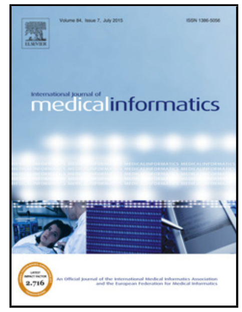

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Google Dengue Trends: An Indicator of Epidemic Behavior. The Venezuelan Case

Manuscript

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Highlights

- Epidemiological data from GDT is highly correlated when compared with official data
- GDT is more accurate when the disease shows the highest incidences
- GDT is a valuable indicator of Dengue in the setting of weak surveillance systems

Abstract

Introduction. Dengue Fever is a neglected increasing public health thread. Developing countries are facing surveillance system problems like delay and data loss. Lately, the access and the availability of health-related information on the internet have changed what people seek on the web. In 2004 Google developed Google Dengue Trends (GDT) based on the number of search terms related with the disease in a determined time and place. The goal of this review is to evaluate the accuracy of GDT in comparison with traditional surveillance systems in Venezuela. **Methods.** Weekly epidemic data from GDT, Official Reported Cases (ORC) and Expected Cases (EC) according the Ministry of Health (MH) was obtained Monthly and yearly correlation between GDT and ORC from 2004 until 2014 was obtained. Linear regressions taking the reported cases as dependent variable were calculated. **Results**. The overall Pearson correlation between GDT and ORC was r=0.87 (p<0.001), while between ORC and EC according the Ministry of Health (MH) was r=0.33 (p<0.001). After clustering data in epidemic and non-epidemic weeks in comparison with GDT correlation were r=0.86 (p<0.001) and r=0.65 (p<0.001) respectively. Important interannual variation of the epidemic was observed. The model shows a high accuracy in comparison with the EC, particularly when the incidence of the disease is higher. **Conclusions.** This early warning tool can be used as an indicator for other communicable

diseases in order to apply effective and timely public health measures especially in the setting of weak surveillance systems.

Abbreviations: CDC: Center for Diseases Control, CDSS: Communicable Diseases Surveillance, DENV: Dengue Virus, DF: Dengue Fever, DHF: Dengue Hemorrhagic Fever, FLU: Influenza, GDT: Google Dengue Trends, GE: Google Epidemics, GFT: Google Flu Trends, MH: Ministry of Health, ORC: Official Reported Cases, WHO: World Health Organization

Keywords: Dengue, Surveillance Systems, Communicable diseases, Internet.

Text

1. Introduction

Dengue is a systemic viral infection transmitted by mosquitoes (1). The primary vector is the urban adapted *Aedes aegypti* largely spread in tropical and subtropical regions (1). The secondary vector, *Aedes albopictus*, although less effective has rapidly spread during the last decade (2). This infection is caused by one of four serotypes, each capable to confer long-lived serotype-specific immunity but only short cross immunity between serotypes. Each year, approximately 390 million cases, of which approximately 96 million have any level of severity (3). The clinical manifestations rank from a mild fever syndrome known as Dengue Fever to a Severe Hemorrhagic Dengue Shock (1). Frequently, the severe cases are a consequence of a secondary infection by heterologous serotypes (1,4).

The sustained number of human movements importing the disease (5), the colonization by *Aedes albopictus* (6) and climate change can play a role on spreading it to areas where the vector was not able to transmit Dengue before. Change in rain patterns plus shifts in temperature can lead local environments to become more prone to the reproduction of vectors that previously found these conditions as barriers (7). During the last century some clusters of autochthonous dengue have been present in Southern Europe (8–12). Although European Dengue is a rare phenomenon, according to a phylogeographic analysis the Dengue cases in Madeira (Portugal) in 2012 were caused for an strain which came through travelers from Venezuela and produced an important outbreak due to the climate conditions (13).

In Venezuela every year dengue accounts for a significant amount of morbidity and mortality. The official bulletin in 2014 reported 87.529 cases, placing the country as one of the most affected by the epidemic (14).

In developing countries, Communicable Diseases Surveillance Systems (CDSS) have many weaknesses. Lack of integrated reporting system, lack of modern technology, and high centralization are some of the challenges CDSS face in this setting (15). As a consequence, there is not only systematic misdiagnosis but also delay in the availability of important data (16). Also, censure and lack of transparency can be other obstacle in countries with authoritarian governments.

Although specific antivirals to treat Dengue do not exist, there is a new recombinant, tetravalent Dengue vaccine approved in Mexico (17). Apart from standard vector control measures, the availability of a vaccine obliges to wisely allocate this resource according to the distribution of the infection in order to increase its effectiveness (18).

On the other hand, in the last decade, the access and the availability of health-related information on internet have changed the way lay people, public health workers and clinicians search the web (19). Even though not every person who search for health related terms is ill, there is a close relation between the number of people searching for symptoms for a determined condition and those who have the symptoms, which can provide an indicator of the spread of some communicable diseases (20,21). Thus, analyzing the pattern of where and when people search about their health concerns related to infectious diseases as Dengue, can make real time data available faster than traditional surveillance systems, where often the data arrives to policy makers too late to establish effective public health measures (22).

Google has developed a query based reporting system for infectious diseases (22). Most of the previous experiences evaluating its accuracy have been done regarding Influenza (FLU) and lately with other diseases including Dengue. Linear models to evaluate the association between FLU Yahoo queries and positive FLU cultures (23) and between Google FLU trends (GFT) and data from the US' CDC influenza Sentinel Provider Surveillance Network have demonstrated the value of this approach (24). Also, Google Dengue Trends (GDT) data has been compared with official data from Asian and Latin American countries affected by this disease, finding not only good correlation and prediction ability (25–29) but also relation with demographic and climatic variables (30).

Due to its particular clinical presentation this strategy can be more accurate with Dengue than with FLU. Furthermore, the accuracy of the prediction of Dengue can allow for more effective public health measures and might improve Dengue predictions in areas with less developed CDSS(26).

This study aims to evaluate the accuracy of GDT as an indicator of the spread of Dengue in Venezuela and to analyze its public health implications.

2. Methods

GDT track the Dengue incidence based on internet search patterns. It cluster weekly queries for key terms related with the disease. We use GDT data from January 1st 2004 until December 31th 2014 and compared with the data from the official Venezuelan weekly Bulletin from the Ministry of Health (MH) during the same time period. This data is collected on a weekly basis via mandatory communicable disease reporting procedures from public and private health care facilities and published on the official website (http://www.mpps.gob.ve/index.php?option=com_phocadownload&view=section&id=4:boletin-epidemiologico&Itemid=915).

2.1. Terms

The spanish terms "el dengue", "dengue síntomas", “síntomas dengue”, "qué es dengue", “qué es el dengue” identified by GDT were included. Isolated symptoms related terms were not included to avoid overlap with other queries for other diseases.

2.2. Statistical Analysis / Statistical Model

The official data was clustered in epidemic and non-epidemic weeks. Epidemic weeks were defined as those which had more than the Expected Cases (EC) according to the MH data. EC is calculated using data from the last 5 years, and is used by the MH to forecast cases, to plan control measures and distribute resources. We calculated “Google Epidemics” (GE) multiplying the number of Dengue related queries registered by Google by a factor to make the data comparable with the ORC. Overall Pearson's correlation between the ORC and GE was clustered in months and years respectively, then correlations regarding epidemic and non-epidemic weeks were obtained. Linear regression using ORC as dependent variable and GE as independent variable was calculated.

Sensitivity and specificity of the model was obtained using cross tabulations for the overall data.

3. Results

A total of 650.293 cases were reported in Venezuela during the period 2004 – 2014. Figure 1 shows data from GE, ORC and EC according to the MH.

The data shows a limited association with season and substantial interannual variation (Figure 2). The overall Pearson correlation during the total period between the ORC and GE was $r=0.87$ ($p<0.001$) while between ORC and EC was $r=0.33$ ($p<0.001$).

Simple linear regression was calculated to predict ORC based on GE during the evaluated period. With a significant regression equation ($p<0.001$) the overall coefficient of determination was R2=0.75.

In table 1, overall data per month show correlations higher than $r=0.92$ ($p<0.001$) between May and November. Between December and April correlations rank from $r=0.48$ ($p<0.001$) (March) and $r=0.87$ ($p<0.001$) (January).^

When overall data where clustered in epidemic (higher incidence than expected cases) and non-epidemic weeks the correlation coefficient is higher in the first case ($r=0.86$; $p<0.001$) (table 2).

Table 3 shows the yearly correlation between Google Epidemics and the Official Data and demonstrate increasing values until 2011 when suddenly decrease for three years to increase again at the last year included.

Using cross tables the model during 11 years (2004 – 2014) regarding correct classification of epidemic and non-epidemic week by google showed a sensibility of 0.79 and specificity of 0.75.

The percentage of internet penetration is a variable that can influence the performance of this tool. Due to socioeconomic disparities the internet penetration considerably variates among different developing countries. The following table shows the percentages of “individuals using internet” in different countries mentioned as a reference in this paper.

4. Discussion

In contrary to findings reported in Mexico where the epidemic seems to follow a seasonal pattern (30), our data from Venezuela show interannual variability over the eleven evaluated years. Similar findings were observed in Thailand where incidence significantly varies between different years (31). In that sense, this limited association with the climatic season makes the availability of early warning systems and timely surveillance structures more useful and needed.

High correlation between the official data and GDT was closely related with high incidence of the disease, which is evident during the months from May to October. Meanwhile months like February and March with the lowest incidences, had also the lowest correlations. Similar associations were found by Gluskin (32) and Althouse (26) who observed that high incidence were related with better performance of the prediction model.

This means that according to the Venezuelan data, people are more likely to seek for health related information when their surrounding environment is affected by the disease. This speaks for the opportunity of using internet query searches as indicator of the behavior of similar diseases.

Regarding the analysis per year, the relatively low correlation in the first three years in contrast with the high correlation from the following years until 2011, can be explained by the increase of the penetration of internet that occurred in Venezuela during the period evaluated (19). Other possible reason for these findings, as the observed in the analysis per month, can be the directly proportional relation between stronger correlations when there are higher incidences (26,32). For example, in the years like 2010 and 2014 the overall highest incidences and strongest correlations were observed. There is no clear explanations for the decrease of the accuracy of GDT during the years 2011, 2012 and 2013. However, the Chikungunya epidemics, which share very similar symptoms with Dengue, appeared in Venezuela by the last months of 2012 becoming a serious epidemic during 2013 and might have affected the seeking behavior of the people.

None of the similar previous studies have compared the performance of GDT against the “Expected Cases” estimated by the proper official health authority. After we compared the accuracy of the “Expected Cases” according MH and the data from GDT with the ORC, GDT showed to be a better indicator of the behavior of the disease across all the years evaluated.

The advantages of this model relies in the possibility of implementing preventive effective public health measures to decrease morbidity and mortality using a cheap and readily accessible tool. Also, traditional surveillance systems can integrate it to improve their accuracy. Thus, a simple tool based on weekly notification data as the infectious diseases "barometer" used by institutions like CDC and other European experiences can be integrated with GDT in order to achieve early detection (31).

This study has some limitations. First, the fact that in developing countries like Venezuela the internet penetration is not uniformly distributed across the territory, which makes this tool less accurate in rural areas where traditionally surveillance systems struggle the most to provide important data. Second, this tool is vulnerable to have spurious spikes due to the "panic induced phenomena" when a new or neglected disease appears. That was evident in the case of GFT that showed important problems of accuracy (34,35) even after changing the algorithm to avoid being influenced by other factors different from the real cases. Third, this paper included only nationwide data, making difficult the use of this tool to carry out local public health control measures.

Since the new dengue vaccine is approved in Mexico, the here described new tool can be applied to prioritize and monitor the application and effectiveness of Dengue vaccine in a low resources setting with weak surveillance systems.

Recent facts confirm the need for facing vectorial diseases like Dengue, Chikungunya and Zika from a continental perspective. Similar previous studies in Brazil, Mexico, Bolivia and Peru (25–27,29,32) have shown that these tools might be useful in Latin American countries taking into account the social-cultural and climatic similarities and the weak performance of their surveillance systems. They can also, be useful for international authorities in a context where national health data could be censured.

The tool presented can be moreover used in regions not yet affected by the disease before an outbreak starts.

The performance of this tool integrated into a traditional surveillance system still needs to be tested. Also, models, which include similar diseases and Internet penetration rates, should be performed in the future. Finally, in order to be able to use this tool for control measures, to evaluate its performance in a local level is still needed.

5. Conclusions

This early detection tool still has a long way to be tested. Up to date, there is no reported experience of its use in a real setting of endemic vectorial diseases or as an indicator to carry out control measures. However, our findings suggest that this tool can be used in a low resources setting where epidemiologic data lags to reach the health authorities. Even though, local data was not completely available to be evaluated, in the Venezuelan case nationwide data can help to timely orient control measures in highly dense populated regions where Dengue is historically endemic.

6. Summary Table

• CDSS from developing countries struggles to provide timely and reliable important data in order to response adequately in front of infectious diseases.
• In the Venezuelan case, Google Dengue Trends appears more accurate when the disease is more prevalent.
• Google Dengue Trends is a valuable indicator and timely available tool

that can be used by public health authorities to monitor the behavior of the disease, and potentially guide the application of control measures against dengue in Venezuela
• This tool could be useful in other countries to track the behavior of other infectious diseases.

7. Disclaimers

The opinions expressed by authors contributing to this journal do not necessarily reflect the opinions of the institutions with which the authors are affiliated.

Authors Contributions

Ricardo A. Strauss[1], Julio S. Castro[1], Ralf Reintjes[1], Jaime R. Torres[1]

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Conflict of Interests: none.

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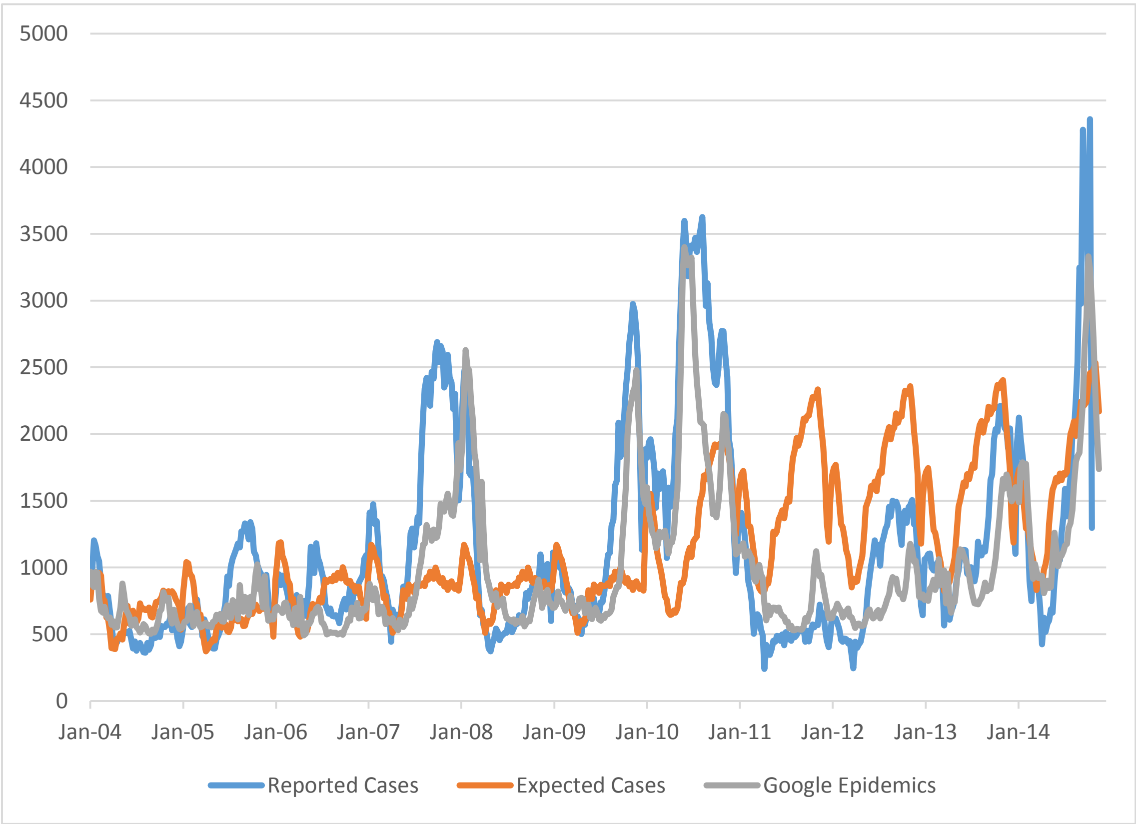

Fig 1 Time series of weekly reported cases and Google Dengue Trends, Venezuela. 2004 – 2014. On the left axis the scale for number of cases. Official Reported Cases (blue), Official Expected Cases (red) and Google Epidemics (grey)

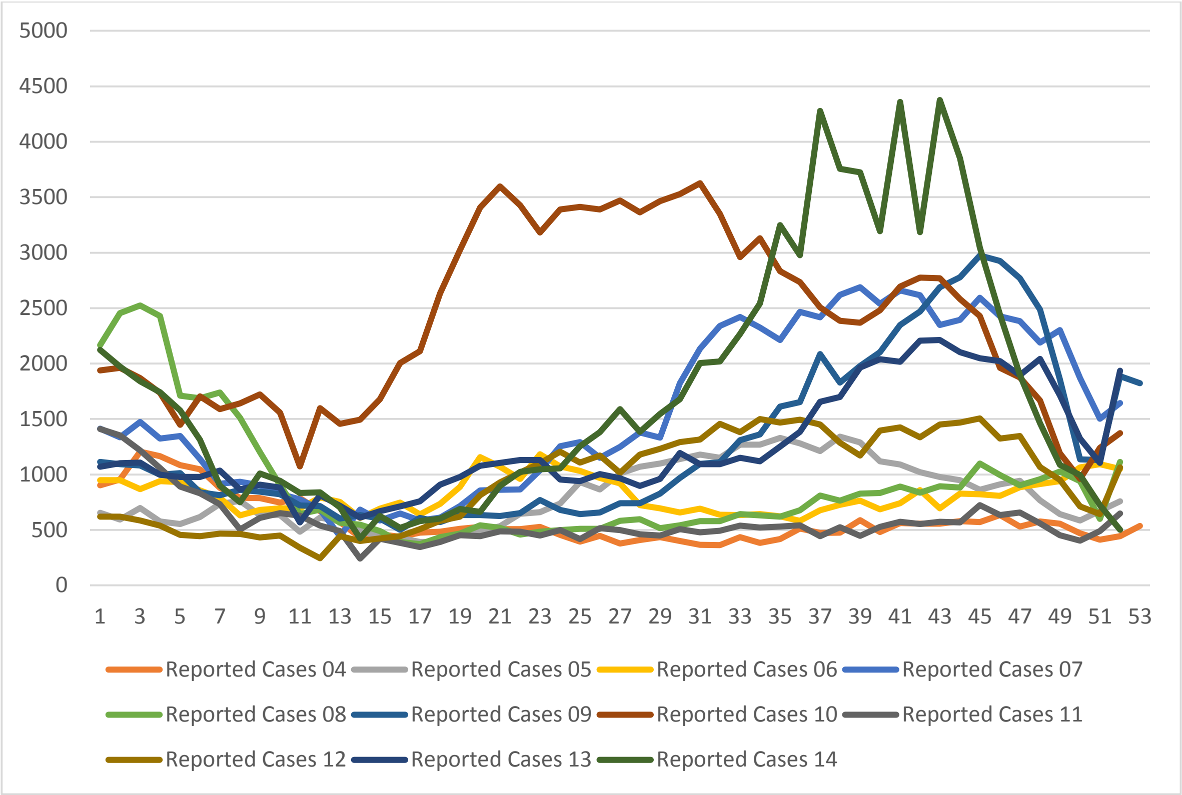

Fig 2 Reported cases per year (2004 – 2014). The graph shows the interannual variability of the cases with tendency to be more incident by the beginning of May.

Table 1. Correlation: ORC and GDT. Matrix per month (2004 - 2014)

Month	**Correlation**	**P-value**
January	0.87	0.001
February	0.73	0.001
March	0.48	0.001
April	0.81	0.001
May	0.93	0.001

June	0.94	0.001
July	0.95	0.001
August	0.95	0.001
September	0.93	0.001
October	0.90	0.001
November	0.92	0.001
December	0.84	0.001

Table reports overall (2004 – 2014) monthly correlation between ORC and GDT.

Table 2. Correlation between GDT and ORC during epidemic weeks or non-epidemic weeks

Type of week	Correlation	P-value
Epidemic	0.86	0.001
Non epidemic	0.65	0.001

Table reports overall (2004 – 2014) correlation divided by epidemic or non-epidemic weeks.

Table 3. Correlation: ORC and GDT. Matrix per year (2004 - 2014)

Years	Correlation	P-value
2004	0.73	0.001
2005	0.62	0.001
2006	0.54	0.001
2007	0.84	0.001
2008	0.85	0.001
2009	0.88	0.001
2010	0.84	0.001
2011	0.70	0.001
2012	0.71	0.001
2013	0.72	0.001
2014	0.84	0.001

Table reports overall (2004 – 2014) yearly correlation between ORC and GDT.

Table 4. Individuals using internet per country of interest

Country	Individuals using Internet (% from total population)
Bolivia	45.1
Brazil	59.08
India	26
Indonesia	21.98
Mexico	57.43
Peru	40.7
Singapore	82.1
Thailand	39.32
Venezuela	61.87

Source: International Telecommunications Union 2016.