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Self-affinity in the dengue fever time series

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Dengue is a complex public health problem that is common in tropical and subtropical regions. This disease has risen substantially in the last three decades, and the physical symptoms depict the self-affine behavior of the occurrences of reported dengue cases in Bahia, Brazil. This study uses detrended fluctuation analysis (DFA) to verify the scale behavior in a time series of dengue cases and to evaluate the long-range correlations that are characterized by the power law α exponent for different cities in Bahia, Brazil. The scaling exponent (α) presents different long-range correlations, i.e. uncorrelated, anti-persistent, persistent and diffusive behaviors. The long-range correlations highlight the complex behavior of the time series of this disease. The findings show that there are two distinct types of scale behavior. In the first behavior, the time series presents a persistent α exponent for a one-month period. For large periods, the time series signal approaches subdiffusive behavior. The hypothesis of the long-range correlations in the time series of the occurrences of reported dengue cases was validated. The observed self-affinity is useful as a forecasting tool for future periods through extrapolation of the α exponent behavior. This complex system has a higher predictability in a relatively short time (approximately one month), and it suggests a new tool in epidemiological control strategies. However, predictions for large periods using DFA are hidden by the subdiffusive behavior.

Keywords: Detrended fluctuation analysis; epidemic process; subdiffusive behavior.

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1. Introduction

Dengue fever is considered to be the most important viral disease transmitted by arthropods[1,2]; it is also the most common and widespread arbovirus in the world and is especially highlighted among reemerging diseases. The main arthropod that transmits dengue is the *Aedes aegypti* mosquito, which is a species that is originally from Africa. This mosquito moved to the American continent during the colonization period.[3] The first related cases of dengue fever occurred in the late eighteenth century on the island of Java in Asia and in the state of Philadelphia in the United States of America. Nevertheless, the World Health Organization (WHO) only recognized dengue fever as a disease in the 20th century.[3]

In the second half of the 20th century, the occurrence of dengue fever also increased because of the urban vector of the disease resulting from the high propagation of urban and *A. aegypti* populations. The fight against *A. aegypti* in domestic habitats, known as source reduction, is the fundamental method to prevent the spread of dengue fever by the public health municipality agents of endemic cities.[4–7]

The dengue fever virus is an international public health problem. Half of the world population is currently at a potential risk of dengue fever infection, and between 50 million and 100 million new cases of infection have been reported each year. Among the infected, 500 000 people had a severe infection that required hospitalization; most patients were children. Approximately 2.5% of those infected died.[8] The lack of effective drugs and vaccines makes vector control the sole tool for primary intervention,[9] and currently, treatments only exist for the symptomatic effects, not the virus itself. In patients with severe infection, shock and bleeding usually worsen the clinical case. If a patient is not treated in time, death often results. Both early detection and correct prognosis can avoid such serious complications.[8]

In Brazil, the Epidemiological Survey of the Health Surveillance Office[3] showed that between January 2012 and April 2012, 286 011 cases of dengue fever were registered. These data demonstrated a 44% reduction in total cases of dengue fever in the country. Despite the decrease in disease transmission rate in the majority of regions, some states did see an increase in the number of incidences in 2012. The state of Bahia stands out among them, with 200.9 cases per 10 000 inhabitants.

In 2011, in Bahia, there were 22 424 cases of dengue fever; in 2012, the number increased to 28 154. Therefore, the incidence of dengue fever in Bahia in 2011 was 160.0 cases per 10 000 inhabitants, and the overall number increased to 200.9 cases per 10 000 inhabitants in 2012.[3]

The evolution of dengue fever must to be addressed using multidisciplinary tools to minimize its propagation during the short term where the disease is present.

The goal of this work is to apply detrended fluctuation analysis (DFA)[10] to study the scale properties of dengue fever incidence to verify its scale behavior. Thus, the time series of incidence in cities in Bahia, Brazil is evaluated. This work is structured as follows: the first section is an introduction to the problem; the second section introduces the DFA method; the third section presents the results; A description and interpretation of the proposed model is done in fourth section.

2. Method

Daily time series of dengue fever incidence in 25 municipalities in Bahia, Brazil, are selected between 2000 and 2010 to analyze their self-affinity properties using DFA. One advantage of the DFA method is that it accounts for the long-range power-law correlations in signals with embedded polynomial trends that can mask the true correlations in the fluctuations of a noise signal.

The DFA method is proposed for determining the statistical self-affinity of a signal; the method is based on the theory of random walks[11] and is an improvement of the fluctuation analysis (FA) method.[12] The range of systems apparently displays the power law, so the self-invariant correlations have increased dramatically in recent years. It was initially proposed for applications in the sequential analysis of DNA,[10] so the DFA method has been applied for time series analysis in many areas, including the following,[13,14]: cloud structure analysis[15] geology,[16] fluctuation analysis of astrophysical systems,[17,18] phase transitions,[19] sunspot examinations,[20] heart rate variability studies,[21] ion channel studies,[22] protein energy,[23] weather,[24] the interval between successive steps to assess a disease so a patient walks[25] and financial time series.[26,27] The DFA method is excellent at avoiding the false detection of correlations that are artifacts of nonstationary time series.

The following steps are used for the DFA method[10]:

- Consider an original time series, r_i, where $i = 1, 2 \ldots, N$ and N is the total number of daily cases of dengue fever. The time series r_i is integrated to obtain $y(k) = \sum_i^k r_i - \langle r \rangle$, where $\langle r \rangle$ is the average value of r_i.
- The integrated signal $y(k)$ is divided into boxes of equal length n;
- For each n-size box, $y(k)$ is fitted using a polynomial function of order l, which represents the trend in the box. The y coordinate of the fitting line in each box is denoted by $y_n(k)$ because a polynomial fitting of order l 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

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

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

The scaling exponent α is defined whenever such a relationship is characterized by a power-law $F(n) \propto n^{\alpha}$. Therefore, the scaling exponent α is a self-affine parameter expressing the long-range power-law correlation properties of the incidence of dengue fever. Moreover, the scaling exponent α allows for the assessment of how the long-range correlation influences the future behavior.

The α exponent is classified as follows[13,14,28,29]:

- If $0 < \alpha < 0.50$, the time series has an anti-correlated behavior, indicating an anti-persistent signal, i.e. when large values (small) occur, in the future, fluctuations tend to have small values (large);
- If $\alpha = 0.50$, the time series is uncorrelated, like white noise with no memory;
- If $0.50 < \alpha < 1$, the fluctuation in the time series has a correlated behavior, i.e. large (small) fluctuations tend to keep this behavior in the future, as a persistent signal;
- If $\alpha = 1$, the time series shows a noise type $1/f$;
- If $1 < \alpha < 1.5$, the signal is not stationary, as a subdiffusive process[29];
- If $\alpha = 1.5$, a brown noise is present, which is the integration of white noise or noise of the 141 Brownian type[29];
- If $\alpha > 1.5$, a superdiffusive process exists.[29]

The α exponent depicts future scenarios that can be used in the epidemiological control strategy as a possible statistical support.

3. Results

3.1. *DFA application—results and discussion*

The daily impact of dengue fever in the municipalities of Bahia collected from the Brazilian Diseases Notification System (SINAN) databases were analyzed (Fig. 1, Ref. 30). Furthermore, the DFA method was applied to study the long-range correlation of dengue incidence for 25 selected municipalities by the highest population index (Table 1). Two distinct behaviors for all municipalities were detected from the findings. The first behavior showed that the time series presents a persistent

Table 1. Long-range correlation exponents exponents, α and the standard deviation, σ, for 25 selected municipalities for the month and the year. From 2000 to 2010 data.

Code	Municipality	α_{Month}	σ	α_{year}	σ
1	Salvador	0.98	0.04	1.35	0.03
2	Feira de Santana	0.72	0.05	1.20	0.02
3	Vitória da Conquista	0.55	0.02	1.23	0.01
4	Camaçari	0.50	0.02	1.34	0.02
5	Itabuna	0.76	0.06	1.31	0.03
6	Juazeiro	1.04	0.06	1.09	0.02
7	Ilheus	0.68	0.04	1.28	0.02
8	Lauro de Freitas	0.88	0.02	1.18	0.01
9	Jequie	0.88	0.06	1.49	0.03
10	Teixeira de Freitas	0.54	0.01	1.18	0.02
11	Alagoinhas	0.59	0.05	1.26	0.03
12	Barreiras	0.74	0.03	1.09	0.02
13	Porto Seguro	0.79	0.04	1.02	0.03
14	Simões Filho	0.63	0.02	1.45	0.02
15	Paulo Afonso	0.65	0.03	1.11	0.01
16	Eunápolis	0.58	0.01	1.16	0.01
17	Santo Antônio de Jesus	0.58	0.03	1.22	0.02
18	Valença	0.68	0.02	1.05	0.01
19	Candeias	0.65	0.02	1.08	0.01
20	Guanambi	0.76	0.01	1.14	0.01
21	Jacobina	0.57	0.04	1.27	0.02
22	Serrinha	0.67	0.02	1.09	0.01
23	Senhor do Bonfim	0.71	0.05	1.11	0.02
24	Dias d'Avila	0.54	0.01	1.13	0.01
25	Itapetinga	0.62	0.02	1.32	0.02

α exponent for a period of one month ($0.50 < \alpha < 1.00$). Furthermore, for larger time periods, the time series signal approaches the subdiffusive behavior ($1.00 < \alpha < 1.50$). The subdiffusive behavior is observed for periods between one month and one year.

Table 1 provides the average value of the α exponent; its expected values are $\alpha = 0.69 \pm 0.14$ for periods of less than one month, and $\alpha = 1.21 \pm 0.12$ for the periods from one month to one year. On the other hand, Fig. 1 shows the uncorrelated behavior between α_{Month} and α_{Year}.

Figure 2 depicts the behavior of the α exponent of the time series of dengue incidence for all of the recorded data from Bahia. Figure 2 also shows that Bahia follows the same pattern described in Table 1 compared to the time series of some municipalities in Bahia. Besides, the long-range correlation in this time series follows the observed behavior in the time series of all 417 municipalities of Bahia.

3.2. *Data fluctuation behaviors*

Seasonal phenomena in the time series are detected by the regularity of events because events are observed from year to year, e.g. the increase in rainfall and

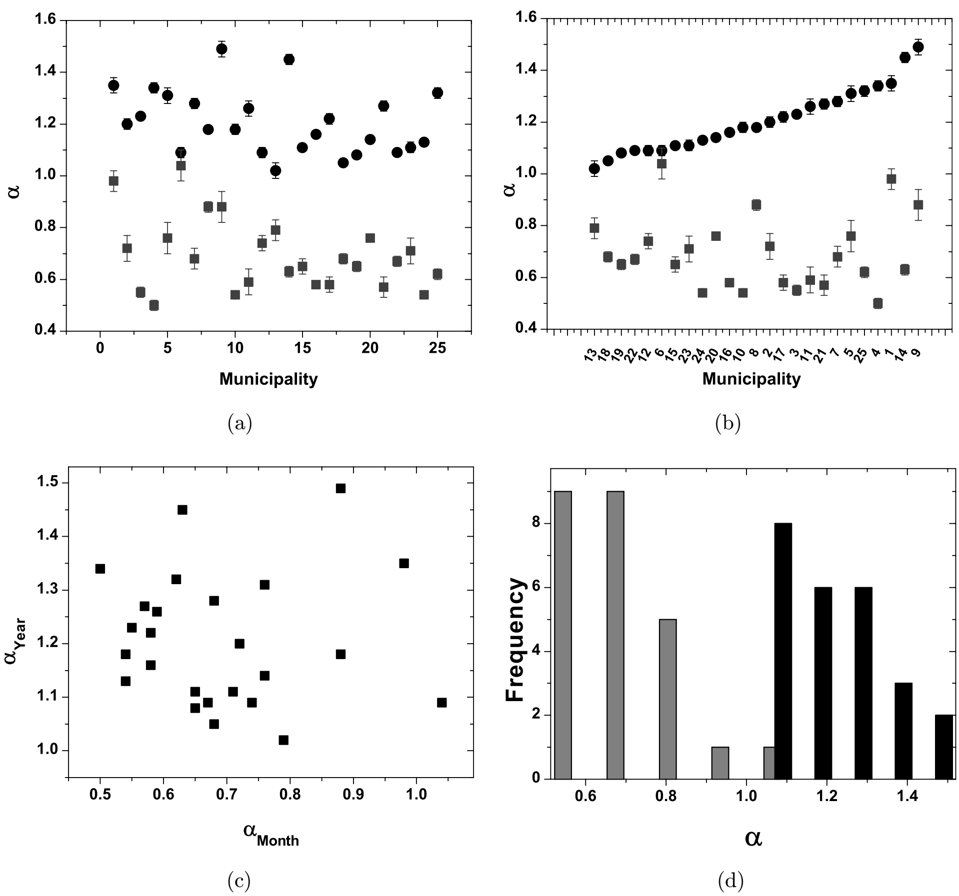

Fig. 1. Scaling exponent α for periods of less than one month (gray squares) and exponents for the periods from one month to one year (black circles) (a); Scaling exponents growth for periods from one month to one year (b); Scaling exponent for periods less than one month (α_{Month}) as function of exponents for the periods from one month to one year (α_{Year}) (c); And the distribution of the scale exponent (α). The dark gray columns are the counts for one month behavior. The light gray columns are the counts for the periods from one month to one year (d).

temperature index during certain times of the year or the increase in retail sales during the Christmas season. Normally, it is not easy to analyze a time series when the seasonality component is embedded. Indeed, it tends to "disturb" other statistical components embedded in the time series, such as tendency.[31] Hence, some statistic fluctuation properties of dengue incidences in the city of Feira de Santana are verified to assess its forecasted behaviors.

Table 2 shows the seasonal fluctuations where most of total of incidences of cases are concentrated during the fall and summer months, whereas the winter and spring months have less accumulated quantities. Therefore, the behavior confirms that the infection pattern of dengue fever in Brazil follows the trends described in Refs. 1 and 2.

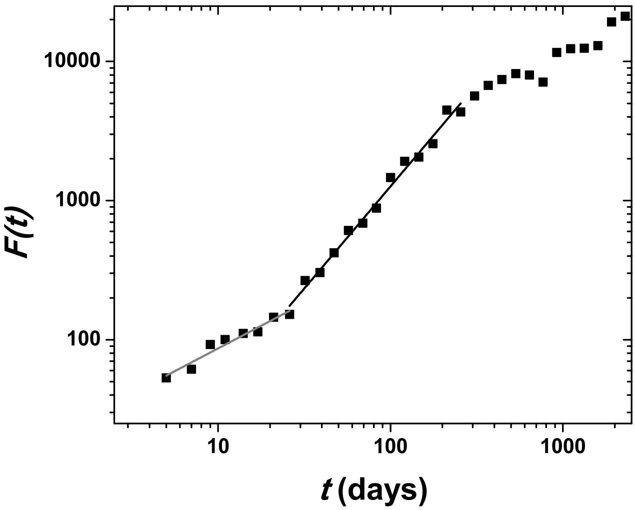

Fig. 2. The daily incidence of dengue fever cases in the state of Bahia time series from 2000 to 2010. The gray curve for these 30 days is $\alpha = 0.63 \pm 0.05$. The black curve for one year is $\alpha = 1.45 \pm 0.04$.

Additionally, strong evidence of cyclical movements is presented in the data incidences that confirm the seasonal component of the virus. In 2000, 2001 and 2002, an abrupt growth from 2% to 38% was observed (see the Percentage column, in Table 2). In 2006, 2007, 2008 and 2009, the periods of growth were not abrupt as in the first period.

In 2001, there was 6% growth in virus incidence that increased to 38% in the following year; in 2003, the incidence dropped to 18%, from 766 to 4867 and down to 2241 cases, respectively. The sudden decay has similarities with some physical, economic and biological complex systems that were studied by self-organized criticality (SOC), which is concerned with the patterns of collective behavior for complex

Table 2. Cumulative season distribution of dengue fever cases in city of Feira de Santana between the years 2000 and 2009.

Year	Summer	Fall	Winter	Spring	Total	Percentage
2000	5	134	91	15	245	2
2001	74	350	177	165	766	6
2002	1522	2932	209	204	4867	38
2003	680	1075	347	139	2241	18
2004	66	52	55	33	206	2
2005	32	118	167	110	427	3
2006	80	157	122	74	433	3
2007	222	327	188	108	845	7
2008	45	622	417	66	1150	9
2009	251	1303	0	0	1554	12
Total	2977	7070	1773	914	12734	100
Average	298	707	177	91	1273	

systems.[30] The critical and cyclical phenomena found in the aggregated data may be associated with the subdiffusive coefficients ($1 < \alpha < 1.5$),[29] as shown in Table 1.

Furthermore, the highest dengue incidences were caused by the new serotype introduced in the state in the year of 2002.[3] When water accumulated longer in the fall season, it contributed to an increase in the spread of dengue eggs and *A. aegypti*. The accumulation is assumed to be a result of the slowdown of the heavy summer rains. Moreover, there was also a certain amount of control between 2004 and 2006 because of less records available when compared to the average value of the period.

4. Discussions and Conclusions

In summary, there are two distinct behaviors in the time series, as presented in Fig. 2. For one month, the value of the α exponent obtained by the DFA method varies between 0.50 and 1.00, indicating that the self-affinity properties and the original time series have persistent long-range correlations, i.e. large values (small) that are likely followed by large amounts (small). For an annual period, the α exponent varies between 1.00 and 1.50, which characterizes as a nonstationary time series, similar to the behavior of the nonstationary random walks in a subdiffusive process, i.e. the behavior tends to be seasonal, without presenting similar epidemics from year to year.

The self-affine incidence analysis of dengue (i.e. the data reported for infected people) from the 25 municipalities is useful as a forecasting tool by extrapolating the long-range correlation that is observed from the behavior of the scaling exponent (α). It allows authorities to take actions to prevent future illness. These actions can promote the minimization of dengue fever cases and predict the hospital demand in these communities. The behavior of dengue fever has a higher predictability in a relatively short time (approximately one month), and the occurrence of infection (the daily incidence) has a long range persistent behavior. For periods of longer than one month, the method only provides the tendency of certain seasonality. However, it is not possible to predict a future epidemic only using DFA with the current information regarding infected people.

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