

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 to estimate areas of epidemic risk.*

1. Introduction

Models describing the population dynamics of *Aedes aegypti*, classified as deterministic [Ferreira and Yang 2003] or stochastic [Otero et al. 2006; Focks et al. 1993A], share a common structure based on System Theory [Bertalanffy 1975]. A typical example [Ferreira e 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: $\sigma1$ - egg to larva, $\sigma2$ - larva to pupa, and $\sigma3$ - 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.

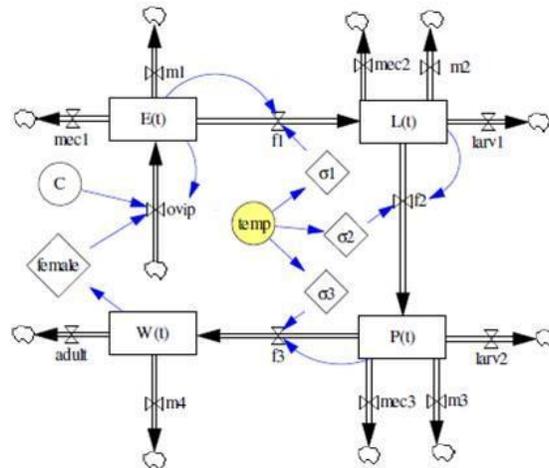


Figure 1. Flow diagram describing *Aedes aegypti* life cycle (adapted from Ferreira e Yang, 2003). Temperature (*temp* in yellow circle) controls three development rates: σ_1 - egg to larva, σ_2 – larva to pupa, and σ_3 – pupa to adult; *ovip* is the oviposition rate; *m1*, *m2*, *m3* and *m4* are natural 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.

To understand the spatial-temporal dynamics of these populations, 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

Few computational models are capable of simulating *Aedes aegypti* population spatial-temporal patterns. Otero et al. (2008) proposed a stochastic spatially-explicit model in which changes are modelled considering cells as occupied by autonomous mosquito populations interconnected by flows of flying individuals. 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. 1993a] 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.

3. Methodology

A deterministic *Aedes aegypti* population dynamic model, modified from Ferreira and Yang (2003) [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 [Camara 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 are traps that attract mosquito females looking for places to lay eggs. [Fay and Eliason 1966; Reiter et al., 1991]. Forty ovitraps were randomly placed in a 0,25 km² area. Each week, the ovitraps' contents were taken to the laboratory and number of *Aedes aegypti* eggs was 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.

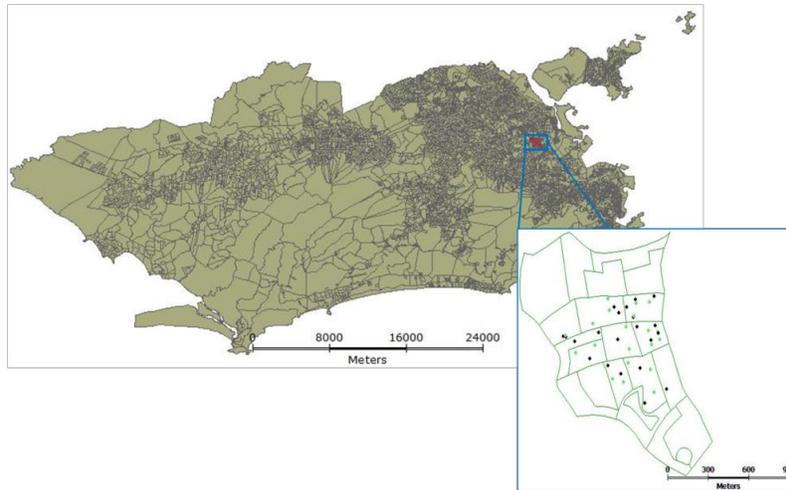


Figure 2. Study area and ovitrap locations – Higienópolis, Rio de Janeiro, RJ.

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).

$$\frac{dE}{dt} = ovip(t)W(t) \left[1 - \frac{L(t)}{C} \right] - [\sigma_1(t) + m_1(t) + mec_1(t)]E(t), \quad \text{Equation 1}$$

$$\frac{dL}{dt} = \sigma_1(t)E(t) - [\sigma_2(t) + m_2(t) + larv_1(t) + mec_2(t)]L(t), \quad \text{Equation 2}$$

$$\frac{dP}{dt} = \sigma_2(t)L(t) - [\sigma_3(t) + m_3(t) + larv_2(t) + mec_3(t)]P(t), \quad \text{Equation 3}$$

$$\frac{dW}{dt} = \sigma_3(t)P(t) - [m_4(t) + adult(t)]W(t). \quad \text{Equation 4}$$

Equation 1 describes the dynamic of the egg stock. Eggs are layed at a temperature and density-dependent rate. $ovip(t)$ is a quadratic function describing the effect of temperature on oviposition rate. Individuals leave the egg stage by either natural death, induced death (by mechanical control) or by ecloding into larvae. Equation 2 describes the dynamic of the larva stock. Larvae eclode at a temperature-dependent rate. Individuals leave the larva stage by either natural death, induced death (by mechanical control and larvicide) 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, induced death (by mechanical control and larvicide) 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 or induced death (by adulticide).

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 layed at a temperature and density-dependent rate. A quadratic relation between oviposition and temperature sampled was found to Higienópolis district (Figure 3).

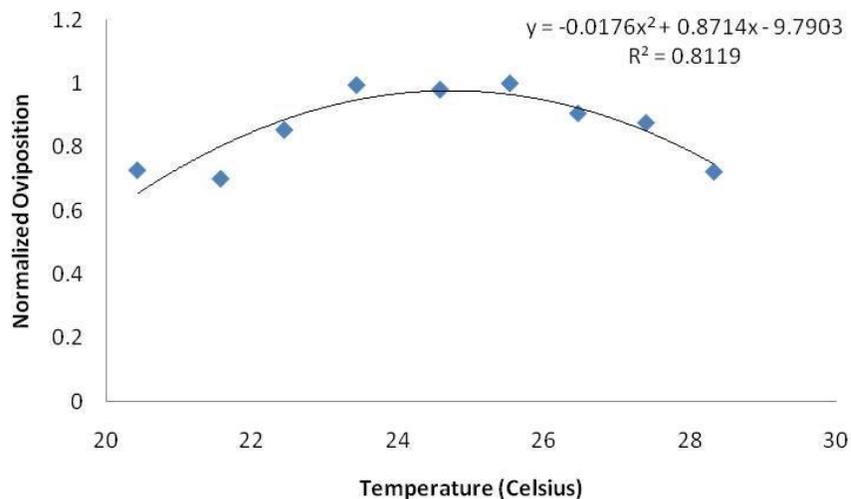


Figure 3. Quadratic function describing the relationship between oviposition rate and air temperature. The source of data is of Honório et al. (2009).

3.3. Calibration and Validation

The model presents only one free parameter, the carrying capacity C . The other parameters are maintained fixed (Table 1).

Table 1: Parameters used in the dynamic model

Parameter	Value
$ovip(t)$	(Quadratic function in Figure 3)
$\sigma 1(t), \sigma 2(t), \sigma 3(t)$	Fixed (equation proposed by Sharpe e DeMichelle, 1977)
$m1(t), m2(t), m3(t)$	Fixed (1/100, 1/3, 1/70 respectively)
$mec1(t), mec2(t), mec3(t)$	Fixed (0)
$larv1(t), larv2(t)$	Fixed (0)
$adult(t)$	Fixed (0)
C	Fitted

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. 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 (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 4a). A census tract with only one trap was excluded from the analysis (marked with a white X in Figure 4a). The carrying capacity of the dynamic population model was calibrated separately for each census tract. Figure 4b 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.

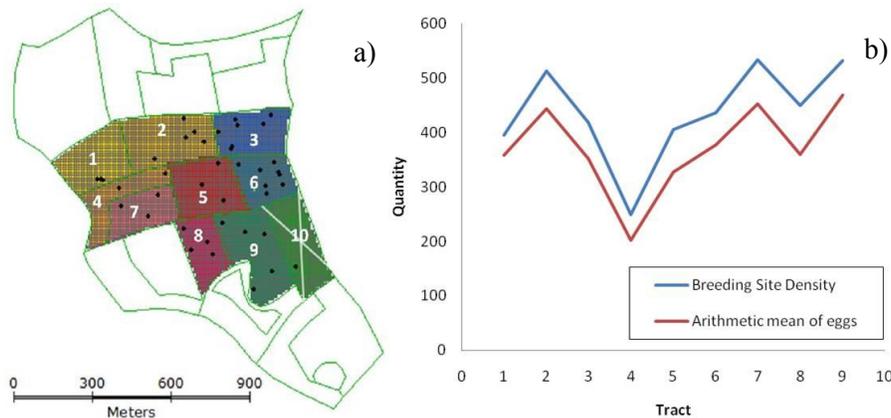


Figure 4. (a) The Higienópolis district divided in census tracts (a). The census tracts within the study area are colored and enumerated. The 10th census tract was excluded from the analysis. (b) Comparison between the estimated carrying capacity per census tract and the mean number of eggs. The red line was increased five times to facilitate comparison with the blue line. Applying a linear regression we obtain the equation $C = 37.48 + 5.387 * \text{mean (Eggs)}$, 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 5). This map was used as input to the spatially-explicit allocation model described below.

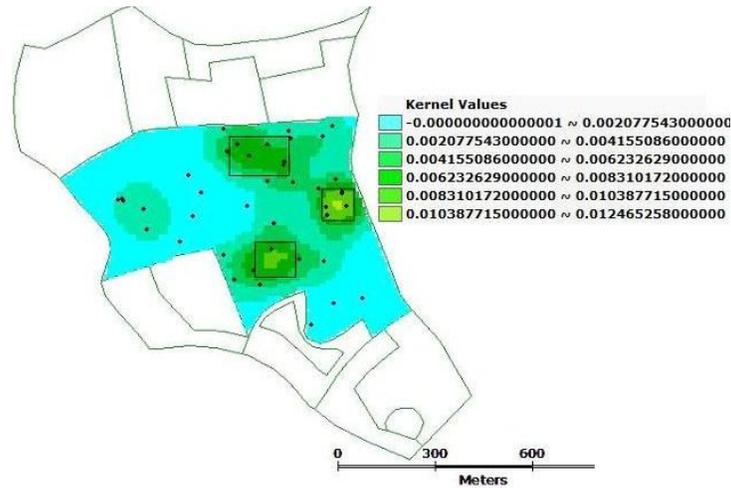


Figure 5: Average kernel map of egg density.

3.6. Allocation model for spatialization of the *Aedes aegypti* population

Some assumptions were considered in order to develop an *Aedes aegypti* population allocation procedure.

- Cells of 10 by 10 meters were generated and adopted as the spatial scale for this approach.
- The estimated egg population is distributed through space according to the kernel map of egg density (Figure 5). 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 6. 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.

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for each time step t do
  estimatedPop = DynamicModel(t)
  allocatedPop = 0
  while (allocatedPop < popEstimated) do
    for each cell in decreasingOrder( averageKernelMap )
      quantity = 63 * cell.KernelIntensity
      cell.eggPop = cell.eggPop + quantity
      allocatedPop = allocatedPop + quantity
    end for each cell
  end while
  t = t + 1
end for each time step
    
```

Figure 6. *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 7). 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.



Figure 7. Graph of comparing between Observed oviposition (OO) and Simulated oviposition (SO). The blue line, *temp*, is the temperature time series.

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 8). 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.

The allocation 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.

Future works will investigate integrated methods to develop spatial dynamic models for the *Aedes aegypti* life cycle. In this new approach, the spatial structure will be dynamic and population dynamics will be governed by autonomous populations located in each cell, as in Figure 9. Dispersion of mosquitoes by flight will be also considered. 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.

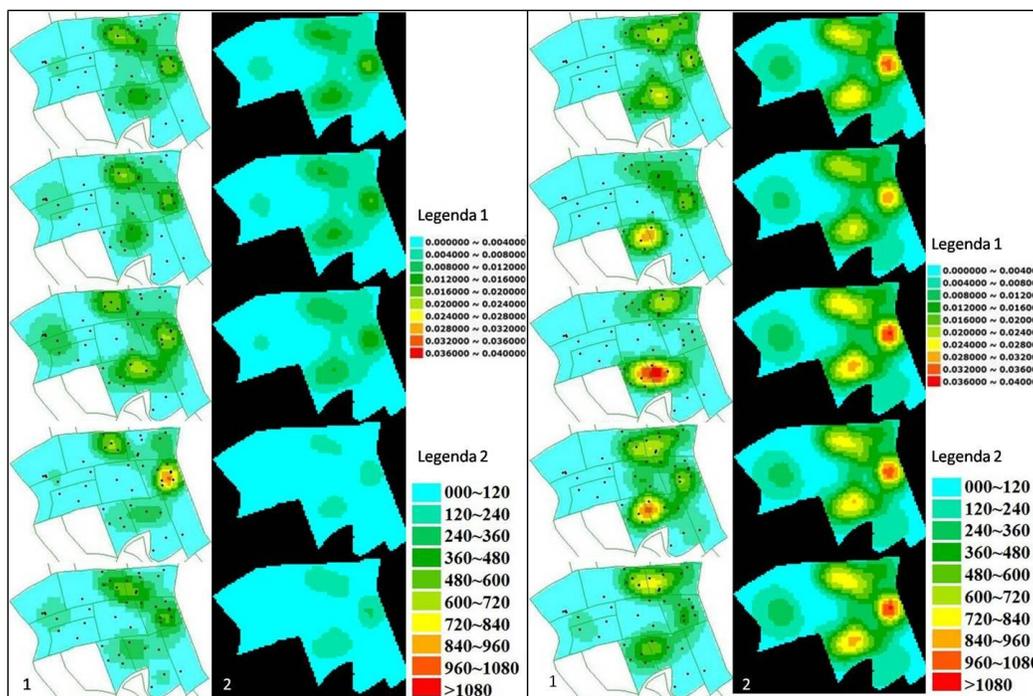


Figure 8. Comparing observed (white background) and simulated (black background) infestation maps – left maps show results for the winter season, right maps show results for the summer season.

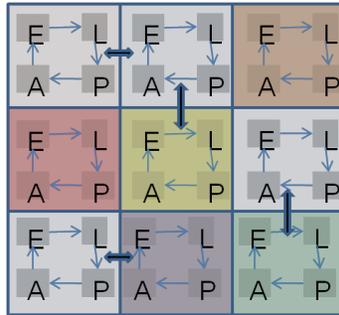


Figure 9. Autonomous *Aedes aegypti* populations occupy each space cell. Mosquitoes may fly to the neighbor cells indicated by blue arrows. E: egg, L: larva, P: pupa and A: adult.

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