Short Communication

The Dynamics of Temperature-And Rainfall-Dependent Dengue Transmission in Tropical Regions

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Abstract

Dengue represents a serious public health problem in the world, and human global travel has contributed to new outbreaks or epidemics in propitious places around the world. Mathematical models that employ climatic information and associated social variables are crucial for predicting epidemics in cities at risk of dengue outbreak. In this work, we described a time-dependent model of dengue virus transmission in which we consider human and vector (mosquito) populations. Additionally, we incorporate climatic variables as explicit functions of entomological parameters of Aedes aegypti mosquitoes to demonstrate the climatic aspects of disease outbreak in a particular location. The model was applied to two Brazilian cities with a very high contamination risk index, which indicates elevated transmission of dengue virus in the population. Additionally, it is possible to verify the rainfall effect on summer and autumn seasons. In conclusion, our model can be directly applied to rainfall or temperature variations in various geographical locations so as to avoid “uncomfortable” atypical climatic events.

ABBREVIATIONS

NCEP: Tropical Rainfall Measuring Mission; TRMM: National Center of Environment Predictions

INTRODUCTION

Dengue is an acute infectious disease whose onset occurs within a short period of time, has variable severity and is caused by arboviruses of the genus Flavivirus. The major vector of the dengue virus is the Aedes aegypti mosquito [1-3]. Some mathematical models have been expanded upon to predict the dynamics of possible new dengue cases in a susceptible population by considering air temperature [4,5] or flooding [6-8] but not directly considering seasonal aspects simultaneously embedded in entomological parameters of vectors such as A. aegypti.

Some of mathematical models demonstrated a positive effect of rainfall on female mosquito egg-laying conditions [9-11] near water household reservoirs or flood areas. When associated with elevated temperature, rainfall positively affects the abundance of A. aegypti and favors egg hatching and its spreading through a particular area [12-18]. These dynamics increase human-mosquito contact and increase the risk of dengue infection.

It is known that the extrinsic incubation of the virus is directly affected by temperature changes and is related to the transmission ability of A. aegypti. Incorporating the climatic data and mosquito and human dynamics into a model may have a direct application for the estimation of mosquito infestation [19-23].

The aim of this study is to provide a tool to help the Public Health field devise plans of action in locations with a high incidence of A. aegypti and dengue virus infection, in order to prevent new epidemic outbreaks.

MATERIALS AND METHODS

Modeling temperature and daily rainfall variation

To incorporate weather-dependent factors into entomological parameters, the temperature and rainfall data from the cities of Salvador and Corumbá were collected between 1999 and 2009. The climatic conditions are represented by the daily average temperature and monthly mean rainfall, and mathematical expressions of these variations are expressed by Eqs (1) and (2). These cities were selected because they reported dengue cases.

The mathematical expression $T_{air}$ is the following:

\[ T_{w}(t) = \beta_0 + \beta_1 \text{Longitude} + \beta_2 \text{Latitude} + \beta_3 \text{Altitude} + \sum_{n=1}^{\infty} \left( a_n \sin(n wt) + b_n \cos(n wt) \right) \tag{1} \]

Equation (1) considers geographical features agglutinated under the \( \beta_i \) parameter set, and seasonal variations are represented by a Fourier series [24,25]; their respective definitions and values are shown in (Table 1).

Equation (2) represents the monthly mean rainfall recorded from the same region as the temperature data. This mathematical relationship was chosen to adequately represent seasonal precipitation.

Thus, the rainfall \( \text{Rain} \) expression is,
\[
\text{Rain}(t) = \beta_1 \sin(\beta_2 + \beta_3 t) \cos(-\beta_4 + \beta_5 t) + \beta_6;
\tag{2}
\]
the parameter values and definitions are summarized in (Table 1). The precipitation data were downloaded from the NCEP website [1], and rainfall data were obtained from Temporal Resolution Monthly (TRMM) with 0.25\(^\circ\) x 0.25\(^\circ\) grid resolution and average area time series.

All of the meteorological data were fitted using R software 2.11.0 and evaluated by (Table 1) Curve 2d software (Sigma Plot Inc.). The “goodness of fit” was estimated by the coefficient of determination \( r^2 \) and the Willmott’s index of agreement \( d \), shown in (Table 1).

After obtaining the temperature and rainfall profiles, the values were incorporated with the biological parameters of the mosquito, and we simulated the number of individuals infected with dengue virus.

**Entomological climatic-dependent parameters**

Five entomological parameters (including extrinsic incubation time, adult mosquitoes and eggs death rates) and those engaged in egg population balance, such as oviposition and hatching rates, were treated as temperature-dependent, and the latter two were treated as rainfall-dependent in the modeling process. All of these parameters were chosen due to the observed or experimental values available from the literature or relevance to the dynamics of vector-host relationships. Table 2 reports the means and values of these parameters found.

**Oviposition rate**

Oviposition rate can be affected by factors such as female mosquito metabolism, adult body size, and breeding sites chosen by female mosquitoes to lay eggs [26]. If conditions become favorable, as when temperature begins to rise and there is sufficient rainfall, the ovipositing period is reduced and the final rate is perturbed.

The oviposition rate \( b \) was modeled as a function of average daily temperature (Eq. (3)) and of rainfall (Eq. (4)) [25]; it is expressed as
\[
b(T_{ir},\text{Rain}) = p_1[1 - \exp(p_2(T_{ir} - 40)](T_{ir} - 9)^{p_3},
\tag{3}
\]
and
\[
b(\text{Rain}) = \left( \frac{p_4}{1 + p_5(\text{Rain} - p_6)^{p_7}} \right)^{p_8} + p_9
\tag{4}
\]
Equation (4) shows that the effect of varied rainfall on oviposition rate may be a “Student-t”-like mathematical expression, according to Stein and Zeidler [10,11]. The \( p_i \) and \( p_j \) parameters, which represent “location parameter” and “scale parameter”, respectively, describe the relationship between the denominator and the rainfall amount, and the \( p_k \) parameter describes the power-law influence of rainfall on the oviposition rate. The \( p_l \) parameter is associated with other factors that cause fluctuations in hatch rate.

The combined impact of ambient temperature and rainfall affect the oviposition of the egg at egg-laying sites and hatch levels. Even if temperature is high enough to obtain the maximum rate, but the humidity is low, the resulting oviposition rate is significantly reduced. However, if the temperature is close to 30\(^\circ\)C and there is sufficient rainwater, the oviposition rate is estimated to be at its highest.

Under the weather conditions sufficient to maintain *Aedes aegypti* female adult reproduction, the climatic-dependent effects combining the average air temperature (Eq. (3)) and rainwater (Eq. (4)) on oviposition rate are calculated by Eq. (5),
\[
b(T_{w},\text{Rain}) = p_1[1 - \exp(p_2(T_{w} - 40)]
\left( \frac{p_4}{1 + p_5(\text{Rain} - p_6)^{p_7}} \right)^{p_8} + p_9
\tag{5}
\]
Egg "death rate"

The thermal sensitivity of eggs to daily environmental temperature is represented by Eq. 6,

$$\mu_e = p_{1e} \exp^{(\frac{T_{\text{air}}}{p_{10}})},$$  \hspace{1cm} \text{(6)}$$

suggesting that eggs may survive in an arrested development or "dormancy" (egg diapause) if temperature drops, and that the sensitivity of this immature stage increases as temperature rises. $p_{10}$ is the $\mu_e$ at low temperatures, and $p_{11}$ determines the stress of the warm season on egg sensitivity and desiccation [14,25,27].

**Hatch rate**

The temperature-dependent hatch rate, $h(T_{\text{air}})$, expression according to Margon Rossi and colleagues was adopted [25]. Using egg eclosion per precipitation data [10,11], a mathematical expression was formulated to connect the hatch rate to a rainfall profile, $h(Rain)$, resulting in Eq. (7),

$$h(Rain) = p_{17} \exp^{(\ln (Rain) + 1)^{p_{2,7}}}.$$

High tides re-flood drought surfaces and stimulate eggs to hatch into larvae, and they are influenced by environmental and physical factors. The influences of temperature and rainfall are combined in Eq. (8) and represented as $h_e = h(T_{\text{air}}).h(Rain)$,

$$h_e(T_{\text{air}},Rain) = p_{21}T_{\text{air}}^{-1}\frac{\exp^{(p_{17} - p_{21}T_{\text{air}}^{-1})}}{1 + \exp^{(p_{17} - p_{21}T_{\text{air}}^{-1})}} \ln (Rain) + 1)^{p_{21}}.$$

**Adult female mosquito death rate**

Mosquitoes tend to survive well in temperate zones or in warm, wet places, such as tropical zones. The intensity and duration of warm or cold seasons, as well as exposure time under these climactic circumstances, are critical to insect survival. The temperature-dependent adult mosquito death rate is defined by Eq.(9) [25],

$$\mu_a(T_{\text{air}}) = p_{14} \exp(-p_{16}(T_{\text{air}} - p_{21})^1) + p_{22}(T_{\text{air}} - p_{21})^1.$$

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**Table 2: List of values and biological definitions from entomological equations.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_1$</td>
<td>Oviposition constant rate based on temperature</td>
<td>0.0011</td>
</tr>
<tr>
<td>$p_2$</td>
<td>Temperature influence factor</td>
<td>0.0101</td>
</tr>
<tr>
<td>$p_3$</td>
<td>Exponent of low temperature influence</td>
<td>3.445</td>
</tr>
<tr>
<td>$p_4$</td>
<td>Oviposition constant rate based on rainfall</td>
<td>0.0392</td>
</tr>
<tr>
<td>$p_5$</td>
<td>Inverse of &quot;shape&quot; parameter</td>
<td>2.11</td>
</tr>
<tr>
<td>$p_6$</td>
<td>&quot;Location&quot; parameter</td>
<td>3.099</td>
</tr>
<tr>
<td>$p_7$</td>
<td>&quot;Scale&quot; parameter</td>
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</tr>
<tr>
<td>$p_8$</td>
<td>Exponent of rainfall influence</td>
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</tr>
<tr>
<td>$p_9$</td>
<td>Rate rainfall-independent</td>
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</tr>
<tr>
<td>$p_{10}$</td>
<td>Mixed-effect rate</td>
<td>$4.3 \times 10^4$</td>
</tr>
<tr>
<td>$p_{11}$</td>
<td>Initial egg death rate</td>
<td>0.0731</td>
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<tr>
<td>$p_{12}$</td>
<td>Influence of temperature elevation</td>
<td>0.0595</td>
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<tr>
<td>$p_{13}$</td>
<td>Oviposition constant rate</td>
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<td>$p_{14}$</td>
<td>First entropy contribution to hatch</td>
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<tr>
<td>$p_{15}$</td>
<td>Enthalpy contribution to hatch</td>
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<td>$p_{16}$</td>
<td>Second entropy contribution to hatch</td>
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<td>$p_{17}$</td>
<td>Enthalpy contribution to hatch</td>
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<td>$p_{18}$</td>
<td>Hatch constant rate</td>
<td>$f_{\text{hatch}}$</td>
</tr>
<tr>
<td>$p_{19}$</td>
<td>Entropy contribution to hatch</td>
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<tr>
<td>$p_{20}$</td>
<td>Mixed-effect rate</td>
<td>$0.00764/f_{\text{hatch}}$</td>
</tr>
<tr>
<td>$p_{21}$</td>
<td>Eclosion constant rate</td>
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<tr>
<td>$p_{22}$</td>
<td>Exponential constant</td>
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<td>$p_{23}$</td>
<td>Temperature of maximum survival</td>
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<tr>
<td>$p_{24}$</td>
<td>Polynomial correction term constant</td>
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<td>$p_{25}$</td>
<td>Linear temperature-independent term</td>
<td>54.2</td>
</tr>
<tr>
<td>$p_{26}$</td>
<td>Rate of change of incubation temperature-dependent period</td>
<td>23</td>
</tr>
</tbody>
</table>

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\[ \mu_n(T_{wv}) = p_{23} \exp(-p_{23}(T_{wv} - p_0)^2) + p_{23}(T_{wv} - p_0)^2, \]  

where \( p_{23} \) to \( p_0 \) is the parameter set associated with mosquitoes’ metabolism needs for survival in a specific environment, in regard to heat and dryness.

Temperature-dependent extrinsic incubation period

Temperature is a very important factor in the vector capacity or vectorial competence of Aedes mosquitoes [19]. The Dengue viruses replicate very frequently at heightened temperatures, thereby increasing the vector capacity of the mosquito for human infection. The extrinsic incubation period is gradually decreased with the increase of incubation temperature, thereby enhancing a vector’s ability to transmit a viral agent to other susceptible vertebrate hosts (Eq. (10)) [21-23]. This correlation between temperature and the vector-pathogen relationship can be approximated by the following equation,

\[ r(T_{wv}) = p_{23} - p_{23} \ln(T_{wv})^2. \]  

Similar to other entomological mathematical expressions, temperature \( T_{wv} \) values come from the Eq. (1) representation of the seasonal variation. The value of parameter \( p_{23} \) is the maximum rate of the extrinsic incubation process, and \( p_{23} \) is the rate at which temperature fluctuations correlate to this period.

Mathematical model of Vector-Host dynamics

The following model is based on work by Burattini and colleagues [27], and the model of the life-cycle of A. aegypti was developed by Margon Rossi and colleagues [25]. The model is composed of ordinary differential equations that represent the human and mosquitoes populations, climatic-dependent entomological parameters and another parameter set representing the host-vector infectious contact. The goal is to simulate dengue outbreaks based on data and seasonal variations. Seasonal variations are represented by the daily mean air temperature and monthly rainfall (Eqs. (1) and (2), respectively) in a time-continuous form; however, the mathematical expressions allow for a single specific value input for both climatic parameters. We were able to model the infection level in an endemic city. Thus, the model is,

\[ \frac{dH_i}{dt} = R_{nh} \left( 1 - \frac{nh}{K_a} \right) - b \cdot \text{pic} \cdot \frac{H_i}{nh} \cdot \mu H_i \]  

\[ \frac{dH_f}{dt} = b \cdot \text{pic} \cdot \frac{H_i}{nh} \cdot (\mu + \gamma + \alpha) H_i \]  

\[ \frac{dH_z}{dt} = \gamma H_i - \mu H_i \]  

\[ \frac{do}{dt} = b \cdot m_i \left( 1 - \frac{o_i + o_i}{K_o} \right) + (1 - g) b \cdot m_i \left( 1 - \frac{o_i + o_i}{K_o} \right) - \left( \mu_i + h_i \right) o_i \]  

\[ \frac{do}{dt} = g b \cdot m_i \left( 1 - \frac{o_i + o_i}{K_o} \right) - \left( \mu_i + h_i \right) o_i \]  

The stated variables \( H_f, H_i, H_z, H_j \) (Eqs. (11)-(13)) refer to fractions of a human population that are susceptible, infectious (or infected) and recovered, respectively. \( nh \) is the total human population and \( nh = H_f + H_i + H_z \). In the Aedes aegypti mosquito population, the stated variables \( a_i \) and \( o_i \) (Eqs. 14–15) refer to fractions of uninfected and infected eggs, respectively, and the adult mosquito populations \( m_j, m_i \) and \( m_i \) (Eqs. 16-18) refer to the susceptible, latently (or chronically) infected and infectious subpopulations. Here, \( m_j = m_i + m_i + m_i \) The other parameters are \( R \), the human growth rate constant (\( R = 1.10 \)), \( K_h \), the carrying capacity of human population growth per location (\( K_h = 50000 \)), \( \mu \), the death rate (\( \mu = 0.00264 \)), \( \gamma \), the rate infected humans becoming ill (\( \gamma = 0.875 \)), and \( \alpha \), the rate of humans infected with dengue virus (\( \alpha = 0 \)). \( g \) is the estimated proportion of eggs infected via the transovarian infection mechanism. \( c_i \) is the estimated susceptibility to mosquito biting rate of infected humans, \( \tau \) is the temperature-dependent extrinsic rate, \( \mu_{inc} \) are the climate-dependent susceptibility and infective egg death rates, respectively, and \( \mu_{inc} \) refers to the adult death rate. The birth strategies of female adult mosquitoes are shown by the climate-dependent rate of \( b_{ov} \), oviposition, and \( h_j \) which represents the hatching rate.

RESULTS AND DISCUSSION

This work demonstrates a mathematical model to study the transmission dynamics of the dengue virus. It incorporates five temperature-dependent entomological parameters (two of them rainfall-dependent) of the mosquito Aedes aegypti life cycle in a transmission model, and we calculated the reproducibility number, \( R \) of the natural history in the process of dengue transmission. In particular, this model considered only one dengue serotype and one type of mosquito to simplify the equation set.

Corumbá city has an estimated maximum dengue occurrence rate of approximately 0.45% (mean of 0.16%), which is higher than the Brazil Health Ministry's set value (0.3%). It indicates a high level of infected A. aegypti in circulation and a high probability of dengue case progression, which occurred in 2010. The estimated infestation rate was 2.0%, which is below the value of 1.5% in Salvador city. The mean number of recovered humans was 65.7% (maximum 91.1%) of total human individuals. [Figure 1] shows the number of dengue cases and the respective model simulation.

In Salvador city, the infestation rate estimated by our model was 1.5%, which is below the mean value of 3.9% given by the House Infestation Index (an index used by Brazil Health Ministry), and if only considering susceptible individuals, this rate increases to 4.2% of adults susceptible to mosquitoes. The estimated maximum dengue occurrence rate was 1.50% (mean of 0.07%), which is a high value compared to the cut-off value of 0.3%, which probably indicates a high circulation of dengue virus in the human and mosquito populations. Salvador’s estimated...
maximum recovery rate of habitants from dengue infection ($H$) is 78.5% of the total population (mean 5.13%). (Figure 2) shows the number of infected people and the outcomes of the model simulation, showing the agreement between them.

The rate of disease transmission from human to mosquito has been estimated as 300 mosquitoes per infected human (maximum 3000-3400 mosquitoes) in Corumbá city and 30 mosquitoes per infected human in Salvador city (maximum 600-700). The spread of infectious A. aegypti depends on housing density and unoccupied locations with high mosquito density, as well as the climatic conditions existing in these locations.

Transovarian transmission plays an important role in disease progression, and according to simulation runs, the contaminated egg level is more pronounced in Corumbá city than in Salvador, with values ranging from 5% to 14%, respectively. There is a clear relationship between the high proportions of infected A. aegypti eggs (corresponding with the spread of dengue proliferation) and the risk of another outbreak under favorable climatic conditions.

Based on infected mosquito populations, the number of susceptible people in the human population and the parameters $b$ and $pic$, the maximum "force of infection" observed was 54.0 in Salvador city and 82.5 in Corumbá city.

Therefore, the $R$ sensitivity to climatic parameters, according to the relationship $Z_{R = t - t_{0}} + Z_{R = R_{0}} + Z_{R = Rain} + Z_{R = RainZ}$ in our model, considering neither the city location nor a specific location, is -0.1735 + 5.4248 + 0 + 5.3072 = 10.5585, i.e., for each elevation of 1°C and 1 mm of rainfall outcome, the final $R$ value is elevated on of 10.6% on final $R$ value.]

**CONCLUSION**

Dengue disease is a severe Public Health problem, and detailed information on infected people, reports of the environment and meteorological conditions, and temperature variation and humidity, mainly in breeding sites, is needed. The search to understand the dengue dynamics and prediction and control of new outbreaks has guided model development. Using the climatic change predictors of the A. aegypti population, these models have enhanced the knowledge on the impact of this disease on a susceptible human population. This model has shown how the proliferation of this vector expands to new (or different) geographical locations, under favorable climatic changes and elevated population density, which would result in a substantial mosquito infestation and probably new autochthonous cases in susceptible human populations.

Additionally, this model could outline possible outcomes to the Department of Health and provide early warnings of dengue epidemics in micro-regions. These warnings could help reduce or limit the mosquito population and the frequency of human-vector contact in a limited environment.

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