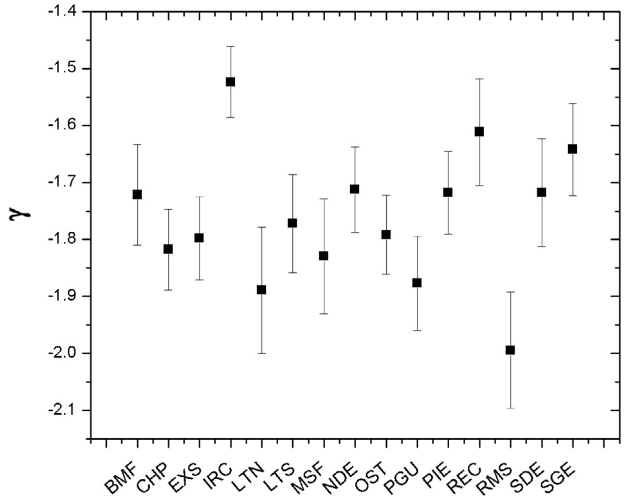

Fig. 6. The γ exponents were obtained from the fifteen economic regions for all period, where the number of class is the $\sqrt{n}$ (*i.e.*, size equal to 58).

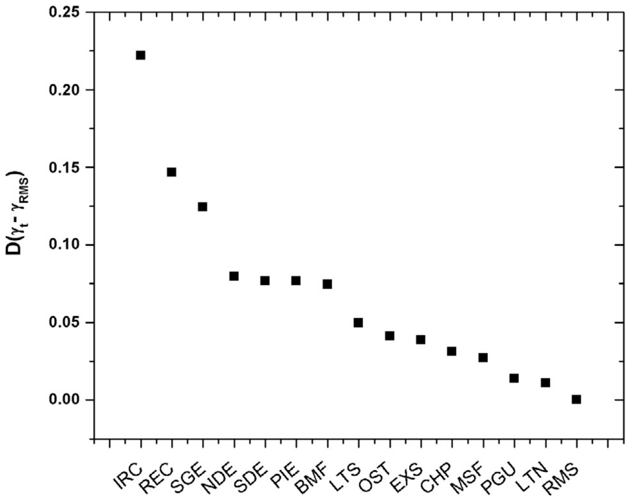

Fig. 7. The distance of the γ exponent in relation to RMS economic region.

For this purpose, the randomization test [39] was applied, by using the Spearman correlation coefficient with 100,000 randomizations of the data. This method confirms the existence of a pattern in the original data, since under the null hypothesis, all possible data orders have an equal chance to occur [39].

A comparison between the distribution of correlation values found for randomizations and correlation of the original data is shown in Fig. 8. The result of the α_{year} and γ presented a ρ equal to -0.215702. That value is outside the distribution, so that we can reject the null hypothesis. According to the Ref. [39], we can confirm a correlated relationship between α_{year} exponent and γ exponent (*i.e.*, that does not occur by chance). See Figs. 9 and 10.

On the other hand, the relationship between α_{month} and γ, suggests that their relation happened by chance. As well as for α_{month} and α_{year}. For both randomization tests were obtained the ρ equal to 0.125194 and -0.113823, respectively. As the result of these was inside the distribution area, we can accept the null hypothesis for them (*i.e.*, they occur by chance).

4. Discussions

The economic regions are diversified, e.g., with universities covering all regions, extensive highways connecting all regions, three harbors, two international airports, among other important economic activities as well as public equipment. At first glance, all these capacities could offer materials, financial resources and conditions to fight against the disease propagation. However, this is not observed, and the disease spreads across all economic regions, as showed in Table 1.

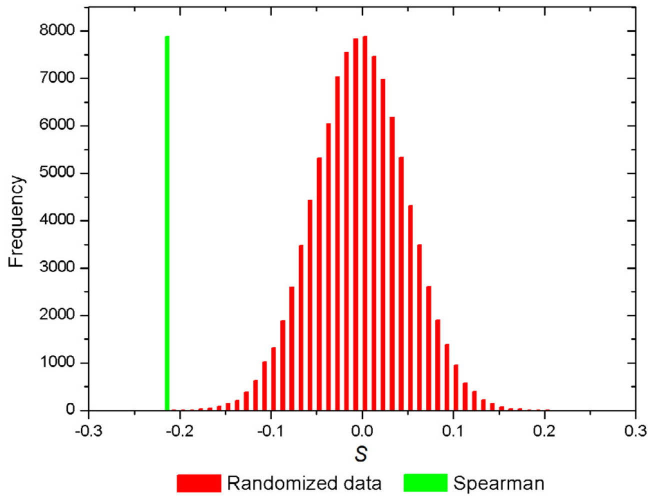

Fig. 8. The randomization test between α_{year} exponent and γ exponent shows that they are negatively correlated. Thus, we must reject the null hypothesis, since that Spearman correlation (ρ is equal to -0.215702) is outside of the distribution area (randomized data).

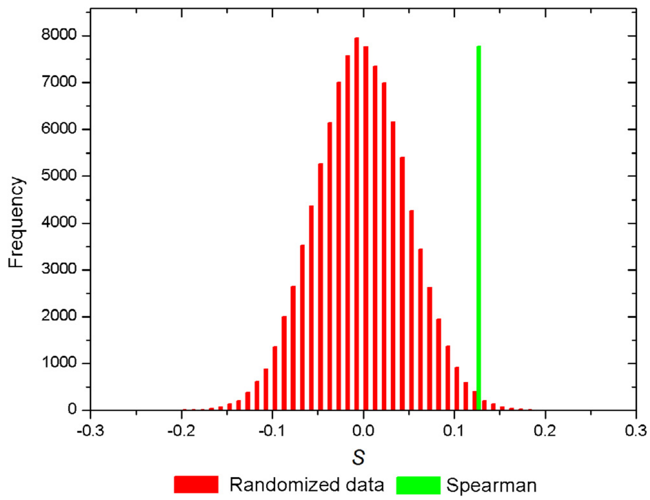

Fig. 9. The randomization test between α_{month} exponent and γ exponent shows that they are not correlated (*i.e.*, the relation between α_{month} exponent and γ exponent occur by chance). Thus, we must accept the null hypothesis, since that Spearman correlation (ρ is equal to 0.125194) is inside the distribution area (randomized data).

In general, dengue spread is directly associated with high levels of precipitation and temperature suitability, although, low precipitation values do not limit the transmission of dengue [1]. According to Fig. 3, Bahia presents low levels of precipitation. On the other hand, greater risk of dengue spread is also linked to the proximity to low-income urban and peri-urban centers, mainly in highly connected areas, bringing the idea that human movement between population centers is an important facilitator of dengue spread [1,7,9,11]. Besides, the diffusion process of dengue reflects the continuous existence of several series of transmission chains, including the spatial and temporal distribution. Where the dengue spread can be explained by the movement of either infected mosquitoes or infected people through a region, area, even neighborhood [7,8,11,13]. Nevertheless, in Bahia does not seem any correlation with economic factors.

4.1. Complexity analysis and implications

The results show that the distribution of the number of cases per day over 9 years follows a power-law behavior in the 15 economic regions studied. This is a characteristic of SOC dynamics [33,37]. Thereby, suggesting that an addition of new cases is similar to the effect of an avalanche, where these avalanches are equivalent to high cooperative evolutionary activities, so that leading to the expansion of the epidemic process among economic regions.

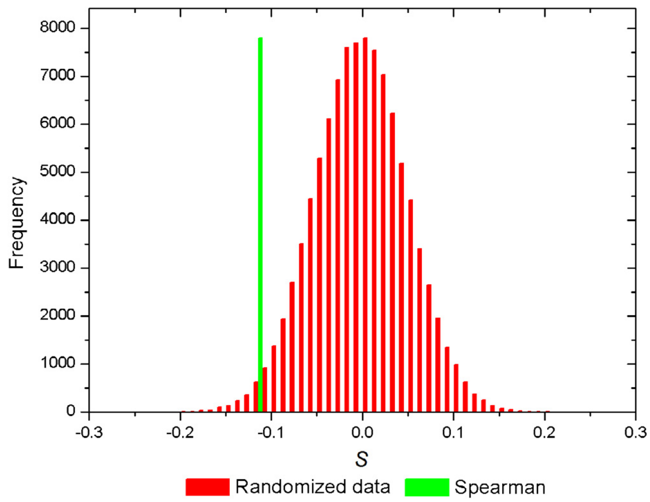

Fig. 10. The randomization test between α_{month} exponent and α_{year} exponent shows that they are not correlated (*i.e.*, the relation between α_{month} exponent and α_{year} exponent occur by chance). Thus, we must accept the null hypothesis, since that Spearman correlation (ρ is equal to -0.113823) is inside the distribution area (randomized data).

Besides, the γ difference ($0.00 < D < 0.25$) did not express relation between economic regions, with no direct relationship with the individual properties of each economic region's cluster is provided, so that it was not possible to recognize similarity in economic regions in the same cluster. In the self-affinity analysis two distinct behaviors were found in time. The first one, a persistent behavior ($0.50 < \alpha_{month} < 1.00$), where there are long-range correlations for all economic regions, *i.e.*, large (small) fluctuations tend to remain in the future. The second one, the subdiffusive process ($1.00 < \alpha_{year} < 1.50$), a state for large time, characterized by nonstationary signals and abrupt changes, which makes prediction difficult [31,27,12,28]. And also, the relationship between SOC and the DFA method was verified. The randomization tests were performed and it detected the existence of a significant relation between high cooperative evolutionary activities (avalanches) and the behavior that tends to be seasonal, without presenting similar epidemics from year to year (α_{year}), once γ and α_{month} as well as for α_{year} and α_{month} happened by chance, according to the randomization test.

4.2. Conclusions and perspectives

The dengue fever transmission dynamic in the economic regions is similar among them, which suggests a similar dynamic underlying the diffusion process of the disease throughout the regions. It increases the risk of major epidemics, since regardless of its origin, it would propagate with the same dynamics across all regions. The dengue fever virus has the evolution capacity to create a challenge for the human immunity system, where it faces a complicated task, leading to four categories of dengue fever virus serotypes (DEN 1, DEN 2, DEN 3 and DEN 4) identified [4], it is a difficult battle for public authorities. Although dengue fever is treated as an aggregated system (economic regions), and our results show these regions resemble themselves, as a single system, with the capacity to produce an emergent property, that is, collective responses like a complex adaptive system [38].

The diffusion, therefore, cannot be explained by the clusters. So the hypothesis that economy features can affect the dengue fever diffusion in this region was rejected. The dengue fever spread was neither influenced by economic aspects nor by regional arrangements. The disease seems to reach critical state as a process of natural evolution, without any intervention, changes in sensitivity, parameter settings, or changes in the initial configuration. However, the dengue fever could be spread for all these regions, with potential to create large-scale epidemic clusters. This observation corroborates that *Aedes aegypti* has a great capability to adapt to different habitats, both in nature and urban environments, where the *Aedes aegypti* does not have natural predators.

For a future research, an investigation on the correlation between spatio-temporal and dengue fever virus serotypes. Since we believe it is necessary to enlarge that kind of research due to the adaptive capability of the *Aedes aegypti*. As the possibilities of new outbreaks in Brazil are real, to explore others computational approach are always welcome, *e.g.*, cross correlation approach and neural artificial network, both applied to the dengue fever spread.

Acknowledgments

This work received financial support from National Counsel of Technological and Scientific Development — CNPq, Brazil (grant numbers 458549/2014-2, 448303/2014-0, 304454/2014-1 and 310133/2016-5) and National Petroleum Agency, Brazil - ANP/PRH55 process number:486100833602013 — FINEP.

References

[1] S. Bhatt, P.W. Gething, O.J. Brady, J.P. Messina, A.W. Farlow, C.L. Moyes, J.M. Drake, J.S. Brownstein, A.G. Hoen, O. Sankoh, et al., The global distribution and burden of dengue, Nature 496 (7446) (2013) 504–507.
[2] A.J. Tatem, S.I. Hay, D.J. Rogers, Global traffic and disease vector dispersal, Proc. Natl. Acad. Sci. 103 (16) (2006) 6242–6247.
[3] O.J. Brady, P.W. Gething, S. Bhatt, J.P. Messina, J.S. Brownstein, A.G. Hoen, C.L. Moyes, A.W. Farlow, T.W. Scott, S.I. Hay, Refining the global spatial limits of dengue virus transmission by evidence-based consensus, PLoS Neglected Trop. Dis. 6 (8) (2012) e1760.
[4] W. H. Organization, S. P. for Research, T. in Tropical Diseases, W. H. O. D. of Control of Neglected Tropical Diseases, W. H. O. Epidemic, P. Alert, Dengue: guidelines for diagnosis, treatment, prevention and control, 2009, World Health Organization.
[5] SVS, Secretaria de vigilnâcia sanitária - boletim epidemiólgico-dengue 43, 2012, p. 11, 2012, available in: http://portalms.saude.gov.br/vigilancia-em-saude/.
[6] W.-J. Chen, S.-L. Chen, L.-J. Chien, C.-C. Chen, C.-C. King, M.-R. Harn, K.-P. Hwang, J.-H. Fang, Silent transmission of the dengue virus in southern taiwan, Am. J. Trop. Med. Hygiene 55 (1) (1996) 12–16.
[7] H. Saba, V.C. Vale, M.A. Moret, J.G.V. Miranda, Spatio-temporal correlation networks of dengue in the state of Bahia, BMC Publ. Health 14 (1) (2014) 1085.
[8] C.-C. Kan, P.-F. Lee, T.-H. Wen, D.-Y. Chao, M.-H. Wu, N.H. Lin, S. Y.-J. Huang, C.-S. Shang, I.-C. Fan, P.-Y. Shu, et al., Two clustering diffusion patterns identified from the 2001–2003 dengue epidemic, kaohsiung, taiwan, Am. J. Trop. Med. Hygiene 79 (3) (2008) 344–352.
[9] H. Cardoso, J.G.V. Miranda, E.M. de Freitas Jorge, M.A. Moret, Correlation between transport and occurrence of dengue cases in Bahia, J. Commun. Comput. 11 (2014) 217–221.
[10] H. Saba, J. Miranda, M. Moret, Self-organized critical phenomenon as a q-exponential decayAvalanche epidemiology of dengue, Physica A 413 (2014) 205–211.
[11] H. Saba, M.A. Moret, F.R. Barreto, M.L.V. Araújo, E.M.F. Jorge, A.S. Nascimento Filho, J.G.V. Miranda, Relevance of transportation to correlations among criticality, physical means of propagation, and distribution of dengue fever cases in the state of bahia, Sci. Total Environ. (2017).
[12] S. Azevedo, H. Saba, J. Miranda, A.N. Filho, M. Moret, Self-affinity in the dengue fever time series, Internat. J. Modern Phys. C 27 (12) (2016) 1650143.
[13] R. Pontes, J. Freeman, J.W. Oliveira-Lima, J.C. Hodgson, A. Spielman, Vector densities that potentiate dengue outbreaks in a brazilian city., Am. J. Trop. Med. Hygiene 62 (3) (2000) 378–383.
[14] S. Thammapalo, V. Chongsuvivatwong, A. Geater, M. Dueravee, Environmental factors and incidence of dengue fever and dengue haemorrhagic fever in an urban area, Southern Thailand, Epidemiol. Infection 136 (1) (2008) 135–143.
[15] SEI, 2012 Superintêndncia, de estudos econômicos e sociais do estado da Bahia (SEI). Regiões econômicas do Estado da Bahia, available in: http://www.sei.ba.gov.br/.
[16] BDMEP, 2017 Banco de dados meteorolgicos para ensino e pesquisa Available in: http://www.inmet.gov.br/projetos/rede/pesquisa/.
[17] NOAA, 2017 National oceanic and atmospheric administration Available in: https://www.esrl.noaa.gov/psd/data/gridded/data.south_america_precip.html.
[18] C.-K. Peng, S.V. Buldyrev, S. Havlin, M. Simons, H.E. Stanley, A.L. Goldberger, Mosaic organization of DNA nucleotides, Phys. Rev. E 49 (2) (1994) 1685.
[19] K. Ivanova, M. Ausloos, Application of the detrended fluctuation analysis (DFA) method for describing cloud breaking, Physica A 274 (1) (1999) 349–354.
[20] K. Ivanova, M. Ausloos, E. Clothiaux, T. Ackerman, Break-up of stratus cloud structure predicted from non-Brownian motion liquid water and brightness temperature fluctuations, Europhys. Lett. 52 (1) (2000) 40.
[21] M.A. Moret, G. Zebende, E. Nogueira Jr., M. Pereira, Fluctuation analysis of stellar x-ray binary systems, Phys. Rev. E 68 (4) (2003) 041104.
[22] M. Moret, Self-affinity and nonextensivity of sunspots, Phys. Lett. A 378 (5) (2014) 494–496.
[23] P. Figueirêdo, M. Moret, P. Pascutti, E. Nogueira, S. Coutinho, Self-affine analysis of protein energy, Physica A 389 (13) (2010) 2682–2686.
[24] L. Telesca, M. Lovallo, V. Lapenna, M. Macchiato, Long-range correlations in two-dimensional spatio-temporal seismic fluctuations, Physica A 377 (1) (2007) 279–284.
[25] L. Telesca, M. Lovallo, Non-uniform scaling features in central Italy seismicity: A non-linear approach in investigating seismic patterns and detection of possible earthquake precursors, Geophys. Res. Lett. 36 (1) (2009).
[26] A. Filho, G. Zebende, M. Moret, Self-affinity of vehicle demand on the ferry-boat system, Internat. J. Modern Phys. C 19 (04) (2008) 665–669.
[27] J. Souza, A. Santos, L. Guarieiro, M. Moret, Fractal aspects in enriched combustion, Physica A 434 (2015) 268–272.
[28] A. Nascimento Filho, J. de Souza, A. Pereira, A. Santos, I. da Cunha Lima, A. da Cunha Lima, M. Moret, Comparative analysis on turbulent regime: A self-affinity study in fluid flow by using OpenFoam CFD, Physica A 474 (2017) 260–266.
[29] Z. Siwy, M. Ausloos, K. Ivanova, Correlation studies of open and closed state fluctuations in an ion channel: Analysis of ion current through a large-conductance locust potassium channel, Phys. Rev. E 65 (3) (2002) 031907.
[30] S. Lahmiri, Long memory in international financial markets trends and short movements during 2008 financial crisis based on variational mode decomposition and detrended fluctuation analysis, Physica A 437 (2015) 130–138.
[31] C. Galhardo, T. Penna, M.A. de Menezes, P. Soares, Detrended fluctuation analysis of a systolic blood pressure control loop, New J. Phys. 11 (10) (2009) 103005.
[32] B.D. Malamud, D.L. Turcotte, Self-affine time series: Measures of weak and strong persistence, J. Stat. Plann. Inference 80 (1) (1999) 173–196.
[33] P. Bak, C. Tang, K. Wiesenfeld, Self-organized criticality: An explanation of the 1/f noise, Phys. Rev. Lett. 59 (4) (1987) 381.
[34] Y.-C. Zhang, Scaling theory of self-organized criticality, Phys. Rev. Lett. 63 (5) (1989) 470.
[35] J. Phillips, Fractals and self-organized criticality in proteins, Physica A 415 (2014) 440–448.
[36] M.J. Aschwanden, A macroscopic description of a generalized self-organized criticality system: Astrophysical applications, Astrophys. J. 782 (1) (2014) 54.
[37] P. Bak, How Nature Works: The Science of Self-Organized Criticality, Springer Science & Business Media, 2013.
[38] J.H. Holland, Studying complex adaptive systems, J. Syst. Sci. Complexity 19 (1) (2006) 1–8.
[39] B.F. Manly, Randomization, Bootstrap and Monte Carlo Methods in Biology, Vol. 70, CRC Press, 2006.