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Spatial variations of dengue fever in Brazil

Abstract

In recent decades, the global incidence of DF has grown dramatically and spread to all regions of the world, still that its major concentration is in tropical and subtropical regions. One of the countries most affected by DF is Brazil. Therefore, investigating the spatial and temporal variations of notified DF infections in Brazilian municipalities from 2001 to 2012, as well as to detect hotspots, is the main goal of this paper. In parallel, we will add the analysis to the urbanization component and verify how important this variable is to understand DF in Brazil. For purposes of analysis, and to reduce variations on dengue incidence in areas with small population, we calculated annual rates of dengue per 100,000 for each county over the three four-year periods 2001-2004, 2005-2008 and 2009-2012, as well as we use spatial smoothing. The identification of specific areas with high incidence of DF will help policymakers to focus on prevention and health care programs, thus allowing an efficient allocation of resources to public health and the adoption of preventive measures to deal with disparities in the country.

BACKGROUND

Dengue fever (DF) is a mosquito-borne viral disease transmitted through bites of female *Aedes aegypti* mosquitoes, although it can also be propagated by *Aedes albopictus*. In recent decades, the global incidence of DF has grown dramatically and spread to all regions of the world, still that its major concentration is in tropical and subtropical regions, much influenced by rainfall, temperature and unplanned rapid urbanization found in these regions and conducive to the development of the mosquitoes. Data from Brady et al. (2012), and corroborated by World Health Organization (WHO, 2017), “estimates that 3.9 billion people, in 128 countries, are at risk of infection with dengue viruses”, i.e., about half of the world's population.

One of the countries most affected by DF is Brazil. According to data from the WHO (2017), “the Region of the Americas region reported more than 2.38 million cases in 2016, where Brazil alone contributed slightly less than 1.5 million cases, approximately 3 times higher than in 2014”. These high numbers occur precisely because of the characteristics mentioned above. In other words, it is a predominantly tropical country, where average annual temperatures are high, and rainfall is considerable (although there is a regional variation in both cases)¹, as well as an unplanned rapid urbanization.

Brazil is a heterogeneous country with regard also to its demographic, cultural, socioeconomic, epidemiological and health issues (BAPTISTA, 2015). Therefore, investigating the spatial and temporal variations of notified DF infections in Brazilian municipalities from 2001 to 2012, as well as to detect hotspots, is the main goal of this paper. In parallel, we will add the analysis to the urbanization component and verify how important this variable is to understand DF in Brazil. The identification of specific areas with high incidence of DF will help policymakers to focus on prevention and health care programs, thus allowing an efficient allocation of resources to public health and the adoption of preventive measures to deal with disparities in the country.

DATA & METHODS

The data used in this study on incidence from dengue fever (DF) were diagnosed based on the results of standardized laboratory tests and epidemiological and extracted from

¹ This paper does not intend to discuss and characterize pluviometric and temperature variations observed in Brazil. It is only worth mentioning that these variations between the regions and the Brazilian states are known by the authors.

Information System for Notifiable Diseases (SINAN). The data are available in the DATASUS², which was created by the Brazilian Ministry of Health in 1975.

The data are organized by year (2001-2012³), sex (males and females), age (<1, 1-4, 5-9, 10-14, 15-19, 20-39, 40-59, 60-64, 65-69, 70-79, and 80 years or more) and incidence from dengue fever (classic dengue fever) as well as by the municipalities (5,570 in total) where the person diagnosed reside. Population data by age and sex were obtained from the 2010 Census and intercensal estimates from the Brazilian Institute of Geography and Statistics (IBGE)⁴.

For purposes of analysis, and to reduce variations on dengue incidence in areas with small population, we calculated annual rates of dengue per 100,000 for each county over the three four-year periods 2001-2004, 2005-2008 and 2009-2012, as well as we use spatial smoothing. To implement this methodology, we used the Spatial Empirical Bayes approach available in GeoDa. The Bayesian Empirical estimator is operationalized as follows (Marshall, 1991):

$$\theta_i = m + C_i * (x_i - m) \quad \text{where } C_i \text{ is given by}$$

$$C_i = \frac{\left(s^2 - \frac{m}{n^M} \right)}{\left(s^2 - \frac{m}{n^M} + \frac{m}{n_i} \right)}$$

Where: θ_i is the smoothed rate; x_i is the gross rate of area i ; m is the average rate of neighbors; s^2 is the variance of the rate to be estimated; n^M is the average population of neighbors; n_i is the population of the area i .

It should be borne in mind that in the Bayesian empirical estimator formula proposed by Marshall (1991), the multiplier C_i will be close to 1 if the population of area i (n_i) shows a high value. In this case, the smoothed rate (θ_i) will tend to have the

² DATASUS. <http://datasus.saude.gov.br/>

³ Last year of data available.

⁴ IBGE. <http://www.ibge.gov.br>

same value as the estimated without applying the procedure, x_i . Otherwise, if the population of area i has a very small population, we have that C_i will be close to zero, implying that the smoothed rate (θ_i) will tend to be close to the average rate (Barbosa and Freire, 2004, p. 6).

To employ the Spatial Empirical Bayes, we first created a spatial weight file in GeoDa that contains neighborhood structure using the K-nearest neighborhood criteria (eight counties in our case) which was later loaded to make spatially smoothed distribution maps. To assess the risk of DF in each county, an excess hazard⁵ map was produced. The excess hazard was defined as the ratio of the observed incidence at each county over the average incidence of the Brazil; the later was calculated by the number of cases over the total number of people at risk instead of the annualized incidence of a county (ANSELIN et al., 2004; LU et al., 2010).

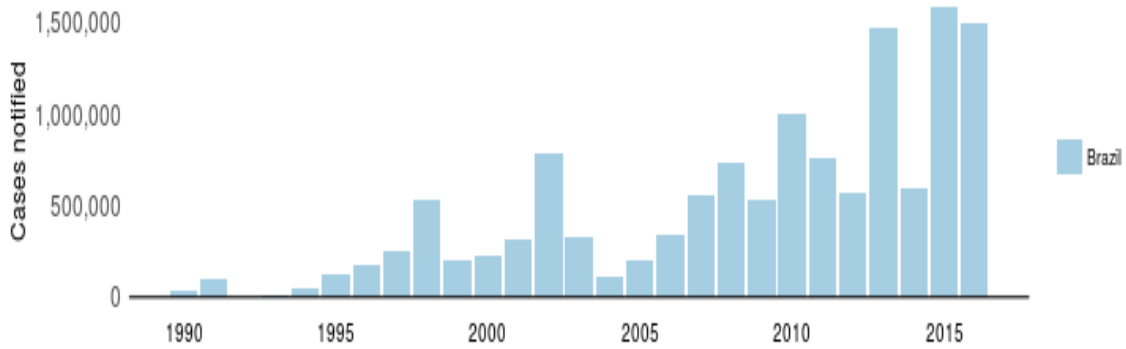
Finally, the annualized incidence rate for each county was calculated and grouped into 4 endemic levels: nonendemic with none cases; low endemic with annual incidence between 0 and 5 per 100,000; medium endemic with incidence between 5 and 10 per 100,000; and high endemic with incidence more than 10 per 100,000.

PRELIMINARY RESULTS

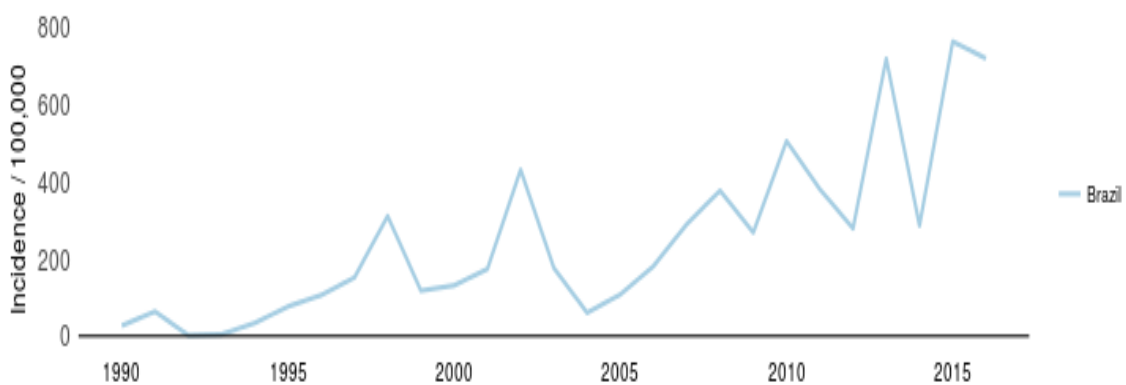
Figure 1 shows the notified DF infections in Brazil from 1990 to 2016. From 2004, there was an increase in the number of notified cases, with peaks in the years 2010, 2013, 2015 and 2016. In fact, in recent years the numbers have reached more than 1.5 million reported cases. Before the trend of increasing from 2004, two more representative peaks happened in the years of 1998 and 2002.

Regarding the incidence of DF in Brazil (Figure 2), the information accompanies the pattern of notified cases brought in Figure 1.

⁵ The excess hazard represents the ratio of observed incidence at each district over the average incidence of all endemic areas. In the excess hazard map, value one is usually determined as a cut-off value whereas below one indicates lower incidence than expected and above it indicates incidence higher than expected.



Source: WHO, 2016



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REFERENCES

Anselin, L.; Syabri, I.; Kho, Y. *GeoDa: An Introduction to Spatial Data Analysis*. Basingstoke, England: Palgrave Macmillan; 2004.

Baptista, E.A. Mortalidade por doenças cardiovasculares na população adulta: um estudo têmporo-espacial e demográfico para as microrregiões brasileiras entre 1996 e 2010. Tese (Doutorado). Universidade Federal de Minas Gerais (UFMG), Centro de Desenvolvimento e Planejamento Regional (Cedeplar), Belo Horizonte.

Brady, O. J.; Gething, P. W.; Bhatt, S.; Messina, J. P.; Brownstein, J. S.; Hoen, A. G.; et al. Refining the global spatial limits of dengue virus transmission by evidence-based consensus. *PLoS Negl Trop Dis*. 2012;6:e1760. doi:10.1371/journal.pntd.0001760.

Lu, L.; Lin, H.; Liu, Q. Risk map for dengue fever outbreaks based on meteorological factors. *Adv Clim Change Res*. 2010; 6: 254-258.

Pringle, D. G. Mapping disease risk estimates based on small numbers: an assessment of empirical Bayes techniques. *Econ Soc Rev*. 1996; 27(4): 341–63.

World Health Organization, 2016. Accessed in Feb, 2018. http://www.who.int/denguecontrol/epidemiology/dengue_data_application/en/

_____, 2017. Accessed in Feb, 2018. <http://www.who.int/mediacentre/factsheets/fs117/en/>