Multiscale Analysis and Modelling of *Aedes aegyti* Population Spatial Dynamics

Raquel M. Lana[1], Tiago G. S. C. Carneiro[1],Nildimar A. Honório[2], Cláudia T. Codeço[2]

[1] Universidade Federal de Ouro Preto
raquelmlana@gmail.com, tiago@iceb.ufop.br
[2] Oswaldo Cruz Institute Foundation, Brazil
honorio@ioc.fiocruz.br, codeco@fiocruz.br

Abstract. Population dynamic models requires the evaluation of the best scale of analysis. This work analyses three spatial scales in the context of the mosquito *Aedes aegypti*, main vector of dengue fever. One scale is the neighborhood, the others scales are the census tract and the lot. A geographical database was developed including point maps with trap locations, number of eggs collected per trap per week, polygons of census tracts, census data, among others. For simulation purposes, a layer of regular cells (10 x 10 meters) was created to store the model's inputs and outputs. A population dynamic model with temperature as input variable was parameterized and fitted to the neighborhood and census tract data. For the lot level, an allocation procedure was developed as the spatial resolution was higher than the data resolution. This procedure couples the population dynamic model with a kernel density map. Results indicate that at the neighborhood level, the population model captured well the overall pattern with lower mosquito density during the cold season and larger during the warm season. However, in the first warm season, two peaks did not fit well, suggesting the importance of investigating the role of other variables in the dynamics of *Aedes aegypti*. At the census tract level, we found no evidence of spatial clustering. At the lot level, the allocation model represented well the overall summer to winter variation in hotspot intensity. The cost of vector surveillance is high and the procedures proposed here can be used to design optimized control strategies and activities.

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

Keywords: *Aedes aegypti*, calibration, population model, spatial model

1. INTRODUCTION

Due to its importance as the main vector of dengue fever and urban yellow fever, the mosquito *Aedes aegypti* has been the focus of several modeling initiatives. Most models seek to represent its temporal dynamic in response to climate and endogenous forces [Focks et al. 1993; Ferreira and Yang 2003; Otero et al. 2006] while others consider their spatial-temporal dynamic by introducing dispersal mechanisms [Otero et al. 2008; Magori et al. 2009; Almeida et al. 2010]. One of the key challenges in modeling *Aedes aegypti* is the lack of adequate data for validation.

Although routine surveys are carried out in endemic areas, the indicators produced from the inspection of indoors and outdoors container habitats are just relative measures of abundance. They do not provide the absolute measures of density required by the models. With the more recent development of species-specific traps for *Aedes aegypti*, though, quantitative measures of mosquito abundance became available. The most popular traps are the ovitrap and the sticky trap. Ovitrap is a small vessel filled with a diluted hay infusion, and a wooden paddle held on the wall. Gravid female mosquitos are attracted to the vessel and lay their eggs on the paddle [Reiter et al. 1991]. Sticky traps are

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Authors thank the Pos-Graduate Program in Ecology of Tropical Biomes and Laboratory of Modeling and Simulation of Terrestrial Systems in Federal University of Ouro Preto (UFOP), Minas Gerais, Brazil. Juliana Moreira Barbosa for all help in LaTeX. This work was supported by CNPq(PRONEX-DENGUE 550030/2010-7) and UFOP.

Journal of Information and Data Management, Vol. 2, No. 2, June 2011, Pages 211–220.

ovitraps with a sticky paper attached to the walls to which ovipositing females get glued [Gama et al. 2007]. By counting the number of captures (eggs or mosquitos), one can generate absolute measures of abundance at the local level (number of captures/house) or at more aggregate spatial levels (block, neighborhood).

Trap data are generally sparse. In studies with high temporal resolution (sampling every week, for example), their spatial distribution is either sparse [Gama et al. 2007] or concentrated in a small study area [Honório et al. 2009]. The problem is that large sample sizes are required to obtain an adequate representation of the mosquito spatial distribution, because of their tendency to form aggregated distributions as well as their poor dispersal ability. On the other hand, studies with higher spatial resolution generally use less frequent sampling [Regis et al. 2008]. High frequency sampling at high spatial resolution poses a prohibitive cost for trap-based sampling of *Aedes aegypti*.

Here we propose a model-based approach that increases the efficiency of trap-based surveys by decoupling the temporal dimension from the spatial dimension problem. The underlying assumption is that the mosquito spatial distribution is mostly driven by environmental variables (availability of breeding sites and blood sources) which vary at a lower rate than the mosquito population itself. So, spatial sampling can occur more sporadically than the temporal sampling and the temporal sampling can be carried out with a smaller number of traps to produce an average index for the whole area.

To reconstruct the spatial-temporal population dynamics, we combine a model of the temporal population dynamics with a spatial allocation procedure. With this approach, it is possible to calculate, at each simulation time step, the variation in local mosquito population size in the geographical space at a chosen resolution.

2. POPULATION MODELS OF *AEDES AEGYPTI*

Models describing the population dynamics of *Aedes aegypti*, either deterministic [Ferreira and Yang 2003] or stochastic [Otero et al. 2006], share a common structure based on the framework of 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 modeled 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 and its formulation as dynamic equations allows the simulation of its temporal dynamics. Since space is not explicited, however, the model does not describe the distribution of *Aedes aegypti* through space.

Few available computational models simulate *Aedes aegypti* spatial-temporal dynamics. [Otero et al. 2008] proposed a stochastic spatially-explicit model, based on their previous temporal model [Otero et al. 2006], in which space is modeled as cells which are occupied by autonomous mosquito populations interconnected by flying individuals. Dispersal between cells is modulated by the availability of breeding sites. A similar approach was used by [Magori et al. 2009]. They considered both the spatial distribution of breeding sites and the dynamics of the aquatic stage of the mosquitoes (larvae and pupae) [Focks et al. 1993]. The breeding site density per house and the house density per area were model parameters. Despite their detailed account of spatial dynamics, neither model was fitted to real spatial data, being used to represent virtual spaces only.

A spatial-temporal model integrated with data from remote sensor images and digital maps were used by [Tran and Raffy 2005] to assess dengue transmission in the municipality of Iracabouro, French Guiana.

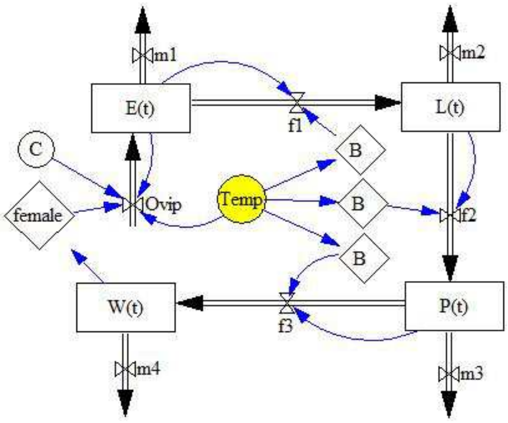


Fig. 1. Flow diagram describing the *Aedes aegypti* life cycle (adapted from Ferreira and Yang 2003). Temperature (temp in yellow circle) controls three development rates: 1 - egg to larva, 2 - larva to pupa, and 3 - pupa to adult; ovip is the oviposition rate; *m1, m2, m3* and *m4* are natural stage-specific death rates. C is the carrying capacity of the area.

3. DATA AND METHODS

3.1 Data

Data used in this work were collected by [Honório et al. 2009], who weekly monitored the *Aedes aegypti* population in Higienópolis, a neighbourhood of Rio de Janeiro, RJ, Brazil, during 1.5 years, using ovitraps (*Figure 2*). Higienópolis is a low middle class residential area, divided into 22 census tracts. The entomological study was conducted in 10 census tracts, with forty randomly distributed ovitraps. Each week, the number of *Aedes aegypti* eggs per trap was counted, generating a 78-week time series of eggs per trap. Since the mathematical model requires temperature data, weekly mean air temperature during the period was obtained from the nearest meteorological station, located at the Rio de Janeiro's international airport. Spatial data was integrated into a geographical database in TerraView, version 3.2.0, including point maps with ovitrap locations, number of eggs collected per ovitrap per week, polygons of census tracts, census data, among others. For simulation purposes, a layer of regular cells (10 x 10 meters) was created to store the model's inputs and outputs.

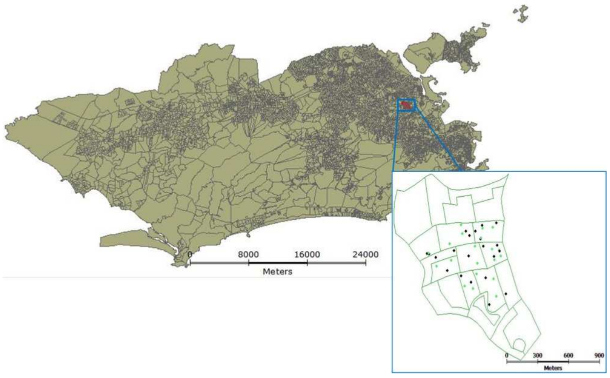


Fig. 2. Study area and ovitrap locations - Higienopólis, Rio de Janeiro, RJ.

3.2 Population Dynamic Model

To model the temporal dynamics of *Aedes aegypti*, an adapted version of the temperature dependent model by [Ferreira and Yang 2003] was implemented in the TerraME modeling environment [Carneiro 2006]. The model [Lana 2009] has four differential equations describing the rate of change of mosquito abundance, per life stage: eggs, larvae, pupae and adult (*Figure 1*).

$$\begin{aligned}
\delta E/\delta t &= ovip(t)(0.5W)[1-\frac{L}{C}] - [\sigma_1(t)+m_1]E \qquad (1)\\
\delta L/\delta t &= \sigma_1(t)E - [\sigma_2(t)+m_1]L \qquad (2)\\
\delta P/\delta t &= \sigma_2(t)L - [\sigma_3(t)+m_1]P \qquad (3)\\
\delta W/\delta t &= \sigma_3(t)P - [m_4]W \qquad (4)
\end{aligned}$$

Equation 1 describes the dynamic of the egg stock. Eggs are layed at a temperature and density-dependent rate where *ovip(t)* is a quadratic function describing the effect of temperature on the maximum oviposition rate. Carrying capacity, *C*, represents environmental characteristics such as breeding sites availabity based on climate variables. Individuals leave the egg stage by either natural death 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 or by evolving into pupae. Equation 3 describes the dynamic of the pupa stock. Pupa emerges at a temperature-dependent rate as well where it remains until natural death or emerging into adulthood. Equation 4 describes the dynamic of the egg-laying adult female stock. Female adults emerge at a temperature dependent rate and die by natural death. In comparison to [Ferreira and Yang 2003], this model has the following modifications: a) It uses the equation proposed by [Sharpe and DeMichele 1977] to describe the temperature-dependent developmental rates, σ_1 to σ_3. This equation describes the rate of development of a poikilothermic organism as the temperature dependent rate of activation and deactivation of an enzyme. Unpublished results show a better fit with a model with this modification (Table I). b) The original constant oviposition rate was replaced by a temperature-dependent function. An empirical function was derived by fitting a quadratic function to the ovitrap data versus temperature (Table I).

3.3 Model Calibration and Validation

All parameters but *C*, the carrying capacity, were parameterized using values from the literature (Table I). We assumed that the carrying capacity, *C*, represented the site-specific environmental conditions available for larval development and should be calibrated locally.

Table I. Parameters used in the dynamic model.

Parameter	Value	Reference
Oviposition rate(ovip(t))	OvipRate $= -0.0176 * (Temp)^2 + 0.8714 * Temp - 9.7903$	[Lana 2009]
Development rates(s):		
1)egg - larva ($\sigma_1(t)$)		[Sharpe and DeMichele 1977]
2)larva - pupa ($\sigma_2(t)$)	$R_D(T) = R_D(298K)\frac{(\frac{T}{298K})exp((\frac{\Delta H_A}{R})(\frac{1}{298K}-\frac{1}{T}))}{1+exp(\frac{\Delta H_H}{R})(\frac{1}{T_{1/2}}-\frac{1}{T})}$	[Schoofield et al. 1981]
3)pupa - adult ($\sigma_3(t)$)		
Death rates (m):		
1)egg (m1(t))	$1/100\ day^{-1}$	
2)larva(m2(t))	$1/3\ day^{-1}$	[Ferreira and Yang 2003]
3)pupa (m3(t))	$1/70\ day^{-1}$	
4)adult (m4(t))	$1/17.5\ day^{-1}$	
Carrying Capacity (C)	Fitted	

To calibrate the model, the ovitrap data was divided into two subsets, each one composed by 20 traps. For each subset, a time series of mean number of eggs per week was calculated. One series was used for the calibration using a Monte Carlo method [Rubinstein and Kroese 2007] that minimizes the mean quadratic error between observed and estimated egg density (2000 iterations were performed in 10000 Monte Carlo experiments).

Once calibration was achieved, the second subset was used to simulate the model again and to calculate a validation error between the calibrated model and the new dataset. Since this error was lower than the calibration error, we considered the model well calibrated.

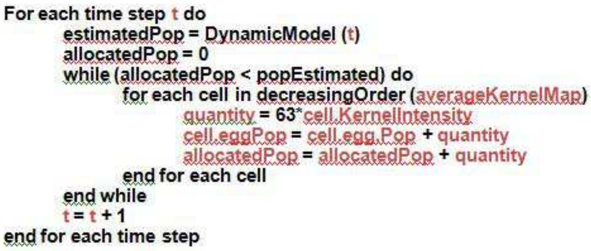
3.4 Spatialization

The population model produced a time series of mosquito density at the scale of the neighborhood. To generate maps of the spatial distribution of the *Aedes aegypti* eggs in Higienópolis, two other spatial scales were considered: one is the census tract scale, which represents an aggregate of more or less 300 domiciles. The second scale is the lot, which can be occupied by a single premise.

3.4.1 *Census tract scale.* The study area consists of 9 census tracts (one was excluded because only one trap was present). We fitted the [Lana 2009] model to each census tract keeping all parameters fixed and allowing only C, the carrying capacity, to vary. Calibration was done as previously described.

3.4.2 *Lot scale.* Since the lot scale is at a higher resolution than the data points, a kernel estimator for point events with adaptive radius was used to smooth the surface by interpolating the weekly density of eggs. To reduce the temporal resolution (not the focus of this work), a single map was created by averaging the weekly maps. This average map displays the most stable infestation hotspots, which we assume to be the areas with larger carrying capacity.

Lots are very small spatial units. Implementing a population model for each one would violate the large number assumption of deterministic population models. We then propose a top-down approach, where mosquito dynamics is modeled at a larger spatial scale (census tract or neighborhood) and an allocation procedure is used to distribute the mosquitoes throughout the lots according to their expected density distribution (based on the kernel density map). The allocation procedure is shown in Figure 3. It traverses the cellular space allocating the *Aedes aegypti* population. First, the space is divided into a grid with 10x10m cells. The cells are visited in a decreasing order of egg density as estimated by the kernel egg density map. 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 by the average kernel map.



```
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.egg.Pop + quantity
            allocatedPop = allocatedPop + quantity
        end for each cell
    end while
    t = t + 1
end for each time step
```

Fig. 3. *Aedes aegypti* population dynamic allocation algorithm.

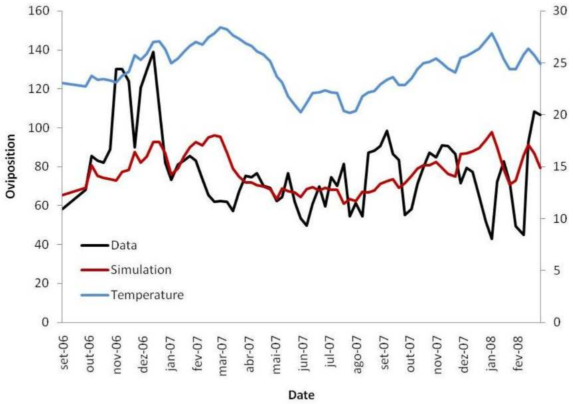


Fig. 4. Graph of comparing between Data and Simulation.

4. RESULTS

4.1 Population model

Figure 4 shows the simulated and observed time series. The model captured the overall pattern with lower mosquito density during the cold and larger density during the warm seasons. The data, however, shows a large variance around this mean tendency, which is not captured by the model. In the first warm season, two large peaks in the data were not captured at all by the model, suggesting that other variables, besides temperature, may have a strong effect on mosquito dynamics. To investigate it, we observed a temporal series of rain for this neighborhood and a difference on the volume of rain between the first and second summer season was clear. So, it will be necessary to include this variable on the model for new tests and verify the fitting.

One cannot disregard also the impact of a short time series on the fitting, and the likely importance of migration in this specific population. Higienópolis is not an isolated place as the model assumes, and its mosquito population can receive and lose individuals from/to the vicinity.

4.2 Spatialization at the census tract level

Figure 5b shows the result of fitting a population model to each of the 9 census tracts of Higienópolis that contained traps.

The estimated carrying capacity doubled from census tract 4 to census tract 7 or 9. By comparing the estimated C with the mean egg density per census tract, one can see that, discounting a scale factor (5.387), C captures the spatial variation in egg density (*Figure 5b*).

4.3 Spatialization at the lot level

Figure 6 shows the kernel egg density map used for the allocation procedure. The map, calculated as an average of all weekly maps, displays three main hotspots. *Figure 7* (white background columns) shows 10 of the 78 weekly maps. One can observe that the hotspots tended to remain in the same places, varying mainly in intensity. When the model-derived population data was allocated to the mean kernel map, the time-spatial series of mosquito abundance was reconstructed. This can be seen in *Figure 7* (black background columns). During the warm seasons, though, mosquito abundance was less intense in the simulated maps than in the observed maps. The opposite occurs during the cold seasons. These discrepancies are more prominent when the population model poorly estimates the true population abundance.

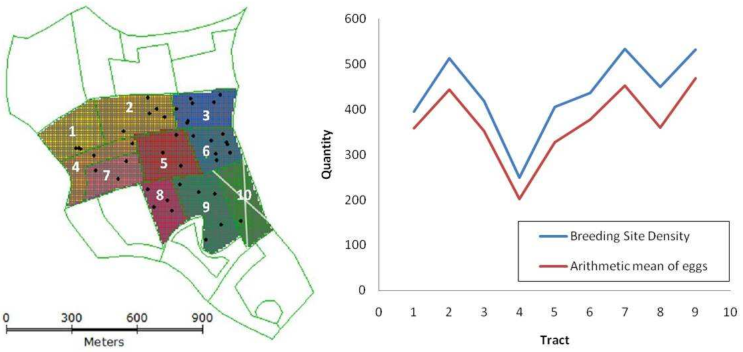


Fig. 5. (a) The Higienópolis district divided in census tracts (a). The census tracts within the study area are colored and enumerated. The 10th census tract was excluded from the analysis. (b) Comparison between the estimated carrying capacity per census tract and the mean number of eggs. The red line 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 $r2 = 96.5\%$.

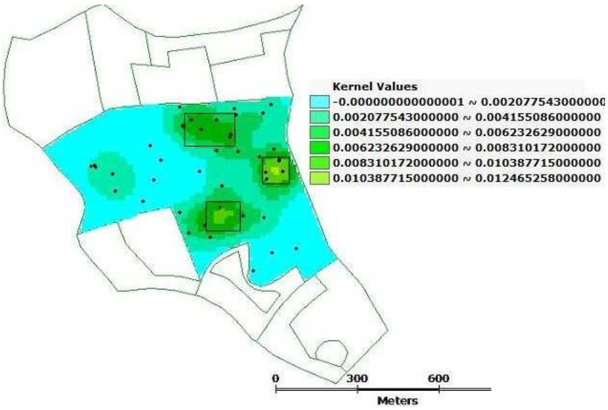


Fig. 6. Average kernel map of egg density.

5. DISCUSSION

This work presents a multiscale analysis of an *Aedes aegypti* population model. Besides the neighborhood scale, two other spatial scales were investigated, that are relevant for mosquito control: the census tract and lot scales. The first approach aggregated egg density per census tract and calibrated the C parameter according to the described methodology. The second approach used an allocation algorithm based on a Kernel density map to generate predictions for each cell in a 10x10m cell grid. Both approaches are applied to a geographical database for the Higienópolis neighborhood, in Rio de Janeiro city, RJ, Brazil.

The population model implemented was an adaptation of [Ferreira and Yang 2003]. This model, as most *Aedes aegypti* models, only uses the temperature as an external driver. Our results suggest that other variables, besides temperature, are necessary to explain the two large peaks in the data. The rainfall maybe a candidate, since a strong difference in the precipitation regime is observed between the first and second warm seasons, which probably influences the carrying capacity $C(Figure\ 7)$.

The ovitrap data showed intense spatial heterogeneity. At the census tract level, we found no evidence of clustering, with high C areas located side by side with low C areas. This result suggests that spatial correlation may not occur at this scale. The census tract division of space probably is not ideal because the same census tract can present different landscapes that are relevant to the

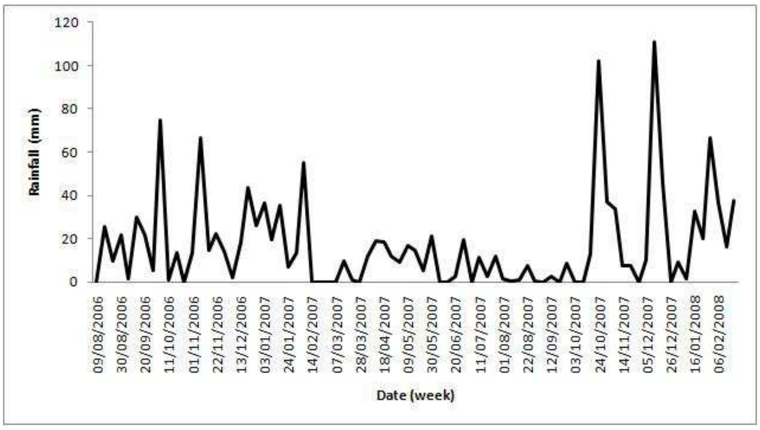


Fig. 7. Rainfall (mm) per week for Higienópolis, RJ between September of 2006 to February of 2008.

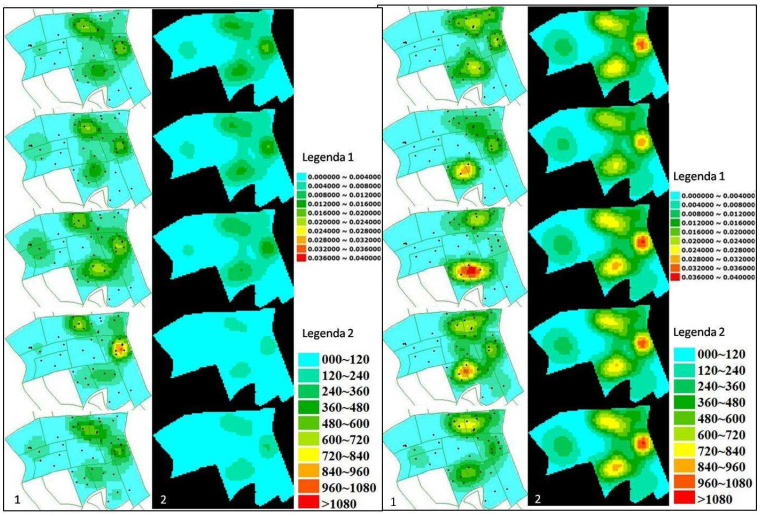


Fig. 8. Comparing observed (white background) and simulated (black background) infestation maps - left maps show results for the winter season, right maps show results for the summer season.

mosquito. For example, [Reis 2010] showed that the study area presented very distinct patterns of urbanization and vegetation coverage levels which do not overlap with the census tract definition. She found differences in traps located in areas with different levels of urbanization.

The allocation procedure used to develop the lot-level map assumes that the spatial distribution does not vary much through time. In *Figure 8*, we see that although a spatial variation occurs, it is not as pronounced as the temporal variation (*Figure 4*). Hotspots are concentrated in four areas, three of them are located in highly urbanized sites, with very low vegetation coverage [Reis 2010]. The allocation model was capable of capturing this overall spatial pattern. Still, as we used a single average map, further fitting improvement could be achieved by developing short term maps instead of a yearly map. Unpublished results suggest that a model with two carrying capacities, one for the rainy season and one for the dry season, has a better fit. This suggests that an allocation model with two maps may also produce better fitted models.

The allocation top-down procedure introduced a simplification. The method does not consider the spread of mosquitoes by flight. For this, a spatial population model would be required. [Otero et al. 2008] propose a model that considers mosquito dispersion. The dispersion was driven by local breeding site availability. Such spatial-temporal model would require more data with higher spatial resolution in the order to be calibrated and validated. With the allocation approach, on the other hand, one can combine sporadic spatial samples with continuous temporal sampling. The frequency of such spatial samplings would depend on the desired precision. Our results suggest that more than a map per year may be necessary since underestimation tended to occur in the warm season and overestimation occurred in the cold season. [Otero et al. 2008] found the same pattern in the cold season, although their model was parameterized for a temperate climate. A lot level model has been proposed by [Magori et al. 2009], however the resolution is prohibitive to parameterize in large scales.

Other modeling initiatives based on geographical information are presented in the literature. [Tran and Raffy 2005] developed a Dengue transmission model in which the vector population mobility was given by environmental information retrieved from a remote-sensing image. But this model was not calibrated for the vector population. With our methodology, it should be possible to calibrate the models like [Tran and Raffy 2005] or [Otero et al. 2008].

Dengue fever is an important cause of morbidity and mortality in many tropical countries. Since a vaccine is not available, disease control targets the mosquito population. The cost of monitoring this population is very high and competes with other interventions such as treatment. Any effort to reduce the cost of vector surveillance will have an important impact in such scenario. In this study, we proposed an allocation procedure that can be used to optimize modeling and, consequently, the development of more effective control strategies. Future work will be devoted to the use of this method in specific control activities.

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