

# Change Allocation in Spatially-Explicit Models for *Aedes aegypti* Population Dynamics

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**Abstract.** This work proposes a new approach to couple *Aedes aegypti* population dynamic models with local scale spatially-explicit computational models for the Geographical Space. A geographic database was developed for a neighborhood in Rio de Janeiro, RJ, and used to estimate the spatial pattern of mosquito infestation in order to estimate areas of epidemic risk.

Categories and Subject Descriptors: H. Information Systems [H.m. Miscellaneous]: Databases

## 1. INTRODUCTION

*Aedes aegypti* population dynamic models have been proposed systematically in different approaches according to the focus of the study. Some models consider the temporal dynamic [Focks et al. 1993], [Ferreira and Yang 2003] and [Otero et al. 2006] and others, the spatial-temporal dynamic [Otero et al. 2008], [Magori et al. 2009] and [de Almeida et al. 2010]. For models that evaluate temporal dynamic, data and model structure are simpler than spatial-temporal models. To study *aedes aegypti* population dynamic with a spatial-temporal model is necessary to have informations about the space and an environmental modeling platform that can support this model. To understand the spatial-temporal dynamics of this mosquito population, this work proposes a new approach to couple *aedes aegypti* population dynamic models with local scale spatially-explicit models, which are integrated with geographical databases. The goal is to calculate, at each simulation time step, the variation in population size given by the dynamic models and allocate it in a grid of regular cells that represents the Geographical Space.

## 2. THEORETICAL FOUNDATIONS

Models describing the population dynamics of *aedes aegypti*, classified as deterministic [Ferreira and Yang 2003] or stochastic [Otero et al. 2006], share a common structure based on System Theory [Bertalanffy 1975]. A typical example [Ferreira and Yang 2003] is shown in *Figure 1*. In this model, the dynamics of a mosquito population is modelled as the flow of individuals between stocks, denoted in the diagram by four rectangles:  $E(t)$  - eggs,  $L(t)$  - larvae,  $P(t)$  - pupae, and  $W(t)$  - adults. Stocks are connected by arrows,  $f1$ ,  $f2$  and  $f3$ , representing the flow of individuals between life stages: 1 - egg to larva, 2 - larva to pupa, and 3 - pupa to adult. Flow occurs at rates that are temperature dependent. New individuals enter in the population by birth (at a rate  $ovip$ ) and mortality rates are stage-specific ( $m1$ ,  $m2$ ,  $m3$  and  $m4$ ). This model structure represents the main demographic events in the life cycle of an *aedes aegypti* population and its formulation in the form of dynamic equations allows the simulation of its temporal dynamics. Since space is not explicit, however, the model does not describe the distribution of *aedes aegypti* through space.

Fig. 1. Flow diagram describing *aedes aegypti* life cycle (adapted from [Ferreira and Yang 2003]). Temperature (temp in yellow circle) controls three development rates: 1 - egg to larva, 2 - larva to pupa, and 3 - pupa to adult; ovip is the oviposition rate; m1, m2, m3 and m4 are natural stage-specific death rates, mec1, mec2, mec3 is a death by breeding site removal (mechanical control); Larv1 and larv2 are death rates induced by larvicidal control. The arrow "Adult" indicates the death rate by adulticide. C is the carrying capacity of the area.

In relation to stochastic model to *aedes aegypti* population dynamic [Otero et al. 2006], the difference is on the flow of individuals between stocks mentioned above. [Otero et al. 2006] proposed a hybrid model that considers a Differential Equations such as [Ferreira and Yang 2003], but the developmental rates are stochastic and given by the Poisson Process. In this work, they consider five stages of mosquito life cycle and the space is also not explicit.

According to spatial-explicit mosquito population dynamic models, considering space is a complex variable to incorporate in the model. Few computational models are capable of simulating *aedes aegypti* population spatial-temporal patterns and all spatial models found on the literature are stochastic or hybrid (deterministic + stochastic). [Otero et al. 2008] proposed a stochastic spatially-explicit model, based on the first model in [Otero et al. 2006], in which changes are modelled considering cells as occupied by autonomous mosquito populations interconnected by flows of flying individuals. The demand of dispersion is given by the necessity to find viable breeding sites. A similar approach was used by [Magori et al. 2009]. However, more realistic simulations of *aedes aegypti* life cycle can be achieved when population dynamic models [Focks et al. 1993] considers the spatial distribution of breeding sites in their formulation as well as the dynamics of the aquatic stage of the mosquitoes (larvae and pupae). The breeding site density per house and the house density per area are model parameters. However, in both studies the simulation experiments were conducted in artificial spaces where the breeding site density and local temperature were also synthetic. In other words, the models were not integrated with geographical databases. Remote sensor images and digital maps were used by [Tran and Raffy 2005] to develop a model to assess Dengue transmission processes in the municipality of Iracabouro, French Guiana. [Chang et al. 2009] also used geographical data to help Dengue control specialists to prioritize specific neighborhoods for targeted control interventions.

The individual based approach was used for the development of a spatial-explicit model in [de Almeida et al. 2010]. Agents represent mosquitoes, humans, mammals and objects embedded in a synthetic environment. [Otero et al. 2008] and [Magori et al. 2009] had also proposed models following the bottom-up approach. This way, the population dynamics may be influenced by the spatial heterogeneity. The main problem with this approach is related to the model parameterization. In this case, the data resolution needs to be in the local scale. Therefore, the models are usually fitted in small regions and in controlled situations. Furthermore, model calibration and model validation processes may generate a huge demand for computer resources. In opposite, the main criticism to the top-down approach is the inability of these models in reproduce the emergence of global patterns from the interaction of local rules. Generally, a combination of these approaches results in better models because it enables to simulate interaction between processes operating at different scales [Verburg and Overmars, 2009].

### 3. METHODOLOGY

A deterministic *aedes aegypti* population dynamic model, modified from [Ferreira and Yang 2003] and [Lana 2009] was implemented in the TerraME modeling environment [Carneiro 2006]. The implemented model was calibrated using data from a real urban area, whose socioeconomic and biophysical properties were organized into a geographical database implemented in TerraLib [Câmara et al. 2000]. The allocation procedure for spatialization was also implemented in TerraME. The kernel estimator provided by TerraLib was used to parameterize the allocation procedure.

### 3.1 Data

The data used in this work was collected by [Honório et al. 2009], who weekly monitored the *aedes aegypti* population in Higienópolis district (*Figure 2*), Rio de Janeiro, RJ, Brazil, during 1.5 years, using ovitraps. Ovitrap traps attract mosquito females looking for places to lay eggs. [Fay and Eliason 1966] and [Reiter et al. 1991]. Forty ovitraps were randomly placed in a 0,25 km<sup>2</sup> area. Each week, the ovitrap's contents were taken to the laboratory and the number of *aedes aegypti* eggs were counted. After that, traps were cleaned and returned to the houses. Week mean air temperature during the period was obtained from the nearest meteorological station, located at the Rio de Janeiro's international airport.

Fig. 2. Study area and ovitrap locations - Higienópolis, Rio de Janeiro, RJ.

### 3.2 Population Dynamic Model

Four differential equations describe the rate of change of mosquito abundance, per life stage: eggs, larvae, pupae and adult (*Figure 1*).

$$\delta E / \delta t = ovip(t)W(t)[1 - \frac{L(t)}{C}] - [\sigma_1(t) + m_1(t)]E(t) \quad (1)$$

$$\delta L / \delta t = \sigma_1(t)E(t) - [\sigma_2(t) + m_1(t)]L(t) \quad (2)$$

$$\delta P / \delta t = \sigma_2(t)L(t) - [\sigma_3(t) + m_1(t)]P(t) \quad (3)$$

$$\delta W / \delta t = \sigma_3(t)P(t) - [m_4(t)]W(t) \quad (4)$$

Equation 1 describes the dynamic of the egg stock. Eggs are laid at a temperature and density-dependent rate.  $ovip(t)$  is a quadratic function describing the effect of temperature on oviposition rate (*Figure 3*). Individuals leave the egg stage by either natural death or by eclosing into larvae. Equation 2 describes the dynamic of the larva stock. Larvae eclose at a temperature-dependent rate. Individuals leave the larva stage by either natural death or by evolving into pupae. Equation 3 describes the dynamic of the pupa stock. Pupa emerges at a temperature-dependent rate as well. Individuals leave the pupal stage by either natural death or by emerging into adult. Equation 4 describes the dynamic of the adult female stock that lay eggs. Female adults also emerge at a temperature dependent rate and die by either natural death. In comparison to [Ferreira and Yang 2003], this model has the following modifications:

- (1) It uses the equation proposed by Sharpe and DeMichelle (1977) to describe the temperature-dependent developmental rates. This equation describes the temperature-dependent rate of development of a poikilothermic organism as the temperature dependent rate of activation and deactivation of an enzyme.
- (2) Eggs are laid at a temperature and density-dependent rate. A quadratic relation between oviposition and temperature sampled was found to Higienópolis district.

### 3.3 Calibration and Validation

The model presents only one free parameter, the carrying capacity  $C$ . The other parameters are maintained fixed  $I$ .

To calibrate the carrying capacity  $C$  to the Higienópolis area, the ovitrap data was divided into two subsets. The first subset (green points in *Figure 2*) was used to calibrate the single free parameter using a Monte Carlo method [Rubinstein and Kroese 2007] to minimize the mean quadratic error.

Parameter	Value	Reference
Oviposition rate(ovip(t))	Equacao 7 da minha dissertacao	
Development rates(s):		
1)egg - larva (s1(t))		Sharpe and DeMichelle(1977)
2)larva - pupa (s2(t))	$R_D(T) = R_D(298K)^{\frac{(\frac{T}{298K})exp((\frac{\Delta H_A}{R})(\frac{1}{298K} - \frac{1}{T}))}{1+exp((\frac{\Delta H_H}{R})(\frac{1}{T_{1/2}} - \frac{1}{T}))}}$	Schoofield et al.(1981)
3)pupa - adut (s3(t))		
Death rates (m):		
1)egg (m1(t))	$1/100 \text{ dia}^{-1}$	
2)larva(m2(t))	$1/3 \text{ dia}^{-1}$	Ferreira and Yang(2003)
3)pupa (m3(t))	$0.01428571 \text{ dia}^{-1}$	
Carrying Capacity (C)	Fitted	

Table I. Parameters used in the dynamic model

2000 iterations were performed in 10000 Monte Carlo experiments. Once calibration was achieved, the second subset was used to simulate the model again and another error value was obtained and compared to the error obtained by the calibration process. Since this error was lower than the calibration error, we considered that the model calibration was adequate. The division into subgroups was done to avoid clusters and guarantee a similar temporal distribution of the two sets of sample points.

### 3.4 Geographical Database

Several layers of information for the study area were integrated into a geographical database developed in the TerraView geographic information system (GIS), version 3.2.0. Informations included point maps with ovitrap locations, number of eggs collected per ovitrap per week, census tracts in the area, census data, and spatial location of schools, houses, water reservoirs, etc (Pereira Passos Institute - Rio de Janeiro Prefecture, 2000). For simulation purpose, a grid of regular cells (10 x 10 meters) was created and its cells were used to store model's inputs and outputs.

### 3.5 Scale Issues and Estimation of the Infestation Spatial Pattern

To generate maps of the spatial distribution of the *aedes aegypti* population in Higienópolis, we used two approaches:

**3.5.1 Census tract scale.** In the first approach, the ovitrap data was aggregated by census tract. Higienópolis is divided in 22 census tracts and the study area has 10 census tracts (*Figure 5a*). A census tract with only one trap was excluded from the analysis (marked with a white X in *Figure 5a*). The carrying capacity of the dynamic population model was calibrated separately for each census tract. *Figure 5b* shows that estimated carrying capacity and the mean number of eggs collected per census tract. We observed that, discounting a scale factor (5.387), the carrying capacity captures the spatial variation in egg density.

Fig. 3. (a) The Higienópolis district divided in census tracts (a). The census tracts within the study area are colored and enumerated. The 10th census tract was excluded from the analysis. (b) Comparison between the estimated carrying capacity per census tract and the mean number of eggs. The red line was increased five times to facilitate comparison with the blue line. Applying a linear regression we obtain the equation  $C = 37.48 + 5.387 * mean(Eggs)$ , with  $r^2 = 96.5\%$ .

**3.5.2 Kernel Estimator.** Our second approach aimed at producing a spatially continuous estimate of mosquito abundance (defined by our grid). To achieve this goal, we used a variation of the Kernel estimator for point events with an associated real value [Bailey and Gatrell 1995]. The method smooths

the surface interpolating the density of eggs in each location, without modifying the data statistical characteristics and variability. In this work, the Kernel estimator with adaptive radius provided by TerraView software was used to generate 78 weekly maps of egg density from the observed data. These maps could be used to parameterize the allocation model proposed below. Since models with many parameters are difficult to calibrate, as a first approximation, the 78 maps were summarized into a unique average map of egg density. Therefore, the final kernel map is an aggregation of all 78 weeks into a single map (*Figure 6*). This map was used as input to the spatially-explicit allocation model described below.

Fig. 4. Average kernel map of egg density.

Some assumptions were considered in order to develop an *aedes aegypti* population allocation procedure. a) Cells of 10 by 10 meters were generated and adopted as the spatial scale for this approach. b) The estimated egg population is distributed through space according to the kernel map of egg density (*Figure 6*). It is important to note that we found the carrying capacity to be proportional to the mean egg density, so the underlying assumption is that eggs are distributed according to the carrying capacity. For example, if the calculated average egg population is 400 eggs, some cells will have a null quantity of eggs, others can have 100, 200, 400 eggs, or even a higher concentration of eggs. The resulting algorithm used to allocate egg populations is shown in *Figure 7*. It traverses the cellular space allocating the *aedes aegypti* population. The cells are visited in a decreasing order of egg density estimated by the average kernel map of egg density. At each cell, the algorithm deposits a quantity of eggs that is proportional to the average capacity of an adult female to lay eggs [Otero et al. 2006] and proportional to the local egg density estimated in the average kernel map.

Fig. 5. *Aedes aegypti* population dynamic allocation algorithm.

#### 4. RESULTS AND FUTURE WORKS

This work presents an approach to allocate the *aedes aegypti* population on the real space. The allocation algorithm uses a Kernel estimator based map and a ranking mechanism to traverse the space allocating the mosquito population in a 10x10m cell grid (change). In this study, the model was parameterized and integrated to a geographical database for the Higienópolis district from Rio de Janeiro city, RJ, Brazil. The population dynamic model, parameterized for the study site in Rio de Janeiro, presented some problems to fit to the data (*Figure 8*). Contrary to our expectations, the observed time series appears to be less responsive to temperature than expected by the model. This result suggests that other variables may have a bigger effect on the control of the week oviposition rates, for example, the rain regime or air relative humidity. In the winter, we observed the largest discrepancy between simulated and observed oviposition. Most of the time, the model underestimates the quantity of weekly deposited eggs. Several factors can be contributed for this imperfection. The oviposition statistic is just based on 1.5 years of sampling. Besides, the Higienópolis district is not an isolated place as the model assumes, thus the mosquito population can receive and lose individual for neighborhoods. Despite the simplifications introduced in the spatialization of the model, the model was capable of capturing the spatial pattern of mosquito abundance, with four hotspots that vary in intensity through time. Despite this spatial similarity, though, simulated and observed maps differ in the intensity of the mosquito abundance (*Figure 9*). During the warm seasons, mosquito abundance is less intense in simulated maps (black background) than in the observed maps (white background). The opposite occurs during the cold seasons. These discrepancies occur due to the errors in the estimation of population size by dynamic model discussed above.

Fig. 6. Graph of comparing between Data and Simulation.

The allocation top-down procedure introduced here is a simplification. The method neglects the interactions between spatial heterogeneity and the growth of the mosquito population. It considers the whole district as a homogeneous area during computation of the population size and, then, it distributes the individuals over the space. It does not consider the spread of mosquito by flight. Other simplification is the use of an egg density average map to base the allocation. The average map fixes the spatial structure while the intensity of eggs changes during the time. Hence, we consider that the average map is only an indicator of average risk. However, in the case of mosquito infestation and Dengue transmission, it is a common sense that processes taking place at local scale and that spatial heterogeneity may play a strong effect on the *aedes aegypti* population dynamics. Therefore, in order to improve the applicability of this work to the assessment of alternatives public policies for the control of *aedes aegypti* populations, a bottom-up approach should be combined with the top-down approach we have presented. In future works, we will investigate integrated methods to develop spatial dynamic models for the *aedes aegypti* life cycle. The spatial structure will be considered dynamic and population dynamics will be governed by autonomous populations located in each space cell, as in *Figure 9*. Dispersion of mosquitoes by flight will be also considered such as found on the literature [Otero et al. 2008], [Magori et al. 2009] and [de Almeida et al. 2010]. These improvements will allow for the simulation of control strategies to evaluate their efficiency. For instance, strategies as the use insecticides in risk areas or the elimination of breeding sites of certain regions can be evaluated through simulated scenarios.

Fig. 7. Comparing observed (white background) and simulated (black background) infestation maps - left maps show results for the winter season, right maps show results for the summer season.

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