Identifying Geographic Dengue Fever Distribution by Modeling Environmental Variables

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Abstract
During 2012-2015, the municipality of Guarulhos, inserted in the São Paulo Metropolitan Region (the 4th largest metropolitan region in the world), recorded about 7540 cases of dengue fever. Given this situation, the work presented a prediction of the geographical distribution of this disease, using dengue fever occurrence records and environmental variables, through the MaxEnt distribution modeling. As the main result, it was observed that about 10% of the territory of Guarulhos presented high suitability for the disease occurrence (> 0.7). Areas with around ~900 inhabitants/ha inserted in regions with a mean surface temperature between 18 ºC and 25 ºC, inadequate household water storage, irregular disposal, and absence of waste recycling services may increase the risk of dengue transmission in prolonged drought periods. Finally, the work contributes to the development of public health strategies indicating areas for mitigation and environmental education actions in Guarulhos.

1. Introduction

Data on Land Surface Temperatures (LST) are of prime importance for the study of urban climatology; because they modulate the temperature of the air in the lower layers of the atmosphere and control, the exchange of energy in the city, and others things (Voogt and Oke, 2003). In this sense, the spatial variation of the LST presents a significant correlation with the land cover patterns, mainly due to their different behaviors regarding the emission of heat or infrared radiation (Voogt and Oke, 2003, Gartland, 2008 and Weng, 2009). More than that, the thermal images can be indicative of the environmental conditions of the ecosystem service of thermal regulation for human well-being (Oliveira et al., 2010).

Among the most common problems in cities whose urban expansion is characterized by the radical elimination of vegetation cover are the changes in local patterns of energy balance and temperature (the phenomenon of the urban heat island) (Oliveira et al., 2010 and Prata-Shimomura et al., 2015). For human well-being, these environmental changes may represent a heavy burden on public health services in triggering and aggravating epidemiological diseases such as the ones transmitted by vectors (Hopp and Foley, 2001 and Liu et al., 2015). Climate change or extreme weather events at regional and local scales like periods of drought, floods, or heat waves can also impact on the increase in dengue cases. Because it can promote inadequate water supply (a consequence observed during the 2014 drought in the São Paulo Metropolitan Region - SPMR), the accumulation of rainwater and increasing of the temperature of places previously not favorable to the development of the mosquito *Aedes aegypti* (Reiter, 2001 and Li et al., 2018).

Diseases like the dengue fever, transmitted by the *Aedes aegypti* mosquito (similarly as zika, chikungunya, yellow fevers, and others arboviruses) have a strong correlation with environmental factors such as variability of surface temperature and humidity (Fatima et al., 2016). Other factors, such as the low coverage of regular water supply, sanitary sewage, solid waste collection, rainwater drainage, and irregular housing, are suitable factors to promote the appearance of the disease (Glasser and Gomes, 2000). In these sites with inadequate infrastructure artificial containers that can accumulate water are often found, like rubbish, tires, among others; providing excellent breeding habitats (Fatima et al., 2016). In this context, the MaxEnt model can help to predict the spatial distribution of species or arboviral diseases through occurrences records and environmental layers (Phillips et al., 2006, Elith et al., 2010 and Lorentz et al., 2017). Thus, the main focus of the work is recognizing geographic dengue fever distribution by exploring the dynamics of environmental factors. Our analysis took into account the identification and quantification of environmental variables associated with this disease in Guarulhos city, a suburban area of Sao Paulo, the fourth largest metropolitan area in the world, with 20 million inhabitants.

2. Methodological Approach

The methodology is divided into four stages (Figure 1): i) Selection of records of occurrence of dengue cases by means of a geo-referenced database; ii) Selection of thematic maps of the environmental layers; iii) Prediction of geographic distribution of dengue fever in Guarulhos, through the MaxEnt modeling tool; iv) Indication of priority areas for mitigation and/or prevention actions.

2.1 Study Area

The São Paulo Metropolitan Region (SPMR) is made up of 39 municipalities with approximately 20 million inhabitants containing large industrial, commercial and financial complexes, which accounts for 18% of the country's and more than half of the State of São Paulo GNP. The study area, selected for this analysis, is located at the Guarulhos Municipality, the second largest city in São Paulo state (SE - Brazil) with 31,870 ha and a population of more than 1,349,113 inhabitants (IBGE, 2017) (Figure 2). The climate is the subtropical and humid (Nimer, 1989), with dry winters and rainy summers, influenced by oceanic humidity and cold Antarctic fronts (Ribeiro et al., 2018). Rainfall data of the Tropical Rainfall Measuring Mission 3B43_v7 (TRMM, 2011) and relative humidity of the AIRS3STM model of the Earth Observation System of the AQUA satellite (Airs and Teixeira, 2013) pointed out that for the analyzed period (2012-2015), the annual rainfall and relative humidity climatological averages were 1599 mm and 65%, respectively, for the entire municipality of Guarulhos.

Information derived from the reanalysis MERRA-2 model (GMAO, 2015), showed that the average annual temperature for the same period ranged from 16 °C to 23 °C. The coldest month was July, with 11.6 °C while the hottest month was February, with 29 °C. Global Land Data Assimilation System (GLDAS) models pointed out that in the study area, the prevailing winds were ESE with an average speed of 2.5 m/s (Beaudoing et al., 2016).

2.2 Dengue Occurrence Data and Environmental Variables

Data on the occurrence of positive dengue cases were obtained through the Department of Health of the Municipality of Guarulhos-SP, in the Public Health/Dengue sector. In total, 7540 positive cases of the disease were obtained between the years of 2012 to 2015, which were later transformed into monthly climatological averages (12 layers) containing their geographic location. The environmental variables used in the research were obtained from several databases, classified and grouped according to their nature, such as (i) urban infrastructure - distance from slum (Slumdist) and drainage (Draindist) in meters, as well as population density (Denspop) per hectare; ii) climatic data - images of the monthly climatological averages (12 layers) of the Land Surface Temperature (LST) in degrees Celsius (°C) between 2012-2015, for the whole year (LST-annual), the day (LST-day), night (LST-night), thermal amplitude (LSTS-range) and Surface Heat Island (SHI).

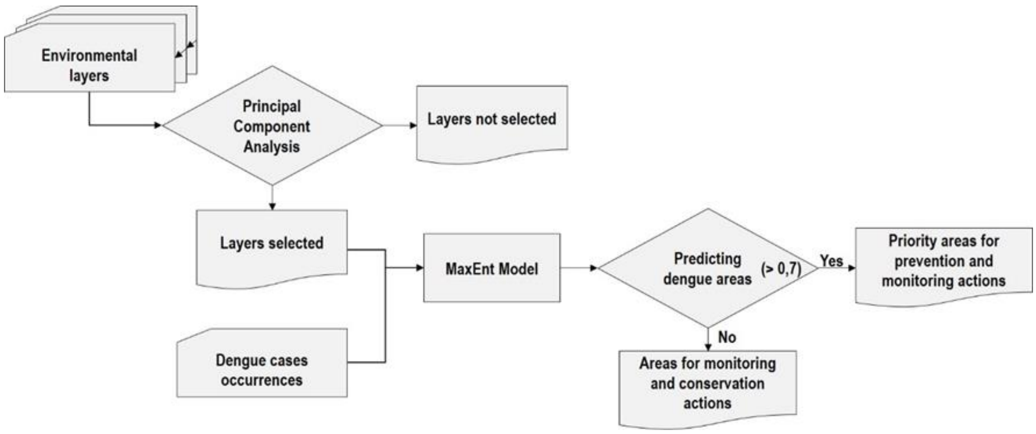

Figure 1: Flowchart of the methodology used

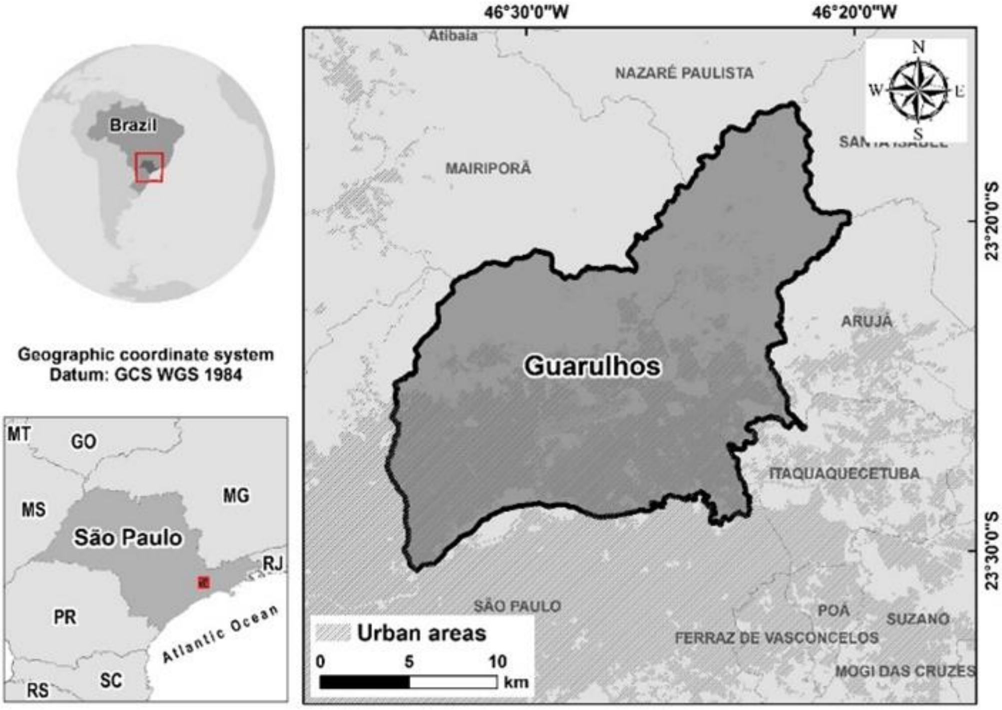

Figure 2: Location of the Municipality of Guarulhos, São Paulo, Brazil (SE, Brazil)

Data on urban infrastructure related to slum distance and the population density were obtained from the last national census survey "Information Base of the Demographic Census 2010: Results of the Universe by census sector" of the Brazilian Institute of Geography and Statistics (IBGE, 2011). The distances of the drainage were obtained from the Geoenvironmental Bases for an Environmental Information System of the Municipality of Guarulhos (Oliveira et al., 2009).

The Land Surface Temperature images were derived from the products MOD11A1 and MYD11A1 (version 5), respectively from satellites TERRA and AQUA, from the channels 31 (10.780 - 11.280 µm) and 32 (11.770 - 12.270 µm) by generalized split-window algorithm with an accuracy of 1-2 °C of the sensor Moderate-resolution Imaging Spectroradiometer - MODIS (Gorelick et al., 2017). It has a heliosynchronous orbit, together with the quality band (Wan, 2015a; 2015b). The images acquired, daily at approximately 10:30 a.m. and 10:30 p.m. (TERRA) and at 1:30 a.m. and 10:30 p.m. (AQUA), for every day between 2012 and 2015. Then, the original pixel values (Digital Numbers) were converted to land surface temperature values (TS°C), according to Equation (1) and depending on the Quality Control band (QC) of the image (Wan, 2013).

$$LST°C = (DN * 0{,}02) – 273{,}15$$

Equation 1

Where DN is the "Digital Number" referring to the pixel of the image. To identify the Surface Heat Island (SHI), as well as the comparison of thermal patterns over the analyzed period, Alcoforado et al., (2009), suggested the normalization of the Land Surface Temperature value of a given site (LST_{pixel}) in relation to the mean of the entire area (LST_{mean}) and its respective standard deviation (SLT_{sd}), for a given period analyzed according to Equation (2). This methodology allows identifying positive or negative LST anomalies on a region over time.

$$SHI = (LST_{pixel} – LST_{mean}) / LST_{sd}$$

Equation 2

The use of LST images is justified because they represent in a "faithful" way the climatology of the dengue cases occurrence period (2012 to 2015).

2.3 The MaxEnt Features and Environmental Variable Selection

The modeling method used in this work was the Maximum Entropy algorithm (MaxEnt) version 3.4.1. MaxEnt generates habitat suitability models based on known distributions and the series of environmental layers. This model has a great capacity for prediction occurrence areas for certain phenomena (Phillips et al., 2006 and Elith et al., 2010). In MaxEnt settings, 70% of the present records were allocated to the training data and 30%

to the test data, with a selection of "random seed" so that on every replicate the model uses a different set of presence records for training and testing. In order to improve the performance of the models, 10,000 background points were generated, distributed randomly to each of the models. In that way, MaxEnt was able to construct very complex nonlinear response curves using a variety of resources classes (Merow et al., 2013).

The importance of each variable was determined using the Jackknife test and by the percentage of the contribution in the final model (Phillips et al., 2009). The resulting map of the model presents the values of the prediction as values between 0 and 1, which represents the suitability of the habitat in the pixel; values closer to 1 indicate greater suitability, that is, the higher probability of the presence of the disease in the pixel (Phillips and Dudik, 2008). The model evaluation was performed according to the Receiver Operational Characteristic (ROC) curve that ranged from 0 to 1. The closer to 1 means, the better the model. ROC of 0.5 indicates that the discrimination of the model is no better than a random model (Fielding and Bell, 1997). These results were compared using the respective Area Under the Curve (AUC) of the ROC. Models with ROC values > 0.9 are considered highly accurate, values between 0.7 and 0.9 are useful, and those smaller than 0.7 are less accurate (Elith et al., 2006).

Distribution models obtained from a large set of environmental variables may present high correlation or multicollinearity, making estimates of these variables statistically biased (Cruz-Cardenas et al., 2013 and Fatima et al., 2016). In order to remove data colinearity, Principal Component Analysis (PCA) was applied. This technique has as main characteristic the reduction of the number of correlated variables for a data set, preserving their total variance (Cruz-Cardenas et al., 2013). Thus, the variables used in the model were uncorrelated, derived from the PCA whose sum of the percentage of eigenvalues accumulated 100% and whose loads or eigenvectors were higher than |0.32|. The limit value of |0,32| was chosen because it represents 10% of the variance within the PCA (Dormann et al., 2012). Based on the parameters described above, three urban infrastructure variables and five surface temperature variables were selected (Table 1).

On Table 1 the Urban infrastructure elements are: LCZ – Local Climate Zone; SlumDist – Slum Distance; DrainDist – Drainage Distance; MinWage – Minimum Wage; HouseDens – House Density; PopDens – Population Density; GarbCol – Garbage Collected; WaterNet – Water Net and SeageNet – Seage Net. Finally, the model was fed with the dengue occurrence data (monthly) and the layers of the selected environmental variables. These were processed to Guarulhos municipality limit in the formats "*.csv" and "*.asc," respectively for the dengue occurrence data and the pixel values of the environmental layers interpolated to 100 m x 100 m, using a Geographic Information System (GIS) environment, in ArcGIS 10.2 software. The projection system used was the Geographic, datum WGS1984.

Table 1: Variables selected (in bold) as a function of the percentage of eigenvalues (100%) and eigenvector load above |0.32| (10% of the variance)

Variables

Urban infrastructure

Eigenvectors			
Input	*PC1*	*PC2*	*PC3*
LCZ	0.00	-0.02	-0.03
SlumDist	**1.00**	0.01	0.03
DrainDist	-0.01	**0.99**	-0.15
MinWage	0.00	0.00	0.00
HouseDens	-0,01	0.04	0.24
PopDens	-0.03	0.14	**0.96**
GarbCol	0.00	0.01	0.04
WaterNet	0.00	0.01	0.04
SeageNet	0.00	0.01	0.03

PC	*Eigenvalues*	*%*	*Acc*
1	**24373100.0**	**99.2**	**99.2**
2	**108650.3**	**0.4**	**99.6**
3	**86308.0**	**0.4**	**100**

Land Surface Temperature

Eigenvectors			
Input	*PC1*	*PC2*	*PC3*
LST	**0.51**	**0.36**	**-0.64**
SHI	0.25	0.17	**-0.32**
LST-Day	**0.66**	-0.08	**0.48**
LST-Night	0.21	**0.61**	**0.50**
LST-Range	**0.45**	**-0.68**	-0.02

PC	*Eigenvalues*	*%*	*Acc*
1	**7.88**	**98.8**	**98.8**
2	**0.08**	**1.0**	**99.8**
3	**0.02**	**0.2**	**100**

3. Results and Discussion

In general, over the years analyzed, about 55% of dengue cases occurred between 2013 and 2014. That coincided with a prolonged warm and dry period in the RMSP (Ribeiro et al., 2015). In these years, the annual cumulative rainfall was approximate 288 mm minor than the climatological average of the region (Figure 3). In Figure 4 (a), approximately 80% of dengue cases were observed between March (3) and May (5), totalizing 5820 of the 7540 cases occurring between the analyzed period (2012-2015). For those same months, the average precipitation represented about 24% of the entire accumulated annual (Figure 3).

Thus, the highest occurrence of dengue cases occurred in periods of low precipitation. Lorenz et al., (2017) pointed out in their studies about emerging arboviral diseases that the rains do not contribute to the spread of these diseases in Brazil, differently from the seasonality of temperature. On Figure 3 the black line represents the monthly cumulative climatological average of rainfall (mm) between 1931 and 1991 (INMET, 2018). The table shows the annual cumulative (mm). Modeling results showed that the distribution of dengue cases occurs in almost all the urban part of the municipality of Guarulhos. The areas with the highest probability of occurrence (> 0.7) were those marked in orange and red, which represented about 3,308.3 hectares or approximately 10% of the territory of Guarulhos (Figure 4 - a and b). The model's performances were compared using the AUC measurement. In all of them, the performance varied from 0.7 to 0.9, demonstrating that the models are considered useful and have sufficient accuracy and sensitivity to predict the sites most likely to present the dengue cases.

Different environmental variables that affected the distribution of dengue cases were compared statistically by the importance of contributors (Figure 4**c**). The highest annual contributions were observed for the variables in the following sequence: 1) population density (popdens); 2) mean Land Surface Temperature (LST-mean); 3) slum distance (slumdist); 4) mean Land Surface Temperature - night (LST-night); 5) Land Surface Temperature range (LST-range); 6) mean Land Surface Temperature - day (LST-day). In contrast, the contribution from Surface Heat Island (SHI) and drainage distance (draindist) did not high influence the model.

For the months with the highest occurrence of cases, March to May on Figure 4c's histogram, the population densities, slum distance, as well as the mean Land Surface Temperature were the variables that presented the highest contributions (Figure 4c). These variables perform an important role in the dynamics of the distribution of dengue cases in Guarulhos and the performance of the models. In the other months (from June on), climate and urban variables such as Surface Heat Island (SHI), drainage distance (draindist), slum distance (slumdist) and Land Surface Temperature range (LST-range) gain influence in detriment of others variables (Figure 4 - c). The response curves for the most significant environmental variables are shown in Figure 4d. Among the variables, the probability of occurrence of dengue cases is strongly associated with areas with a population density of ~900 inhabitants/ha. In these regions of the city, most of the population resides mainly in low and compact houses with up to three floors that are sometimes associated with slums near creek and rivers (Figure 5 - a and b). These same areas (Figure 5 - c and d), in general, are arranged in a disorderly and dense way, lacking infrastructure and urban public services essential as regular garbage collection, connection to the sewage system, water, and energy (Reiter, 2001 and Schmidt et al., 2011). Areas with higher population density (> 1000 people/ha), presented lower probabilities to occur dengue cases because they were composed of high (> 25 meters) and compact buildings, served by good urban infrastructure (Araújo et al., 2015).

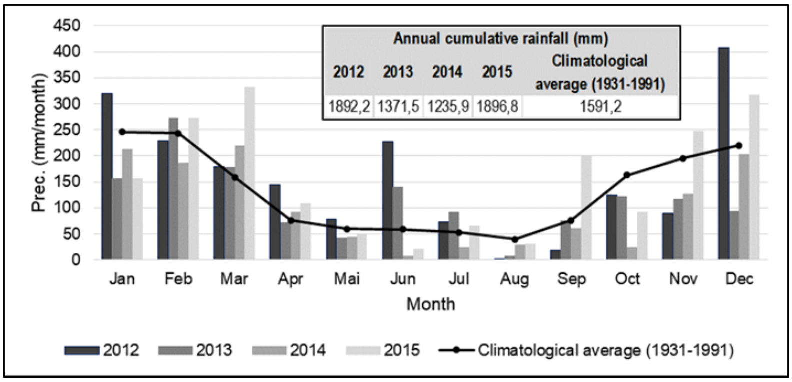

Figure 3: Vertical bars represent cumulative monthly precipitation (mm) for the years 2012 to 2015 (TRMM, 2011)

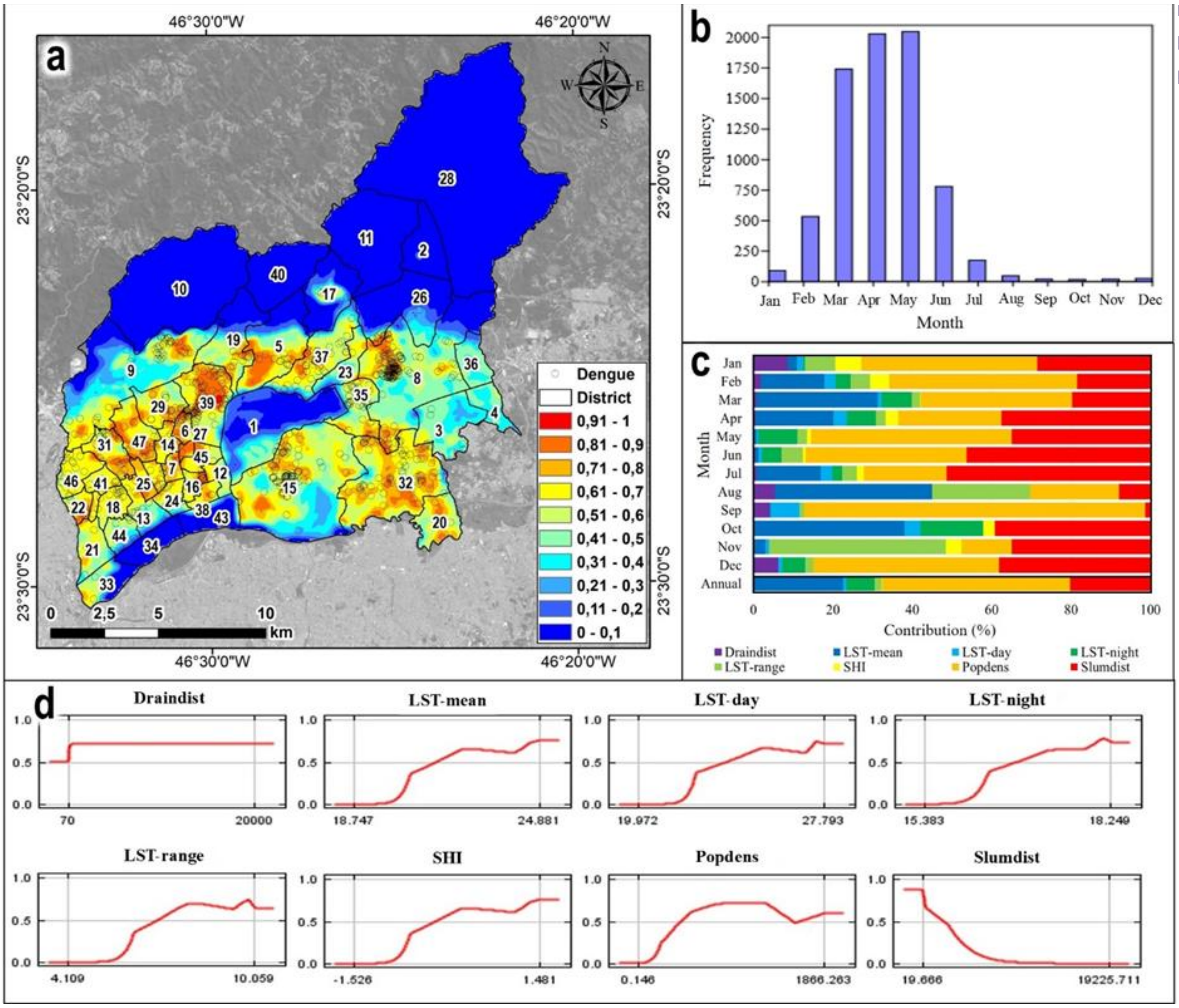

Figure 4(a): Habitat adequacy map of dengue cases in Guarulhos. (b) Number of dengue cases occurrences per month between years 2012-2015. (c) Relative variable contributions to the respective MaxEnt models (monthly and annual) between years 2012-2015, is given as a percentage. (d) Response curves of the most relevant environmental variables in predicting the distribution of the probability of occurrence of dengue

In this context, the response probability curves to the disease appeared throughout the year in a mean temperature range from 18 ºC to 27 ºC, in regions whose mean SHI anomaly was +1.5 ºC. Peaks of maximum and minimum LST were recorded respectively during the days of December (~36 ºC) and the nights of July (13 ºC). These temperatures are considered critical, because they decrease the longevity and fecundity of the mosquito *Aedes aegypti*, restricting the propagation of the disease (Costa et al., 2010 and Tsai et al., 2018). On Figure 4 each curve is a unique model created using only the corresponding variable and represented the mean response. The values of LST and SHI variables are given in °C, and the distances of the drainages (Draindist) and the distances of the slums (Slumdist) are in meters (m). The circles indicate the occurrence records of the disease. The numbers from 1 to 47 represent the districts of Guarulhos.

For the months with the highest occurrence of dengue cases (March to May), the ideal LST for the onset of the disease was on average between 18º C and 25 ºC, with diurnal variations from 19 ºC to 27 ºC and nocturnal temperatures of 15 ºC to 19 ºC. Thermal amplitudes of 4 °C to 8 °C, as well as positive anomalies of SHI (2.5 °C), were also observed as predictive for dengue fever between March and May. LST patterns analogous to those in this work were also observed by Araújo et al., (2015) and Azevedo et al., (2018) respectively in the city of São Paulo and St. Bárbara d'Oeste, São Paulo State/Brazil.

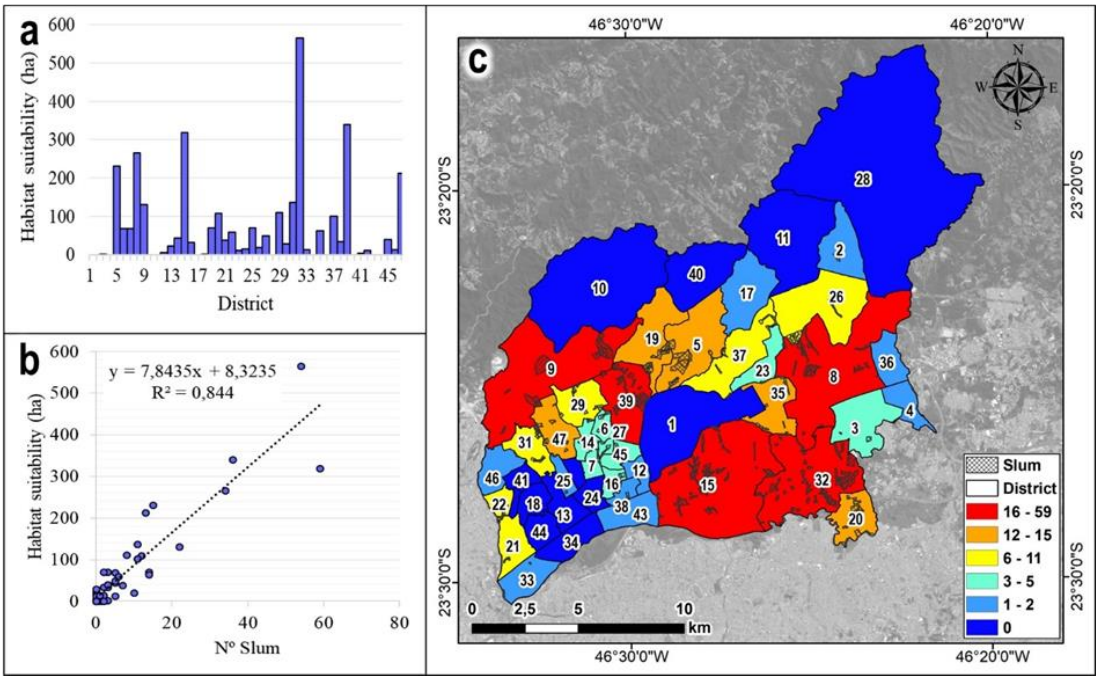

Figure 5(a): Area of habitat suitability for dengue cases occurrence for Guarulhos per hectare (ha). The numbers 1 to 47 represent the districts of Guarulhos. Habitat adequacy map of dengue cases in Guarulhos. (b) Number of occurrences of dengue cases per month between years 2012-2015. (c) Numbers of slums per district

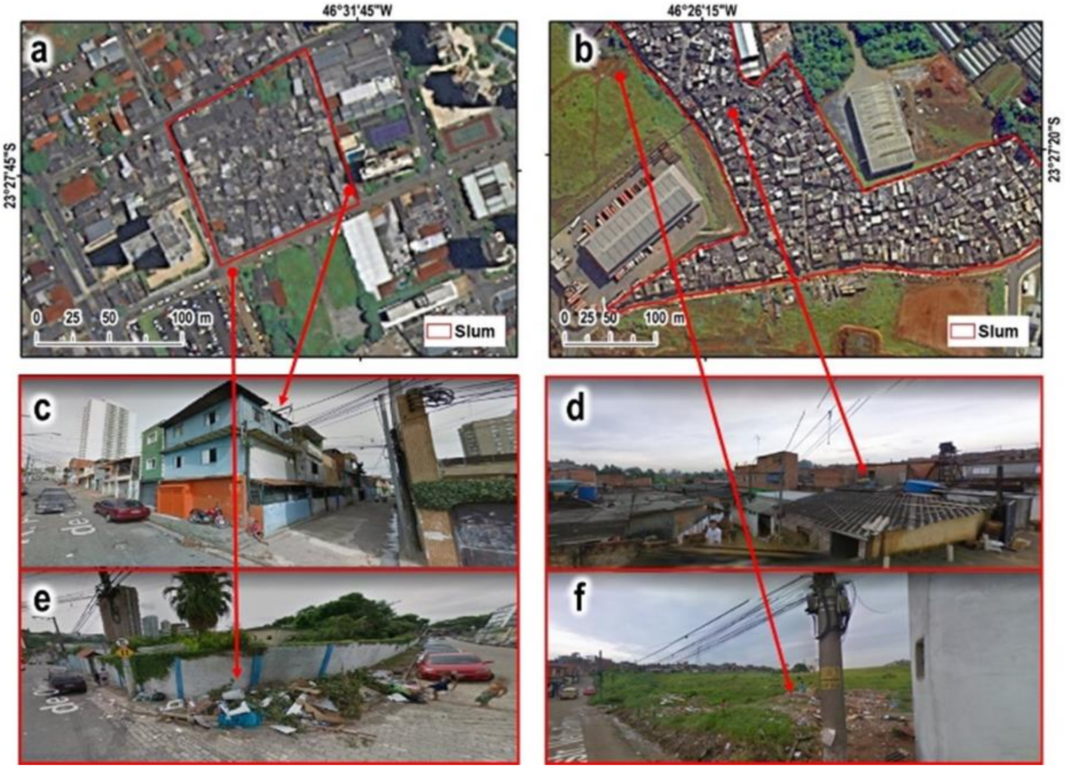

Figure 6 (a) and (b): WordView-3 satellite orbital images, respectively from November 27, 2015, and May 29, 2016, respectively, highlighting examples of slums (red-marked areas) and their chaotic occupancy patterns (DGF, 2017). (c, d, e, and f). Examples of the type of constructions and illegal waste disposal sites commonly found close to slums (Google Maps, 2018)

The author's *op. cit.* related the incidence of dengue cases with diurnal surface temperatures of approximately 26 ºC and urban surface heat islands. Moreover, temperature fluctuations up to 7.6 °C around the diurnal mean temperature of 26°C are considered most favorable for the proliferation of *Aedes aegypti* and consequently for the dengue disease. However, fluctuations above this value (> 7.6 ºC) become unfavorable to the disease transmission (Lambrechts et al., 2011 and Carrington et al., 2013a, 2013b).

Figure 5 (a) indicates the districts with the highest habitat suitability area for dengue cases occurrence for Guarulhos per hectare. In these districts, it was found that the higher the number of slums, the greater the suitability of occurrence of dengue cases (Figure 5(b)). Thus, actions to prevent the disease require the immediate attention of the government and should be primarily targeted for those districts with higher dengue habitat suitability (Figure 5 (c)). A similar situation was found in Barbados by Lowe et al., (2018), where drought conditions were associated with extended dengue outbreaks periods. This situation increased potentially larval habitat due to increasing the number of water storage containers around the houses (Pontes et al., 2000).

The high-resolution multispectral images (up to 30 cm) from the WordView-3 satellite for November 2015 and May 2016 (Figure 6 (a) and (b)) show examples of slums, usually inserted in areas favoring the occurrence of dengue (> 0.7, in the map of Figure 6 (a)). In these areas, the chaotic occupation pattern (Figure 6 - c and d) and high social vulnerability represent ideal environments for the development of the *Aedes aegypti* mosquito. Due to the lack of adequate infrastructure with open sewage, inadequate storage of water for supply (rustic water tanks and badly closed), absent waste recycling services, among other traps that favor the mosquito breeding (Figure 6 (e) and (f)) (Misslin et al., 2016 and Azevedo et al., 2018). These features added to prolonged drought periods with reduced water supply suggest a possible connection between drought and high dengue fever occurrence in metropolitan regions such as São Paulo (Du et al., 2013 and Lee and Yu, 2015).

4. Conclusions and Suggestions

The results indicate that for the analyzed period (2012-2015), the months with the highest incidence of dengue cases were from March to May. Variables such as population density (around ~900 inhabitants/ha), slum distance, and mean Land Surface Temperature obtained more contribution and consequently more significant influence on the incidence of dengue in Guarulhos. Districts of the city with high numbers of slums, were highly favorable to the emergence of dengue, mainly due to the disordered occupation and as well as lack of infrastructure and essential urban public services. Likewise, inadequate household water storage, irregular disposal, and absence of waste recycling services may increase the risk of dengue transmission in prolonged drought periods.

Finally, the work can contribute to the development of public health strategies for the surveillance and prevention of dengue, indicating areas for mitigation and environmental education actions, mainly those districts with many houses with inadequate water storage in periods of drought, such as slums. It can also contribute to driving more advanced research on the relationship between arboviruses like dengue, environmental variables, extreme weather events, and global environmental changes.

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