Science of the Total Environment 618 (2018) 971–976

Contents lists available at ScienceDirect

Science of the Total Environment

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

Relevance of transportation to correlations among criticality, physical means of propagation, and distribution of dengue fever cases in the state of Bahia

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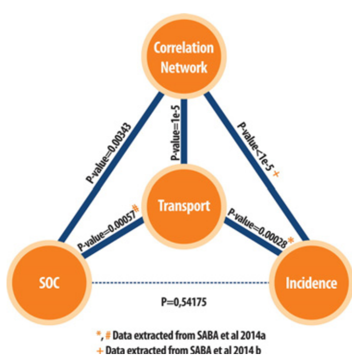
HIGHLIGHTS

- We studied the diffusion of dengue fever disease.
- We discuss nonextensive behaviour of dengue fever.
- We studied the association between dengue fever spread and transportation.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 30 June 2017
Received in revised form 16 August 2017
Accepted 6 September 2017
Available online 27 October 2017

Editor: D. Barcelo

Keywords:
Computational model
Correlation network
Dengue
Epidemic disease

ABSTRACT

Dengue infection is a public health problem with a complex distribution. The physical means of propagation and the dynamics of diffusion of the disease between municipalities need to be analysed to direct efficient public policies to prevent dengue infection. The present study presents correlations of occurrences of reported cases of dengue infection among municipalities, self-organized criticality (SOC), and transportation between areas, identifying the municipalities that play an important role in the diffusion of dengue across the state of Bahia, Brazil. The significant correlation found between the correlation network and the SOC demonstrates that the pattern of intramunicipal diffusion of dengue is coupled to the pattern of synchronisation between the municipalities. Transportation emerges as influential in the dynamics of diffusion of epidemics by acting on the aforementioned variables.

1. Introduction

From the 1990s (Gubler and Meltzer, 1999) to the present (Siriyasatien et al., 2016; Teixeira et al., 2009), dengue has been one of the main re-emerging diseases in the tropics. More than one million

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https://doi.org/10.1016/j.scitotenv.2017.09.047
0048-9697/

cases of dengue infection were reported in Latin American countries in 2002; 17,000 of these cases corresponded to dengue hemorrhagic fever (DHF), and 225 deaths were recorded (Nogueira et al., 2005). In 2012, approximately 2.5 billion people worldwide were at high risk of infection, ranking dengue among the top re-emerging diseases that pose the most serious public health threat (Braga and Valle, 2007). Approximately two-thirds of the world's population is susceptible to dengue infection. Due to the lack of efficacious medications and vaccines, vector control is the single primary intervention resource available. Understanding the dynamics of circulation of the dengue virus and its transmitting agent as well as the interactions between the virus and its hosts is indispensable for the development of epidemiological control strategies (Guo et al., 2010). Among viral epidemic diseases, dengue, a vector-borne infectious disease, has very complex dynamics of transmission. According to estimates by the World Health Organization (WHO), approximately 80 million people are infected annually in many countries, but not in those with a temperate climate that cannot support mosquitoes. Technological advances have provided humankind new possibilities for locomotion. While this fact represents progress in human development, it also represents an increase in the risk of occurrence of epidemics on a wider scale. The development of epidemic models that simulate the dynamics of infectious diseases in evolving societies (i.e., population growth, increasing urbanization, and frequent transit of people using different modes of transport) poses a contemporary challenge. Several studies in the literature (Emmendorfer and Rodrigues, 2001; Holmes, 1997; Guevara-Souza and Vallejo, 2015; Brockmann and Helbing, 2013; Eggo et al., 2011; Flahault and Valleron, 1992; Gautreau et al., 2008; Gomes et al., 2014; Tizzoni et al., 2014) have investigated the dynamics of propagation of epidemics from various perspectives and using different types of models. The state of Bahia, Brazil, has an area of 567,295 km^2 and is divided into 417 municipalities, mainly connected by a land transportation network. Bahia's territorial area is larger than the areas of countries such France (543,965 km^2) and Spain (504,030 km^2). According to the Health Ministry and based on data collected by the National Program for Dengue Control (Programa Nacional de Controle da Dengue - PNCD), among all of the municipalities that comprise the State of Bahia, only 45 (10.79%) are classified as high-priority sites for control actions. Priority is established based on the population and epidemiological characteristics such as capital cities, metropolitan areas, municipalities with ≥50,000 inhabitants, and municipalities with a high immigration rate (i.e., areas near borders and ports and tourist attraction centres) (BRASIL, 2008). *Aedes aegypti* is present in 99.5% of Bahia's municipalities, and four virus serotypes have been found to circulate in these areas: DENV-1, DENV-2, DENV-3, and DENV-4 (CNT, 2011). The virus circulates across municipalities via 22 federal and 11 state highways, totaling 7368 km and consisting of 165 km of four-lane roads and 7203 km of two-lane roads (CNT, 2011). Considering that the diffusion of dengue is a genuinely complex system, its study might be facilitated by the use of complex network tools and critically self-organized systems. The scientific community is developing models for dengue and other epidemics (Brauer et al., 2001; Souza et al., 2006; Souza et al., 2007; Vieira, 2005). According to Adami (1995), sets of entities with auto-replicating characteristics, such as biological systems, naturally evolve into a self-organized critical state. The behaviour of SOC as a mechanism that characterizes the dynamics of epidemics was described by Rhodes and Anderson (Rhodes et al., 1996), in this study was characterized the dynamic patterns of measles outbreaks in the Faroe Islands in the North Atlantic Ocean. Regarding dengue, SOC behaviors were detected in a time series of cases of dengue infection reported in all 417 Bahia municipalities (Saba et al., 2014a). In the Sharma et al. (2014) study, was carried out on the spread of dengue in order to investigate the influence of different road networks on the spatio-temporal distribution of dengue cases associated with transport sites in Trinidad, West Indies.

The complex networks approach involving correlation networks was first applied in a brain activity study (Eguiluz et al., 2005). In this study, networks were constructed based on time series of brain activation, in which the brain areas were represented as vertices, and the correlations among them were represented as edges linking the vertices. A similar approach was applied in epidemiological studies; the authors constructed a correlation network between occurrences of reported cases of dengue infection between municipalities in the state of Bahia. The results indicated a significant correlation between the incidence of dengue in each municipality and the degree of connectivity of each county within the correlation network (Saba et al., 2014b). The objective of this study is demonstrates the presence of correlations among the critical phenomenon, complex network, and physical means of propagation in the distribution of the occurrence of cases of dengue infection in the state of Bahia.

2. Material and methods

The process of data collection, processing, and analysis are represented in Fig. 1. The process begins with the analysed database, followed by data pre-processing, during which the data were separated and clustered (i.e., filtered). The data were then analysed, and the networks were constructed. Finally, the hypotheses of correlations were evaluated, and thus the results were obtained. A detailed description of each step is present below.

2.1. Data collection and mining

About transportation, data were collected on the number of intermunicipal buses for each municipality in the state of Bahia, not considering local lines. The information was collected from the database of the State Agency of Regulation of Public Energy, Transportation, and Communication Services of Bahia (Agência Estadual de Regulação de Serviços Públicos de Energia, Transporte e Comunicações da Bahia - AGERBA) which includes the bus lines in each municipality each day of the week (AGERBA, 2013). The data regarding dengue infection were collected from the records of the National Notifiable Diseases System (Sistema Nacional de Agravos de Notificação - SINAN) and the Health Secretary of the State of Bahia (Secretaria de Saúde do Estado da Bahia - SESAB). All cases of dengue infection reported in the specified period and that met the dengue case definition criteria established by the healthcare services and standardised by the Health Ministry were included in the study. The variables considered included the municipalities in which the cases occurred and the date of notification. We recall that all data used in this paper are public and can be obtained from AGERBA and SINAN websites. Daily occurrences of dengue cases in all 417 municipalities of Bahia from January 1, 2000 to April 26, 2009 were considered. The number of occurrences totalled 353,022 cases. The road maps of Bahia (MAPA) were analysed, and a survey of the federal and state highways interconnecting the state municipalities was performed.

The method used in the present study consisted of assessing correlations among municipalities with respect to three types of networks: the transportation network of Bahia, a transport flow network, and Pearson's correlation networks.

2.2. Transportation network of Bahia

The federal and state highways that interconnect the municipalities of Bahia were surveyed based on an analysis of the state road maps. In the construction of the state transportation network, each of the 417 municipalities was represented by a vertex (i.e., node), and the stretches of federal and state highways interconnecting the counties were represented by edges joining one vertex to the others. All 22 federal and 11 state highways across Bahia were considered, totalling 7368 km and consisting of 165 km of four-lane roads and 7203 km of two-lane roads. Towns and districts were not considered nodes

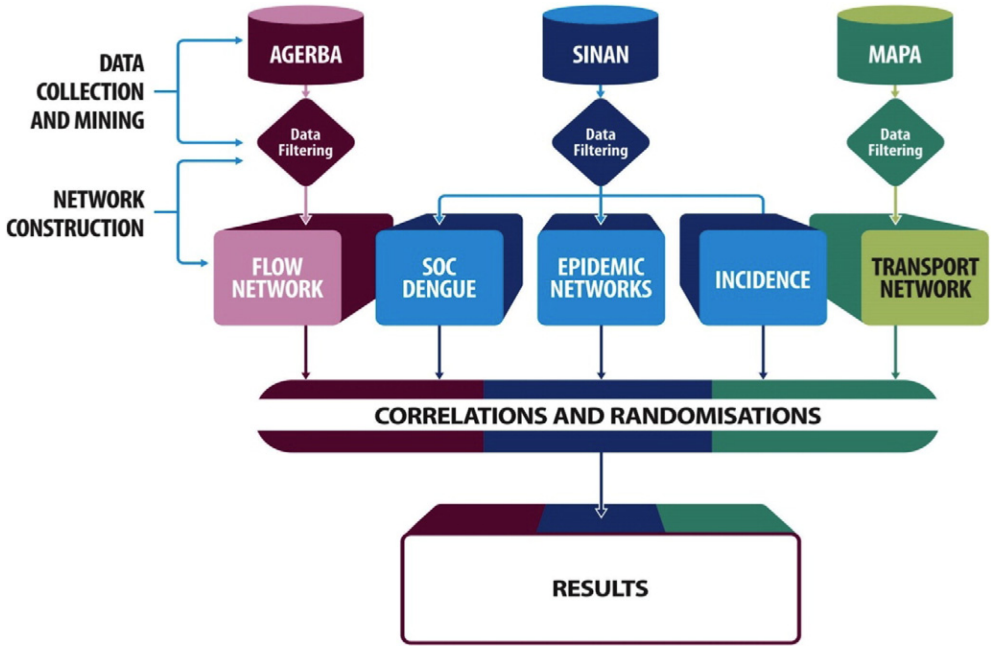

Fig. 1. Study flowchart. Agência Estadual de Regulação de Serviços Públicos de Energia, Transporte e Comunicações da Bahia - AGERBA, Sistema Nacional de Agravos de Notificação - SINAN and Mapa Rodoviário da Bahia - MAPA.

(i.e., vertices) because dengue cases, the focus of the present study, are recorded by the municipal health secretaries (Saba et al., 2008).

2.3. Transport flow network

In the construction of this network, the nodes represented municipalities, and the edges represented the availability of intermunicipal lines between any two municipalities. The node degree was defined based on the number of intermunicipal buses in each municipality.

2.4. Pearson's correlation networks of dengue infection

Pearson's correlation networks were constructed to examine the diffusion dynamics of the disease (Eguiluz et al., 2005; Abe and Suzuki, 2004). In the present study, we applied the methods formulated by Saba et al. (2014a) to the construction of dengue correlation networks (DCN) formalised within the context of a time-varying graph (TVG). According to Saba et al. (2014a), the DCN nodes represent municipalities, while the edges are defined based on a presence function $F(C_{i,j}, t)$, formally defined as:

$$F(C_{ij}, t) = \begin{pmatrix} 1, & \text{if } c_{ij}(t) \geq \overline{c} \\ 0, & \text{if } c_{ij}(t) < \overline{c'} \end{pmatrix} \{\forall t \in T, \forall c_{ij} \in C\} \tag{1}$$

where $c_{ij}(t)$ represents the correlation between dengue cases in municipalities i and j at time t. This definition implies that any two municipalities are only connected within the network when the measured correlation $c_{i,j}(t)$ reaches a sufficient level ($\leq \overline{c}$). In the present study, for the sake of simplicity, $\overline{c}$ was considered a constant over time, and no loss of generality was found. A collapsed network of each TVG was constructed. A collapsed network consists of the integration of the full set of TVG networks in one single weighted network. The weights of the edges in a collapsed network represent the number of times an edge occurred over the investigated period of time. Thus, collapsed networks allow the assessment of pairs of nodes that are highly correlated over time. The weights of the edges in a collapsed network are formally defined by the following equation:

$$C_{ij} = \sum_{t=1}^{T} F(c_{i,j}, t) \tag{2}$$

where, $c_{i,j}$ represents the weight of the edge in a collapsed network joining nodes i and j, and T represents the total period of analysis of the TVG.

3. Results

An analysis of all dengue cases reported from January 2000 to April 2009 suggest correlations among different municipalities, as illustrated in the example in Fig. 2 between municipalities Feira de Santana and Ilheus. The peak occurrence in the municipalities, shown in Fig. 2, resulted in a heterogeneous distribution of the peaks over time, producing an asynchronous and time variable behaviour. As a result, the number of days in which no case of infection was reported was much smaller in the entire state of Bahia than for each individual municipality. This continuity in the occurrence of cases at the state level might be accounted for by migration between municipalities. This hypothesis was tested by an analysis of the correlation among the following variables: transportation network degree, correlation network degree, criticality exponents, and the incidence of dengue.

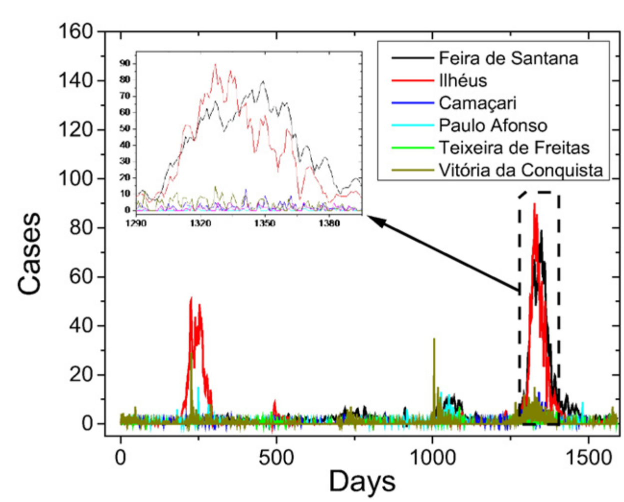

Fig. 2. Occurrences per day in six typical dengue time series in municipalities of Bahia, 2005 to 2009.

The results of the present study are described in four separate sections. In the first section, we discuss the correlation between the degree of the correlation network of cases of dengue (Saba et al., 2014b) and the criticality exponents (i.e., gamma) (Saba et al., 2014a). In the second section, we tested the hypothesis that migration between municipalities, represented by the transportation network, accounts for the correlation of cases between municipalities. The third section addresses the correlation between the criticality exponents (i.e., gamma) (Saba et al., 2014a) and incidence. Finally, the fourth section presents a general view of the correlations analysed in the present study.

3.1. Correlation between the degree of the correlation network of cases of dengue among municipalities of Bahia and the criticality exponents (SOC)

Using Spearman's correlation, after 100,000 randomisations, the p-value was 0.00343, which indicates that the correlation was greater than or equal to the original correlation in only 0.343% of the set of randomisations. These findings are shown in Fig. 3 and indicate a significant correlation between the variables incidence and degree of network correlation in Bahia municipalities.

3.2. Number of weekly intermunicipal buses versus the degree of the correlation network

The study by Saba et al. (2014a) described the correlation between a land transportation network and reported cases of dengue in the state of Bahia. To achieve a more accurate representation of the flow of individuals among municipalities in the present study, the degree of the transportation network was replaced by the number of buses that circulate in each municipality per week. The correlation relative to 100,000 randomisations produced a p-value of 1e-5, which indicates that the correlation was greater than or equal to the original correlation in only 0.001% of the set of randomisations (Fig. 4).

3.3. Criticality exponents versus incidence

A significant correlation was not found between the criticality exponents and disease incidence. A randomisation test was applied, which resulted in a p-value of 0.54175, i.e., the correlation was greater than or equal to the original correlation in 54.17% of the cases.

3.4. General view of the correlations

Fig. 5 provides a general summary of the results of the present and previous studies. Significant correlations were found among the variables associated with transportation, the correlation network, and the SOC. However, the disease incidence exhibited a significant association with the variables transportation and correlation network.

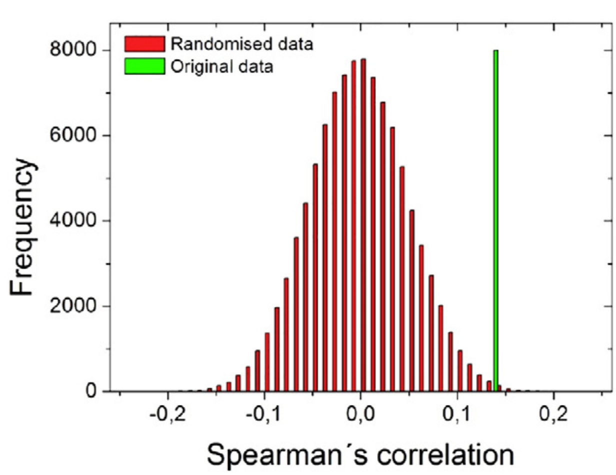

Fig. 3. Randomisation of the relationship between the degree of the correlation network and criticality exponents.

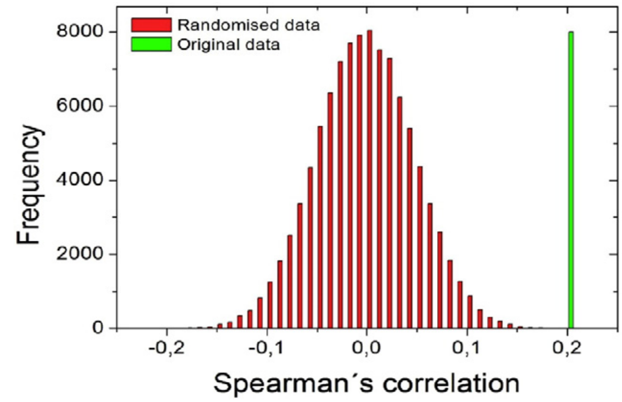

Fig. 4. Randomisation of the relationship between the number of intermunicipal buses per week and the degree of the correlation network.

Fig. 6 shows the combination of correlation, transportation and incidence for the eleven highest degree in correlation network. This combination highlights the municipalities (georeferenced) with the highest risk of dengue spread, since municipalities with a high degree of correlation imply a greater influence on the correlation network, and municipalities with a greater incidence are related with an internal dynamic that foment the onset of the disease.

4. Discussion

The present study assessed the mechanisms of diffusion of dengue based on the results of two general techniques: correlation networks and SOC. These techniques have different scales. The results of SOC represent the diffusion dynamics of dengue at the municipality level (i.e., intramunicipal), and the results of the correlation network reflect the diffusion dynamics at the intermunicipal level. The central hypothesis was that intermunicipal transportation is the main mechanism of diffusion of dengue epidemics. The summary of the results depicted in Fig. 5 confirms this hypothesis, thus indicating that transportation is a relevant physical means for the diffusion of dengue. The correlation between the number of intermunicipal bus lines in the transportation network and the criticality exponents (according to the SOC) demonstrates the presence of a relationship between the flow of people into/out of a given municipality and the pattern of diffusion of the disease in that municipality. A possible explanation for this correlation is the occurrence of a break in the municipality isolation, allowing for the arrival of new cases in the course of the diffusion of the disease. The lack of a significant correlation between the SOC and disease incidence indicates that the latter factor does not influence the pattern of diffusion of the disease within a municipality, thus reinforcing the central role of transportation in the diffusion of dengue at the intramunicipal level. The correlation network of dengue among counties exhibited a significant correlation with the transportation network, which indicates that at the intermunicipal level, an increase in the number of bus lines increases the synchronisation between the occurrences of reported cases of disease in the municipalities, i.e., transportation enables intermunicipal contamination. The significant correlation between the correlation network and the SOC demonstrates that the dengue diffusion inside a municipality is coupled to the pattern of synchronisation between municipalities.

5. Conclusions

In summary, these discussions suggest that Transportation is influential in the dynamics of diffusion of epidemics and affects the other variables. According to the correlations of reported cases of dengue

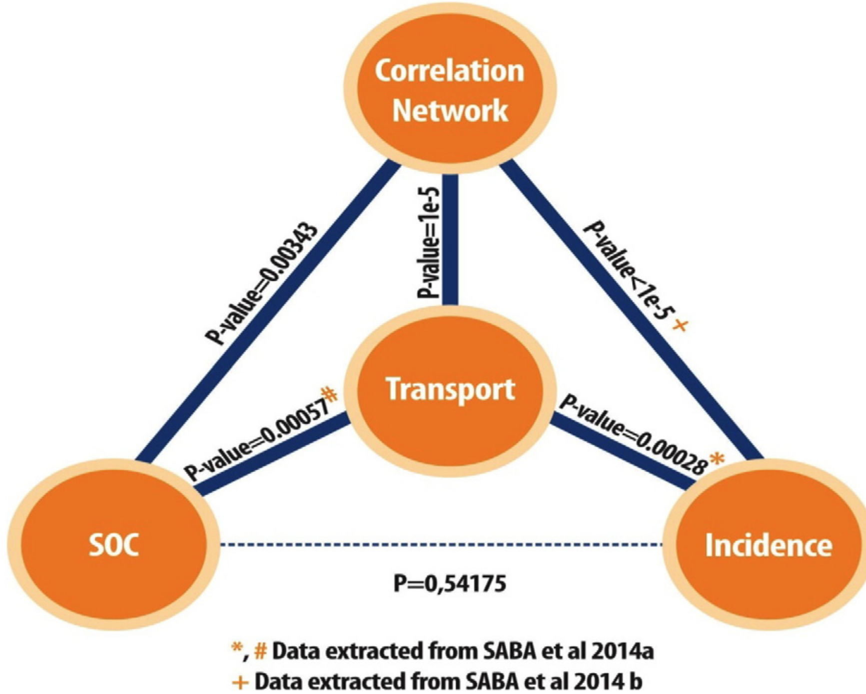

Fig. 5. Correlation network of the results.

among municipalities in the state of Bahia, transportation and SOC might contribute to the development of more efficient strategies for the prevention of dengue. The joint consideration of the connectivity within the correlation network, data on transportation, and the criticality exponents demonstrates the relevance of each individual municipality in the dynamics of the diffusion of dengue in the state of Bahia.

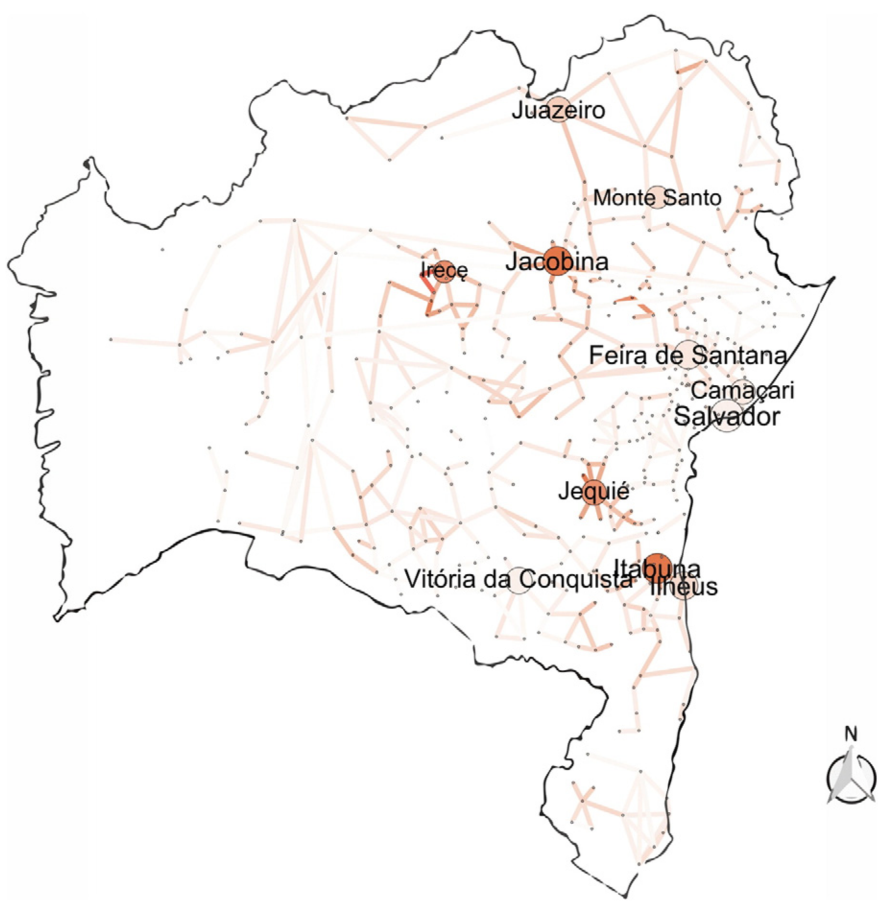

Fig. 6. Transport network showing the eleven-highest municipalities in correlation degree. Colors represent dengue incidence range, from white = 0 incidence to red = maximum incidence. Edges colors are the mean color from adjacents nodes.

Acknowledgements

This work received financial support from National Counsel of Technological and Scientific Development - CNPq (grant numbers 458549/2014-2, 448303/2014-0, 304454/2014-1 and 310133/2016-5).

Author contributions statement

These authors contributed equally to this work. All authors reviewed the manuscript.

Accession codes

Not applicable.

Competing financial interests

The authors declare that they have no financial interests.

References

Abe, S., Suzuki, N., 2004. Scale-free network of earthquakes. EPL (Europhysics Lett.) 65, 581.
Adami, C., 1995. Self-organized criticality in living systems. Phys. Lett. A 203, 29–32.
AGERBA, 2013. Agerba; localidades atendidas por linhas. URL. http://www.agerba.ba.gov.br/transporte/localidadelinha.asp .
Braga, I.A., Valle, D., 2007. *Aedes aegypti*: historico do controle no brasil [*Aedes aegypti*: history of control in Brazil]. Epidemiol. e servic, os de saude 16, 113–118.
BRASIL, 2008. Ministerio da saude; doencas infecciosas e parasitarias [infectious and parasitic diseases]. URL. http://portal.saude.gov.br/portal/arquivos.
Brauer, F., Castillo-Chavez, C., Castillo-Chavez, C., 2001. Mathematical Models in Population Biology and Epidemiology. Vol. 40. Springer, New York.
Brockmann, D., Helbing, D., 2013. The hidden geometry of complex, network-driven contagion phenomena. Science 342, 1337–1342.
CNT, 2011. National transport company; search cnt road. URL. http://pesquisarodovias.cnt.org.br/Paginas/Edicao-011 (accessed in 2011).
Eggo, R.M., Cauchemez, S., Ferguson, N.M., 2011. Spatial dynamics of the 1918 influenza pandemic in England, Wales and the United States. J. R. Soc. Interface 8, 233–243.
Eguiluz, V.M., Chialvo, D.R., Cecchi, G.A., Baliki, M., Apkarian, A.V., 2005. Scale-free brain functional networks. Phys. Rev. Lett. 94, 018102.
Emmendorfer, L.R., Rodrigues, L.A.D., 2001. Um modelo de automatos celulares para o espalhamento geografico de' epidemias [a cellular automaton model for geographic spread of epidemics]. Tendencia em Matematica Apl. e Comput. 2, 73–80.
Flahault, A., Valleron, A.-J., 1992. A method for assessing the global spread of hiv-1 infection based on air travel. Math. Popul. Stud. 3, 161–171.
Gautreau, A., Barrat, A., Barthelemy, M., 2008. Global disease spread: statistics and estimation of arrival times. J. Theor. Biol. 251, 509–522.
Gomes, M.F.C., et al., 2014. Assessing the international spreading risk associated with the 2014 West African ebola outbreak. PLOS Curr. Outbreaks.
Gubler, D.J., Meltzer, M., 1999. Impact of dengue/dengue hemorrhagic fever on the developing world. Adv. Virus Res. 53, 35–70.
Guevara-Souza, M., Vallejo, E.E., 2015. A computer simulation model of wolbachia invasion for disease vector population modification. BMC Bioinforma. 16, 1.
Guo, X., et al., 2010. Response of the mosquito protein interaction network to dengue infection. BMC Genomics 11, 1.
Holmes, E.E., 1997. Basic epidemiological concepts in a spatial context. Spatial Ecology: Role Space Population Dynamics Interspecific Interactions. Princet. Univ. Press, Princeton, NJ, pp. 111–136.
Nogueira, R.M.R., et al., 2005. Dengue virus type 3, Brazil, 2002. Emerg. Infect. Dis. 11 (1376).
Rhodes, C.J., Anderson, R.M., et al., 1996. Power laws governing epidemics in isolated populations. Natural 381, 600–602.
Saba, H., de Oliveira, M.A., Miranda, J.G.V., 2008. Modelo computacional para auxilio no combate a epidemias com base em redes sociais [social network-based computational model to aid in the fight against epidemics]. WIVA–2008 1, 10.
Saba, H., Miranda, J.G.V., Moret, M.A., 2014a. Self-organized critical phenomenon as a q-exponential decay? Avalanche epidemiology of dengue. Phys. A: Stat. Mech. its Appl. 413, 205–211.
Saba, H., Vale, V.C., Moret, M.A., Miranda, J.G.V., 2014b. Spatio-temporal correlation networks of dengue in the state of bahia. BMC Public Health 14, 1085.
Sharma, K., Mahabir, R.S., Curtin, K.M., Sutherland, J.M., Agard, J.B., Chadee, D.D., 2014. Exploratory space-time analysis of dengue incidence in Trinidad: A retrospective study using travel hubs as dispersal points, 1998–2004. Parasites Vectors 7 341 11pp.
Siriyasatien, P., Phumee, A., Ongruk, P., Jampachaisri, K., Kesorn, K., 2016. Analysis of significant factors for dengue fever incidence prediction. BMC Bioinforma. 17, 1.
Souza, I.C.A., Furtado, P.C.H., Bezerra, I.S., Moraes, R.M., 2006. Explorando modelos estatisticos de relacoes entre variaveis climaticas, vetores alados e incidencia do dengue [exploiting statistical models of relationships between climate variables, winged vectors and incidence of dengue]. Proc. of Environmental and Health World Congress 2006, pp. 230–233.
Souza, I.C.A.D., Vianna, R.P.D.T., Moraes, R.M.D., 2007. Modelagem da incidencia do dengue na parâ íba, brasil, por modelos de defasagem distribuída [dengue incidence modeling in paraiba by distributed lag models]. Cad. saude publica 23, 2623–2630.
Teixeira, M.G., Boischio, A., Costa, M.D.C.N., 2009. Ecosystem approaches to controlling of vector-borne diseases: dengue and chagas disease. Cadernos de Saude Publica 25, S4.
Tizzoni, M., et al., 2014. On the use of human mobility proxies for modeling epidemics. PLoS Comput. Biol. 10, e1003716.
Vieira, I.T., 2005. Small World Network Models of the Dynamics of HIV Infection. Ph.D. thesis. University of Southampton.