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Dengue Climate Variability in Rio de Janeiro City with Cross-Wavelet Transform

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Abstract

Dengue is one of the most prominent tropical epidemic diseases present in the Rio de Janeiro city and Southeast part of Brazil, due to the widespread conditions of occurrence of the dengue vector, the mosquito *Aedesaegypti*, such as high-temperature days interlaced with afternoon or nocturnal rainstorms in summer. This work has the objective of investigating the relationships between variabilities of the El Niño-South Oscillation (ENSO) and greater epidemics of dengue in Rio de Janeiro city. To accomplish this goal, the analysis and signal decomposition by cross-wavelet transform (WT) was applied to obtain the cross variability associated with variations of power and phase of both signals by characteristic periods and along with the time series. Data considered in the analysis are (the decimal logarithm of normalized value) of the monthly available notifications of dengue worsening, provided by the public health system of Brazil, and the Southern Oscillation Index (SOI) Niño 3.4 data, provided by the National Oceanic and Atmospheric Administration (NOAA), in the period 2000-2017. A maximum cross-wavelet power close to 0.45 was obtained for the representative period of 1 year and also to periods between 3 and 4 years, associated with the positive phase of the SOI index (*i.e.*, La Niña) or with a transition to the positive phase. The evolution of the combined variability of SOI and dengue can be expressed by progressive differences in phase along the time, eventually resulting in yielding phases (*i.e.*, La Niña-Dengue epidemic).

Keywords

Dengue Fever, Cross-Wavelet Transform Analysis, El Niño-Southern Oscillation Index

1. Introduction

Dengue is a viral disease transmitted mainly by the mosquito vector *Aedesaegypti*, being of great importance for the society, mainly in the countries of the tropical region, where there is a high number in case records. Dengue infections occur in more than 100 countries in Asia, the Americas, the Middle East, and Africa, and infection rates continue to rise worldwide, with an estimated 50 million infections occurring each year [1].

Dengue infectious disease in the Americas has an endemic-epidemic pattern with outbreaks every 3 to 5 years [2]. However, the change to a highly endemic pattern is observed with the increase in the number of cases over the years, especially in the first decade of the 21st century with two Pan American outbreaks registered in 2002 and 2010. In Brazil, 3,922,003 notified cases were registered in this period, considering ignored cases, and the state of Rio de Janeiro comprised the highest number of these records, with 576,791 cases [3] [4].

The wavelet transform (WT) has been shown over the years as a useful tool in the study of the transmission of epidemic diseases such as dengue because it allows the decomposition of non-stationary signals, having among its advantages the frequency variations and the detection of structures temporal and/or spatially localized [5].

The transmission of dengue was evaluated in Puerto Rico, Mexico and Thailand using WT, showing that dengue infection in tropical and subtropical areas typically follows a seasonal endemic pattern punctuated by intervals of a few years by a major epidemic [6]. These epidemic areas generally have climatic characteristics of high temperatures and large volumes of precipitation, thus being appropriate environments for the growth of dengue disease. Other researchers have evaluated historical time-series data on dengue outbreaks local between 1998 and 2015 in southern Taiwan, using cross wavelet transform (CWT) coherence to assess the regional oscillation of ENSO associated with the *Indian Ocean Dipole* and local climatic variables, being both associated with yearly non-stationary patterns of dengue transmission. The researchers showed that the *Indian Ocean Dipole* had a greater impact on the seasonality of local climatic conditions. The El Niño-South Oscillation (ENSO) dependency was as well investigated. Among the ENSO representative indices, the one with the best local response is seemly the Niño 3.4, showing high consistency with dengue peak cases [7].

The post-monsoon dengue outbreaks in Ahmedabad city have been analyzed along with the years 2005 to 2012 in western India. In that area, the cross-correlation of dengue with precipitation and temperature was studied to find the presence of 9 weeks (20 weeks) lag between peak precipitation (average temperature) and the peak incidence of dengue. Indeed, a consistency analysis of the incidence of dengue and precipitation incidence revealed a range of 16 to 32 weeks between 2008 and 2012, with a high level of coherence. Also, the analysis for incidences of temperature and dengue shows a coincidence of phase and then a small leadership of dengue cases on the temperature between 2008 and 2012 in the range of 16 to 32 weeks [8].

The WT coherence analysis of meteorological factors and weekly occurrences of dengue have been applied to study possible non-stationary relationships between variables in Davao, Philippines, between 2011 and 2015 [9]. Significant periodicity was detected in the range of 7 to 14 weeks for years 2011-2012 and periodicity of 26 weeks for years 2013-2014. For dew point temperature and incidence of dengue, the results of WT revealed a periodicity of 20 to 26 weeks from 2012 to 2013, as well as a range of 50 to 60 weeks from 2011 to 2015. Although some studies have noticed that *Aedesaegypti* activity would be high in rainy periods, there is some evidence that even in the dry season, the mosquito activity can be increased.

The WT method also has been considered to analyze weekly reports of dengue fever and to attempt to identify patterns of outbreaks in 25 districts in Sri Lanka between 2009 and 2014 [10], showing that dengue dynamics present periodic patterns of 2 to 8 weeks (approximately monthly/bimonthly), 26 to 32 weeks (approximately six months), and 52 weeks (approximately annually). The first pattern showed to be an intermittent characteristic, while the others presented a relatively smaller statistical significance, despite the power spectrum indicating high values.

Dengue epidemics and their association with climatic variability also were investigated in the Guangdong Province in China using monthly data of incidences of dengue fever, meteorological variables, and El Niño index on the 3.4 regions of the Tropical Pacific ocean, in the period 1988-2015 [11]. There, the WT was applied to investigate the periodicity, phase coherence, and delay between dengue, meteorological variables, and ENSO index. Dengue in Guangdong showed a dominant annual periodicity throughout the period. The average minimum temperature, total precipitation, and average relative humidity were positively related to the incidence of dengue for 2, 3, and 4 months time lag, respectively. ENSO may have driven dengue epidemics in 1995, 2002, 2006, and 2010. The authors [11], so complement this research by mentioning that events of *Super El Niño* could double the epidemics of Dengue and, in turn, justify cautionary warnings since the ENSO cycle can become more intense in the future due to the climatic change [12].

A study for the city of Ribeirão Preto, SP State, in Brazil, shows a dependence between the local Precipitation Index and dengue incidence [13]. This evaluation was accomplished with recorded data between 2000-2016. In that work, the water crisis of 2014 in the Southeast part of Brazil was highlighted. A fact that may have contributed to the proliferation of dengue vector *Aedesaegypti* then observed was the unappropriated exposition of new stocks of water, built as a response from the population to the shortage of drink water, in a very hot environment. Regarding the rainfall, it was seen that it has a more significant influence in dengue cases up to a maximum of five months after the occurrence in a given epidemic month. These additional breeding sites to the mosquito *Aedesaegypti* also presented a reasonable correlation in the lags of 2 to 3 months.

The WT co-variation between dengue and surface meteorological variables in the city of Rio de Janeiro, RJ State, in Brazil, has indicated a predominant triennial pattern, evidencing a possible relationship between ENSO and dengue occurrences [14] [15].

Among the techniques applied in the analysis of dengue epidemics, not only environmental and climatic variables have been used but also socioeconomic variables can be considered, for instance in Generalized Additive Models (GAM), Multiple Linear Regression models (MLR), etc. The investigations of climatic and environmental dengue predictors, in general, consider surface variables such as the maximum temperature at the beginning of summer, the degree-days calculated from the winter solstice to the summer solstice, etc. For numerical modeling of population dynamics under dengue epidemics, both initial and boundary conditions must be carefully prepared to obtain reasonable results to support policy decisions or to be integrated into skilled risk models [16]-[22]. A biweekly or monthly forecast of dengue infection can be well-advised to support a decision on strategies for management of tropical infectious disease epidemics, especially when climate changes is increasing the global temperature, that added to the urban heat islands surface warming has consequences beyond the high thermal discomfort, as heat associated diseases, mortality, changing energy and water balance of the cities, etc [23] [24] [25] [26] [27]. The reduction of risks and the build of resilience in the world nations are of the main concern of the United Nations [28] [29].

In the coastal metropolises of Brazil, the circulation of the sea breeze plays an important role in the modulation and development of the Urban Boundary Layer (convective) implying an inner boundary layer. Thus, in coastal tropical cities or plateaus close to the coast, an urban Boundary Layer (and corresponding urban heat island) is defined with differences in intensity and phase concerning the heat islands of medium and high latitude cities [30] [31], resulting in a diurnal characteristic of their heat islands that can be associated with the development of severe storms and heavy precipitation over the conurbation [32] [33] [34]. In the two largest Brazilian conurbations, the Metropolitan Regions of São Paulo and Rio de Janeiro, the heat island is a response to the available energy associated with the evolution of the sensible heat flux and its temporal evolution, In the same direction, the formulation of a risk model for national management emergencies centers should consider the inclusion of modeling and nowcasting of different hazards, among them: hydrometeorological hazards (mainly landslides, floods, droughts), biological hazards (dengue, chikungunya and zika epidemics in tropical areas), etc [35] [36] [37] [38].

The present work explores the possibility of using climate fluctuation indices before the occurrence of dengue epidemics, even though these factors may explain only a part of the variance observed during the transition from dengue-endemic years to epidemic years. The working hypothesis to be evaluated is that multi-year climatic fluctuations can play a role in the dynamics of dengue infection disease for tropical conurbations as such as the city of Rio de Janeiro in Brazil.

2. Methodology

2.1. Dengue Worsening Notifications

The reports of dengue worsening are provided by the Brazilian Public Health System (SUS) and Municipality Health Department (SMS) of Rio de Janeiro city [39]. For this study, the monthly sampling of dengue occurrences is applied between January 2000 and September 2017. Data were organized in annual subsets, containing monthly totals, were transformed [40] by a logarithmic function to accounting the large variation in the number of reported worsening cases.

2.2. ENSO Index

Among the various indexes that represent the ENSO phenomenon, the Southern Oscillation Index (SOI Niño 3.4) available from the National Oceanic and Atmospheric Administration (NOAA) was used in this work, considering a monthly sampling over the same period of dengue data collection. The SOI is described as a standardized index that relates sea level pressure differences observed between the western and eastern Pacific oceans (Darwin, Australia, and Tahiti, French Polynesia, respectively) in the tropical region near the Australian mainland. The SOI negative phase indicates values of atmospheric pressure below normal in Tahiti and above normal in Darwin. As this phase continues, the waters of the tropical east Pacific, coincidentally, show a positive temperature anomaly, characteristic of El Niño periods. Already in the positive phase of SOI, the opposite occurs, inverting the pressure patterns and having anomalously cold waters in the tropical eastern Pacific, defining the La Niña phase of ENSO [41] [42].

2.3. Wavelet Transform Method

The Wavelet Transform (WT) allows for the analysis of periodicity of winds in different scales of temporal variability and does not need stationary series [43]. The wavelet nomenclature refers to the set of small waves formed by dilation and translation of a function, quadraticallyintegrable in the range of the real numbers, that is, it must have finite energy [44]. This function is called the mother-wave, and its derived functions are the daughter waveforms [45]. Thus, it can be used to analyze time series with non-stationary power at different frequencies [46]. To be admissible as a wave, the function must have zero mean and be localized in both time and frequency spaces [47]. A function that satisfies this condition is the Morlet wavelet, which consists of a complex exponential wave (sine wave) multiplied by a Gaussian envelope, that is suitable for the analysis of geophysical signals and time series by their large number of oscillations. The continuous WT can be obtained by a convolution between time series with dilated/translated wavelet function.

The power spectrum of the wavelet represents the energy density of the wavelet through time and frequency domains are obtained as the square power of the wavelet amplitude. In many applications the estimation of the wavelet power for high sample frequencies should be improved with the aid of a function of the expansion parameter, avoiding underestimation [48].

The cross wavelet transforms (CWT) is a powerful tool used for testing the proposed dependence between different variables in time series. The CWT is analog to the co-variance. The phase difference is another important variable used to analyze multi-scale signals. Phase values then indicate the angular difference of wavelet maxima.

The global wavelet spectrum is a way of plotting the behavior of the explained variance associated with every wavelet period, showing those with the higher power among the period separation. The global wavelet spectrum is obtained by consolidation throughout the analysis time.

In this work, WT analyses were obtained by application of the R-library WaveletComp [49].

2.4. Clustering Analysis

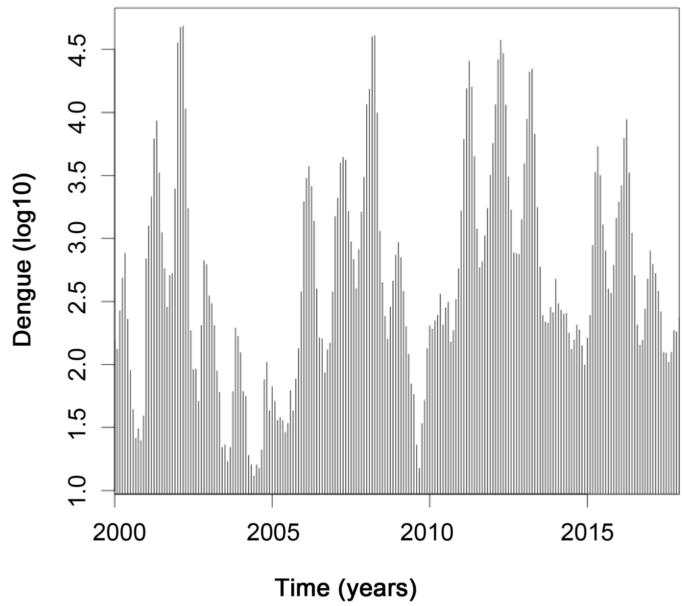
Clustering analysis can be defined as a formal study of methods and algorithms for grouping or grouping objects according to perceived intrinsic measures or characteristics of similarity [50]. One of the ways to perform this type of analysis is through the K-means partitioned algorithm. This algorithm locates a partition that minimizes the square error between the empirical mean of a cluster and proper points within the cluster.

The applied clustering method in this work is the R implementation of K-means [51]. In that method, a heuristic procedure is applied for obtaining the performing groupings. This method is performed here having SOI values, representative of the ENSO as the independent variable and the normalized logarithmic of dengue notifications as the dependent variable.

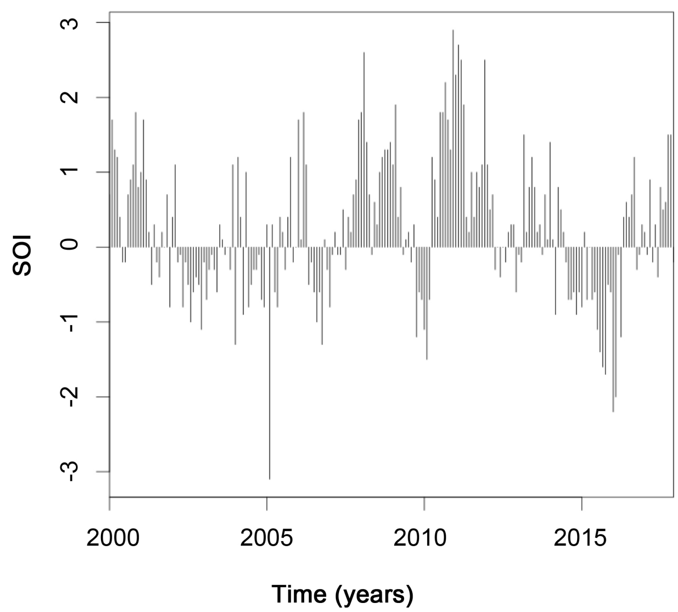
3. Results

The time series of normalized Dengue notifications (using a logarithmic scale) and SOI index (Niño 3.4) in the function of time (years) are shown in **Figure**

1. The epidemic number oscillates with particular periods of variability, with power maximum observed in 2002, 2008, 2012, and 2016 (Figure 1(a)). The first three epidemics occur synchronously with the positive SOI index, *i.e.*, in the La Niña phase of the ENSO, whereas the El Niño phase is evidenced in the last epidemics in the data series (Figure 1(b)). It is important to note that these last events were preceded by a negative SOI phase (*i.e.*, weak El Niño). Progressive phase difference seems to occur between Dengue and ENSO signals.



(a)



(b)

Figure 1. Variable time series: (a) worsening notification due to Dengue and (b) SOI index of ENSO.

All the WTs to be presented below have an influence cone, indicating that the results plotted in the external area (white shading) are susceptible to edge effects and do not have the necessary statistical significance. WTs also present lines of significance for the wavelet power at a specific level of confidence of 0.90. The vertical axis shows the periods in months and the horizontal shows the time interval counting.

In the dengue, WT analysis is possible to observe the intensity of the power signal over the annual occurrences in the analysis series, distributed monthly (**Figure 2**). Noteworthy is fact that the long-term variability of Dengue is shorting, passing from 60 to 48 months (5 to 4 years) (**Figure 2(a)**). This can be understood as a change in period, phase, or both of dependent variables, as the epidemic outbreaks behavior.

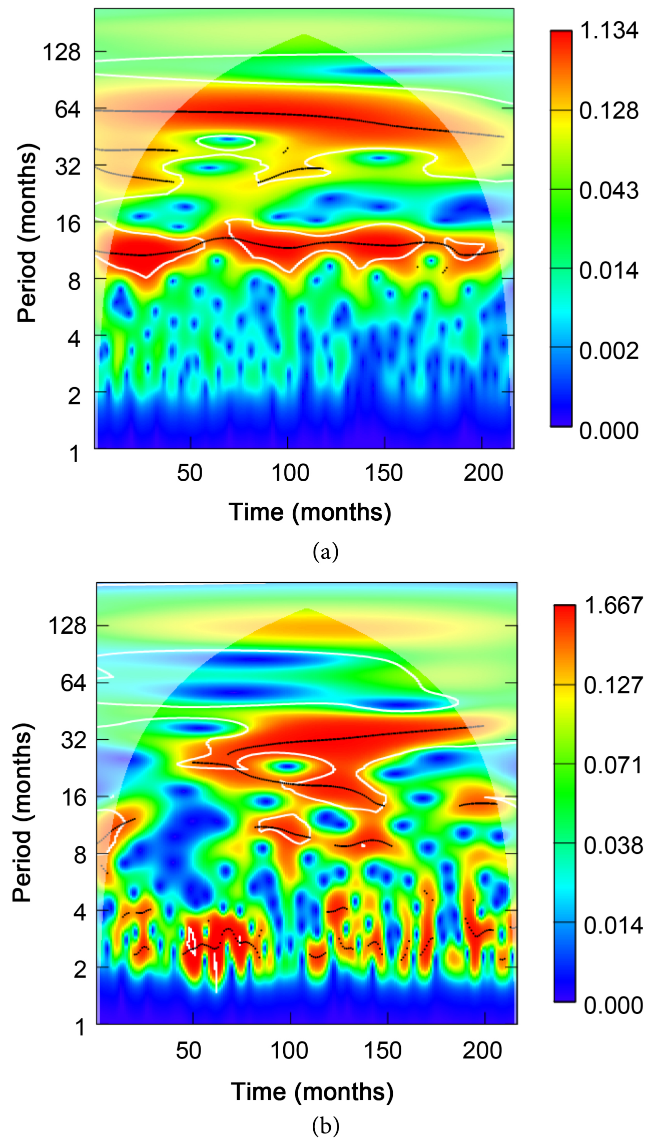


Figure 2. (a) WT of the log10 of dengue; (b) Global wavelet spectrum for log10 of dengue.

The global spectrum (**Figure 2(b)**) emphasizes these periods found in WT, showing that they are more energetic and with significance. A peak over one hundred and twenty-eight months (approximately ten years) is also shown but is located outside the zone of influence of WT. The global wavelet spectra are be presented as the power spectrum averages consolidated throughout the time, and also have demarcations of significance values for 0.05 and 0.10 probability thresholds (red and blue dots, respectively). The vertical and horizontal axes show, respectively, the periods in months and the average wavelet power.

Like the dengue WT, the WT of the SOI (**Figure 3(a)**) presents the annual

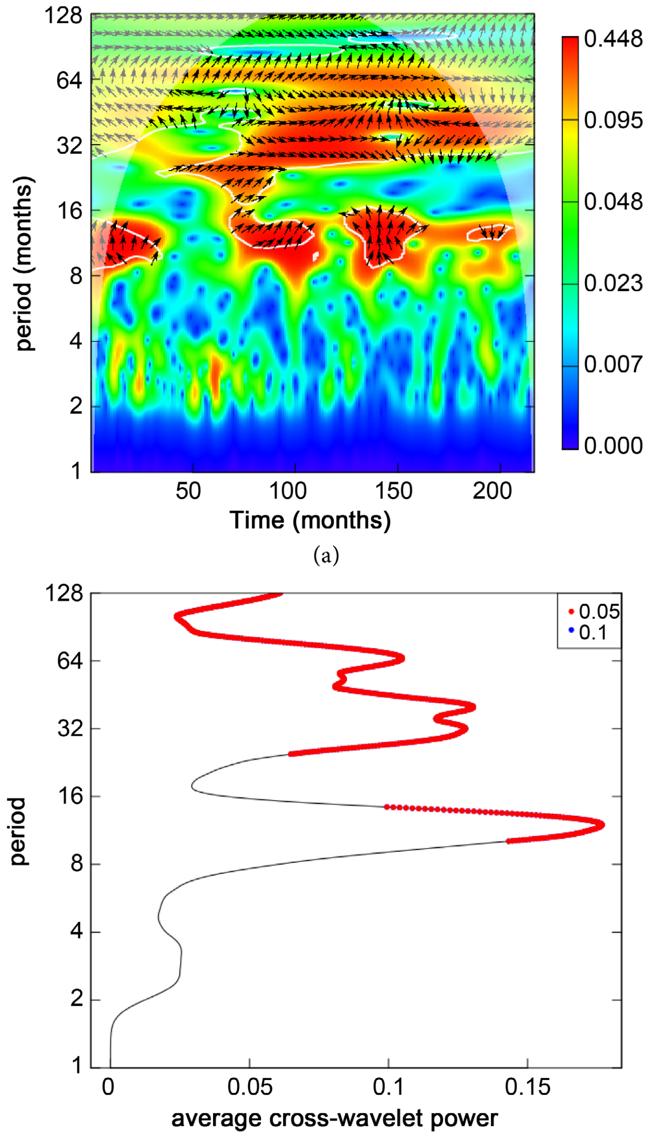


Figure 3. (a) Power of the cross-wavelet transform; (b) global power cross-wavelet spectrum. Arrows in (a) indicate the phase differences between the signals. Bold dot (red) points in (b) indicate the significant values of the global power cross-wavelet spectrum for a statistical confidence level of 90%.

signal, with its most evident power during the years of 2002, 2008, and 2012, which are periods with La Niña registration. It is possible to perceive a signal in thirty-six months (three years) whose effect propagates to an annual scale. In the years preceding the epidemics mentioned above, the power spectrum of WT is weaker, indicating the presence of El Niño. Also, this phenomenon is in the region of the sixty-four month period (approximately five years), emphasizing its occurrence in 2005 and 2010, whose SOIis more negative.

The strongest and statistically significant signals within the IOS global spectrum (**Figure 3(b)**) are located in the annual and triennial ranges, in addition to the five-year range. The period of two months is featured with a considerable level of energy, but it is not demarcated with mean significance. In contrast, the one hundred and twenty-eight month period (approximately ten years), despite having significance, is not mostly within the WT cone.

Arrows in **Figure 3(a)** indicate the phase differences between the signals. The phase difference rotates anticlockwise, with 180 degrees of the phase difference between successive epidemics, e.g., between 2008-2012 (80 and 140 months in the ordered time series).

The cross-wavelet transform presents two important aspects: first, signal strength distribution is observed in the cross variables, and second, the phase difference is present and represented by the angular orientation of vectors (*i.e.*, increasing anticlockwise: 0˚ to the right, 90˚ to up, 180˚ to the left and 270˚ to down) (**Figure 3(a)**).

The maximum power of the WT is as high as 0.45 considering the annual and three annual periods, highlighted in the global spectrum (**Figure 3(b)**). In other words, dengue and ENSO index have a maximum co-variance value of 0.4; this shows that Dengue worsening notification is dependent on the ENSO index (SOI). Therefore, climate fluctuations have the potential to modulate Dengue outbreaks, a typical tropical infectious disease. Certainly, this is not a unique influence.

Regarding the phase, it must consider the vector angular orientation as a wavelet phase difference function in the trigonometric circle. Examining the highlighted regions in WL power within statistical significance, it is possible to detect that in the annual period (24 months) the vector angular difference of phase is close to $\pi/2$, indicating that the variables achieve the maximum at different times. In the three annual periods (64 months), the variables again are in phase, emphasizing the angular positions of the maximum signals (pointing on the right).

The clustering analysis between the ENSO index and dengue is shown in **Figure 4**. The choice of the number of groups is made based on those with significant variances (internal differences added together to explain a good part of the total variance). Only three groups were used that were small enough to facilitate interpretation, and large enough to account for approximately 78% of the distance variance of the points to the group bare-center.

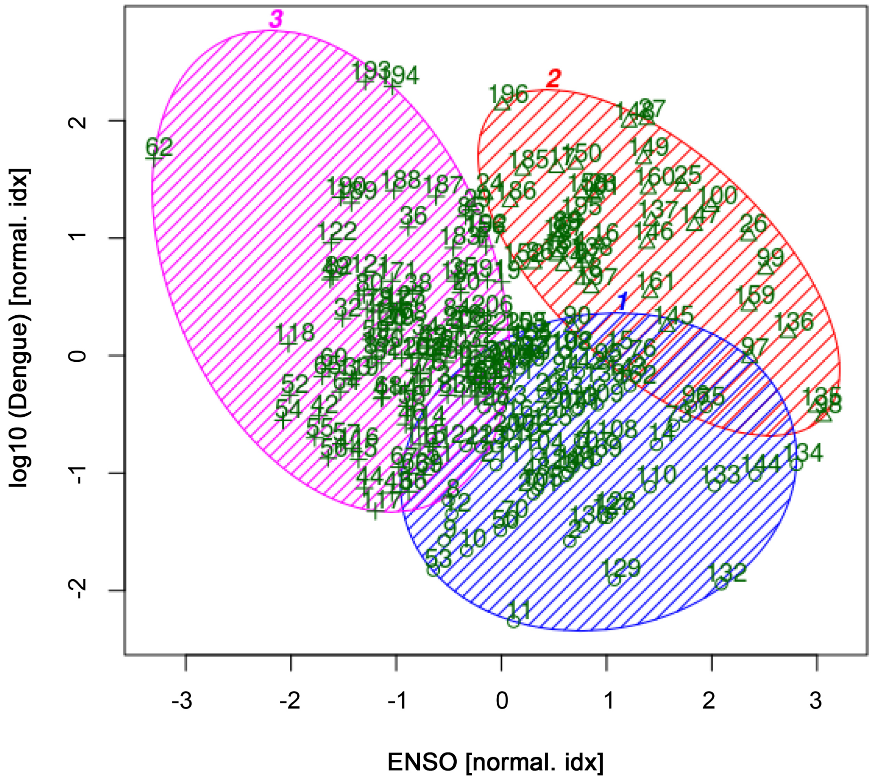


Figure 4. Clustering considering the dispersion SOI index (axis x) and Normalized $\log_{10}$ of dengue notifications (axis y). Three groups are selected to explain the cross-variability during the analysis period. The numbers show the months of occurrence in the data series.

The numbers in green are the months counted continuously in Figure 4. There are 3 representative groups. Group 1 (pink, left) has months concentrated in the weak El Niño region (SOI negative close to zero), associated with a considerable number of cases. Group 2 (blue, lower right) represents the strongest La Niña, having the most sparse months in it, which means fewer cases of dengue in these conditions; this is reinforced by the position of the group itself relative to the vertical axis, where the normalized $\log_{10}$ is smaller. Group 3 (red, upper right) represents the weakest La Niña and is the one with the highest number of dengue cases. Analyzing the days present in it, it is remarkable that they are after days included in group 2, that is, the increase of dengue is preceded by strong La Niña. Anticlockwise rotation is seen in the dispersion of months, seemly from group 3 (−, +) to group 2 (+, −) and to group 1 (+, +) along with the time series.

In recent years, several studies have been done on the dengue tropical infectious disease, including hazards on human health, which may be increasing due to factors such as Global Warming, Urban Heat Islands, and Heat Wave episodes, as well as the form of organization of the population and their social conditions.

Some researchers have applied WT to verify correlation and phase coherence between dengue occurrences and dependence variables: ENSO index, precipitation, and temperature for different places around the world. The present work focusing on Rio de Janeiro dengue epidemics, brings out results on the wavelet transform of individual and cross-dependent variables, relating dengue disease outbreaks with large scale climatic variability of ENSO.

4. Conclusions

This work aims to research the possible relationship between dengue occurrences in the city of Rio de Janeiro and the El Niño-South Oscillation, as well as their cross-variability. El Niño-South Oscillation magnitude here is represented by the SOI index (Niño 3.4). The cross-wavelet power between Dengue and SOI index shows intensified values for annual and triennial or quadrennial periods, approximately 1.18 and 1.13, respectively. A maximum cross-wavelet power close to 0.45 was obtained for the representative period of 1 year and also to periods between 3 and 4 years, associated with the positive phase of the SOI index (*i.e.*, La Niña) or with a transition to the positive phase.

For the city of Rio de Janeiro, the cluster analysis presents three groups that explain a large part of the co-variances of Dengue and SOI index. Dengue tends to begin during weak El Niños while La Niña tends to increase the number of reported cases and causes dengue epidemics. La Niña's weakening tendency likely can be associated with an epidemic maximum in Rio de Janeiro city. It is also possible to note that the months of occurrence are concentrated in the region comprehending weak El Niño and La Niña. A progressive change in phase between the dependent variables can be noted along the years, allowing the passage of endemic to bold epidemic periods.

The cross-WT analysis brings to light some evidence that the annual cycle shows a lag of approximately three months, indicating that the SOI index variability is an early precursor of dengue outbreaks since they present characteristic periods not entirely synchronous. The triennial cycle is approximately in phase in 2008, showing that the frequency of major ENSO events is in line with the major epidemics that occurred in Rio de Janeiro. The cross-wavelet power indicates a maximum value of 0.45 in epidemic years, which can be associated with the progression to the positive phase of the SOI index (*i.e.*, La Niña). It shows that ENSO larger events have a sizable influence on the spreading of dengue fever in Rio de Janeiro town.

The present results indicate the possibility of considering the modeling of dengue evolution in Rio de Janeiro Metropolis, based on the numerical solution of coupled prognostic differential equations for the susceptible population or by evaluations with a statistical model based on Linear Multiple Regression.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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