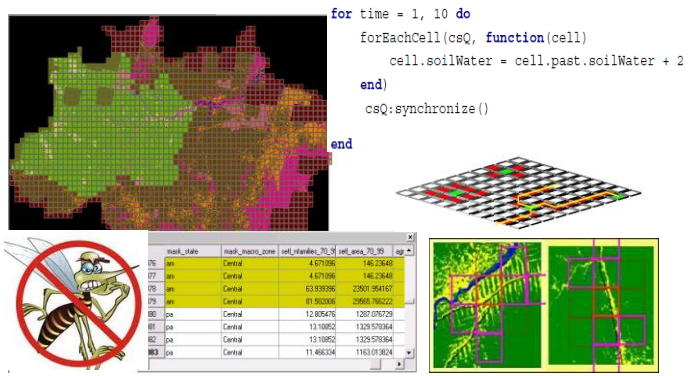
Universidade Federal de Ouro Preto
Departamento de Computação
Laboratório de Simulação e Modelagem de Sistemas Terrestres

Simulation of population dynamics of *Aedes aegypti* using TerraME

I Oficina Técnica da Rede Pronex
de Modelagem em Dengue

Prof. Dr. Tiago Garcia de Senna Carneiro
Raquel Martins Lana
Fernando Felipe Morais Reis
Fevereiro/2011



Summary

Spatially-explicit model of population dynamics of *Aedes aegypti*

Comparison of population dynamics models

Chronogram

Partnerships

Spatially-explicit model of population dynamics of *Aedes aegypti*

(GeoINFO 2010)

Aedes aegypti population dynamic models

- *Aedes aegypti* population dynamic models: deterministic or stochastic

- Common structure based on System Theory [Bertalanffy 1975]

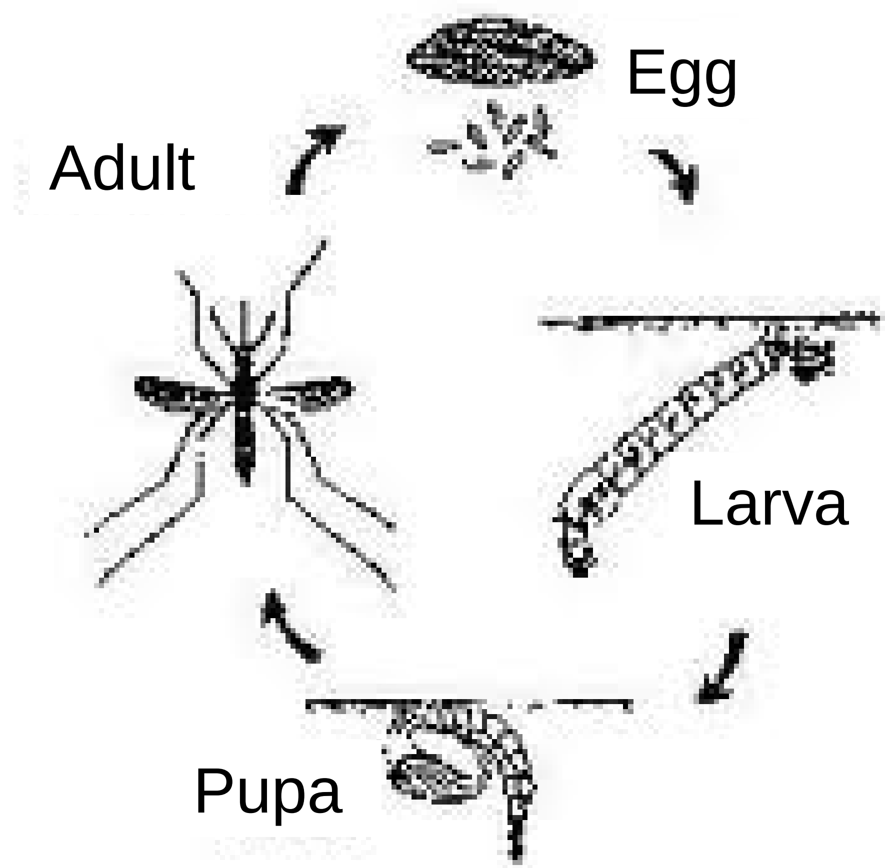


Figure 1. *Aedes aegypti* life cycle.

Ferreira e Yang (2003) population dynamic model

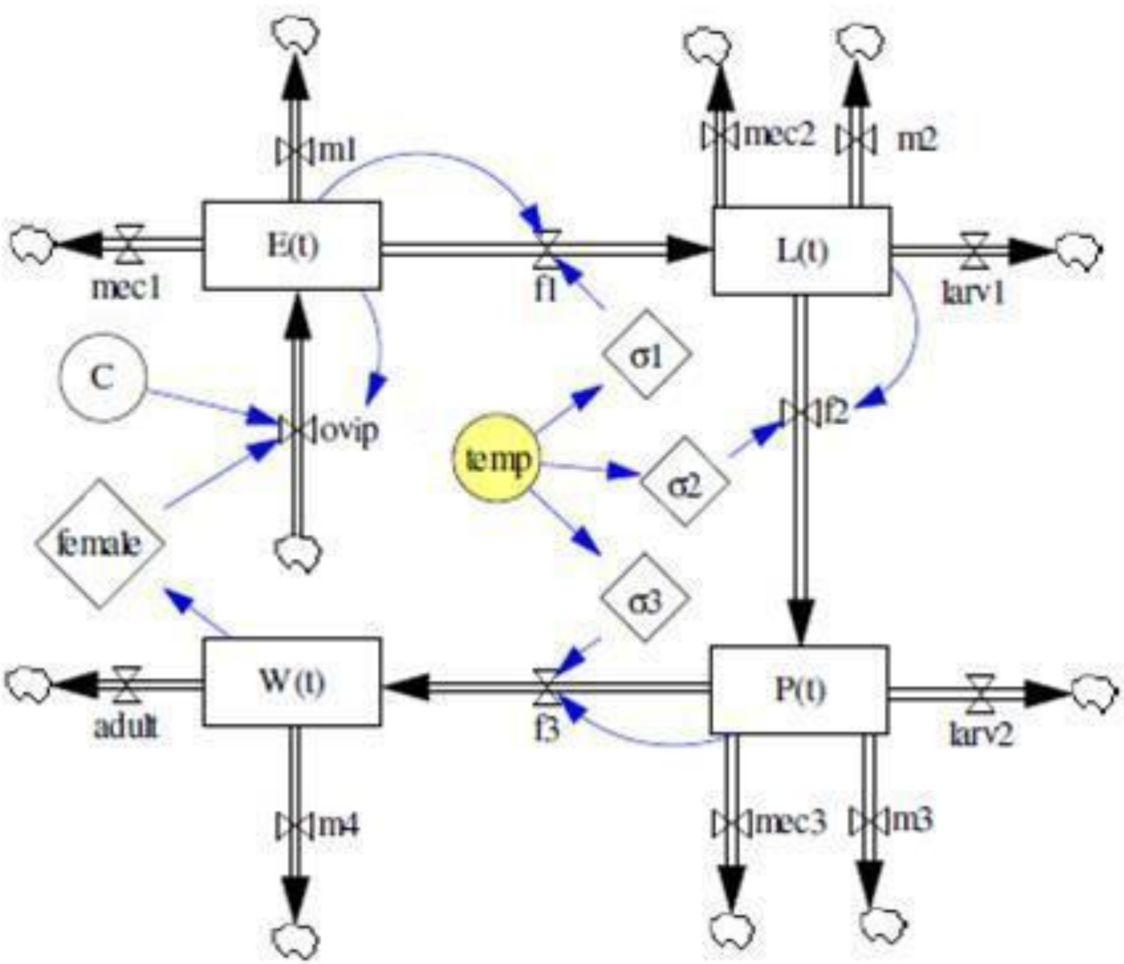


Figure 2. Flow diagram describing *Aedes aegypti* life cycle (adapted from Ferreira e Yang, 2003).

Objectives

Understanding the **spatial-temporal dynamics** of *Aedes aegypti* populations.

Proposing 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**.

Study Area and Sample Design

The data used in this work (eggs collection) was collected by Honório et al., (2009).

1.5 years of weekly collections with ovitraps (Honório et al. 2009).

Temperature was collected from Rio de Janeiro's international airport.

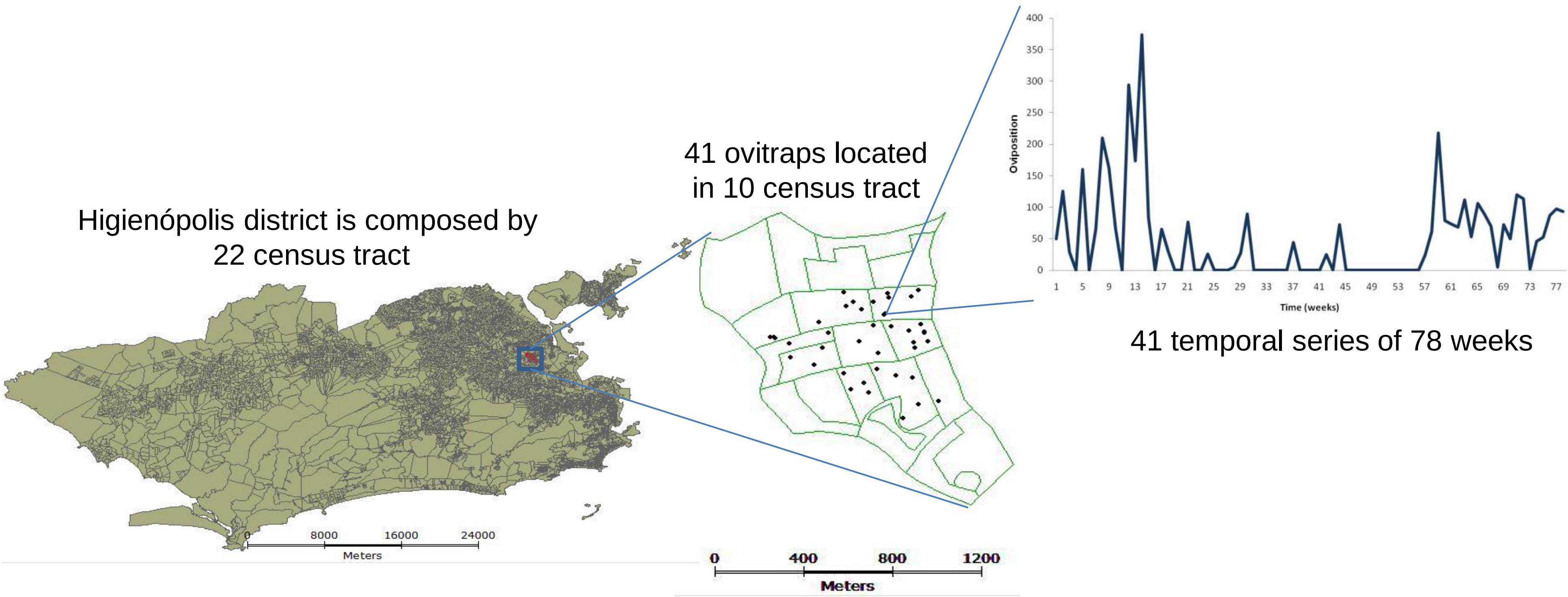


Figure 3. Study area and ovitrap locations – Higienopólis, Rio de Janeiro, RJ.

Steps of the model construction

1. **Dynamic Model Development**

   Modified from Ferreira and Yang (2003) [Lana 2009]

2. **Model Calibration and Validation**

   Real data stored in **TerraLib** [Camara et al. 2000]

   Calibration at several scales: whole region, census tract and lot scale

   Monte Carlo simulations

3. **Spatial Model Development**

   Kernel Estimator has been used for smoothing egg density surface

   Allocation algorithm based on egg density surface and the female egg carrying capacity

All components have been implemented in the TerraME modeling environment [Carneiro 2006].

Population Dynamics Model Adopted

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

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

$$\frac{dL}{dt} = \sigma_1(t)E(t) - \left[\sigma_2(t) + m_2(t) + larv_1(t) + mec_2(t)\right]L(t),$$

$$\frac{dP}{dt} = \sigma_2(t)L(t) - \left[\sigma_3(t) + m_3(t) + larv_2(t) + mec_3(t)\right]P(t),$$

$$\frac{dW}{dt} = \sigma_3(t)P(t) - \left[m_4(t) + adult(t)\right]W(t).$$

Improvements Inserted in the Model

Temperature-dependent developmental rates [Sharpe and DeMichelle, 1977].

Eggs are layed at a temperature and density-dependent rate.

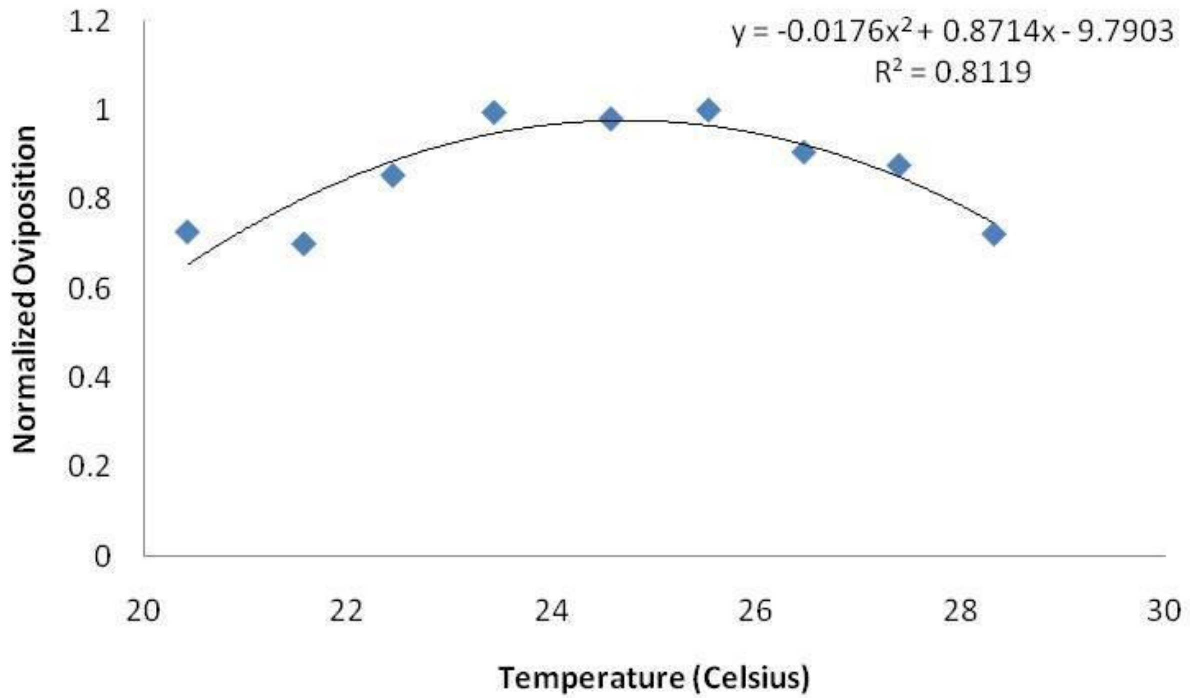


Figure 4. Quadratic function describing the relationship between oviposition rate and air temperature. The source of data is of Honório et al. (2009).

Parameters of the Model

The model presents only one free parameter, the carrying capacity *C*.

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

Sensitivity Analysis

Models Behavior

Free parameter: Carrying Capacity, C

Values: 100, 500, 1000

Calibration and Validation

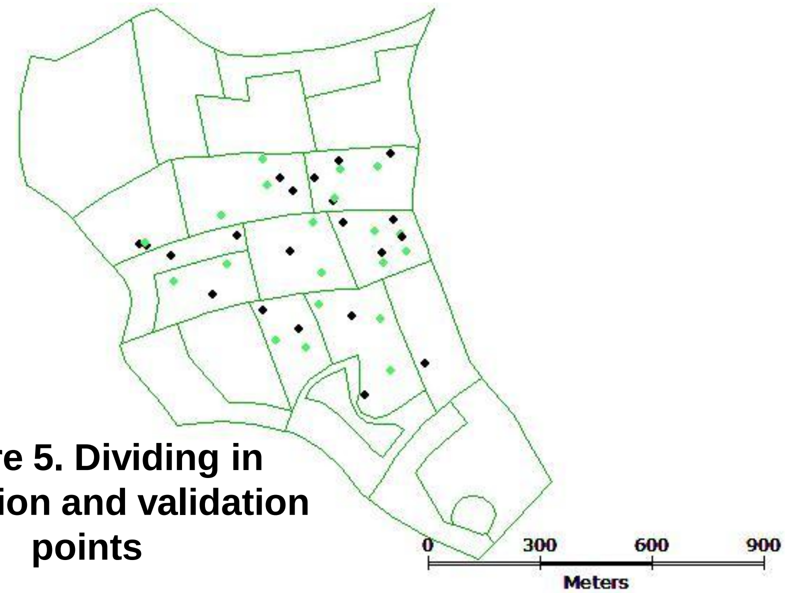


Figure 5. Dividing in calibration and validation points

Dividing into two subsets

First subset: calibration

Monte Carlo method

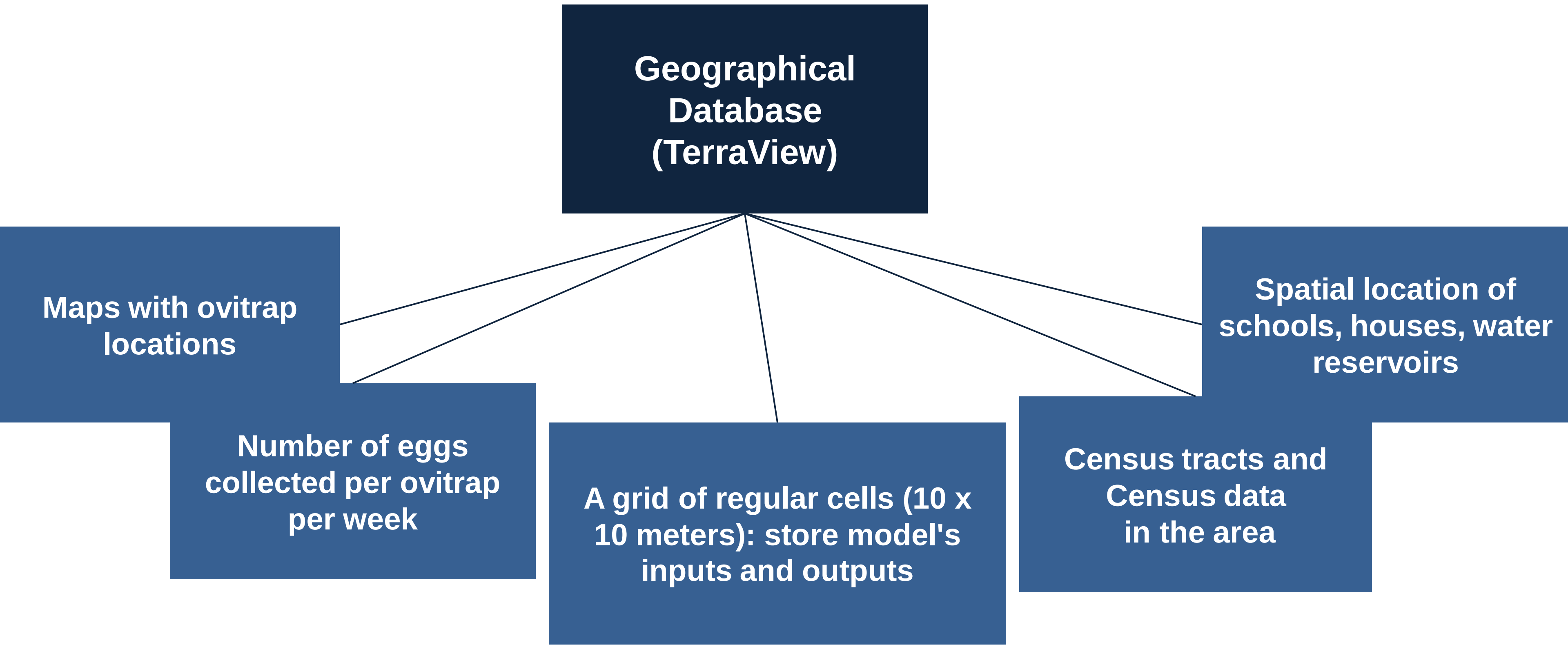
Mean Quadratic Error

2000 iterations were performed in 10000 MC method experiments

Second subset: validation

The validation error was compared to the error obtained by the calibration process.

Geographical Database

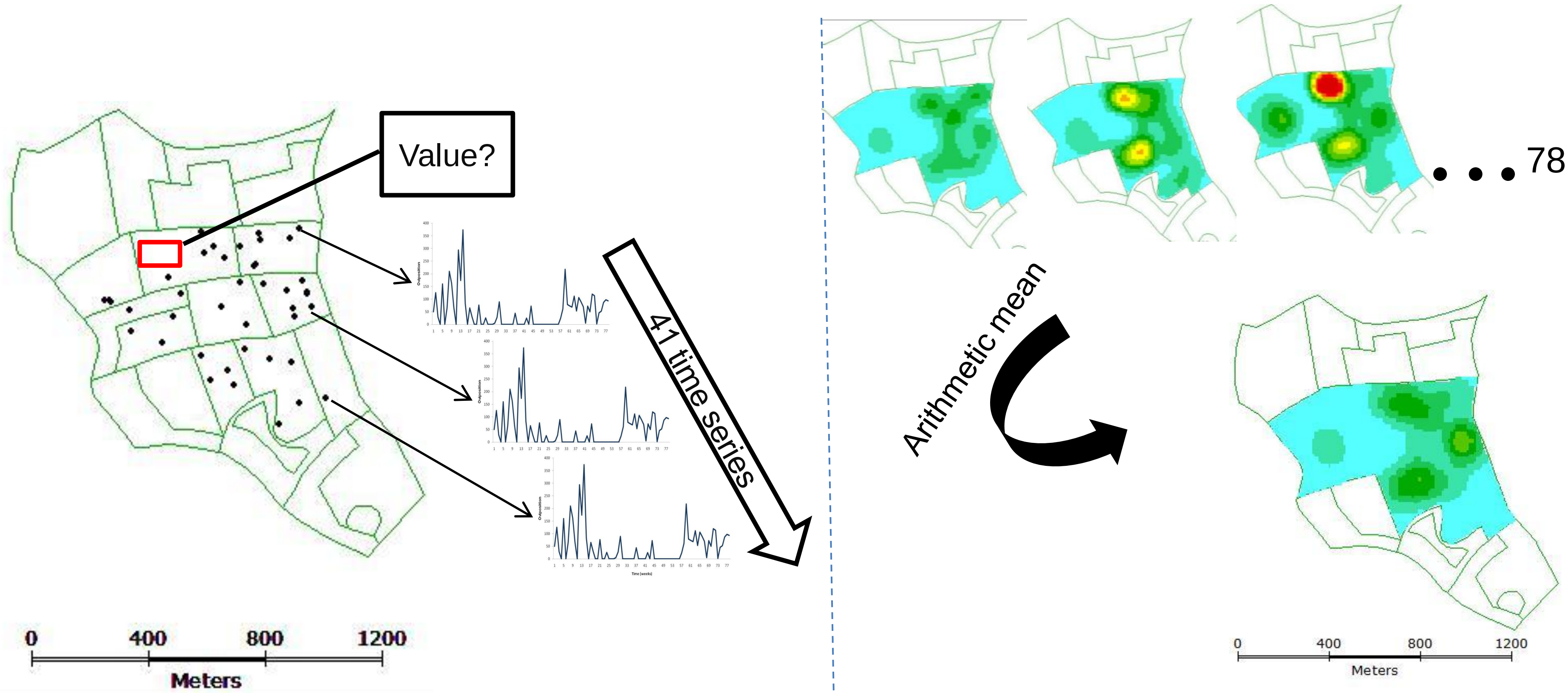


Scale Issues and Estimation of the Infestation Spatial Pattern

Three scales for the spatial distribution of the *Aedes aegypti* population in Higienópolis:

- Whole region (Population Dynamic Model)
- Census tract scale
- Lot scale

How to calibrate the allocation model?



INPUT DATA

OUTPUT DATA

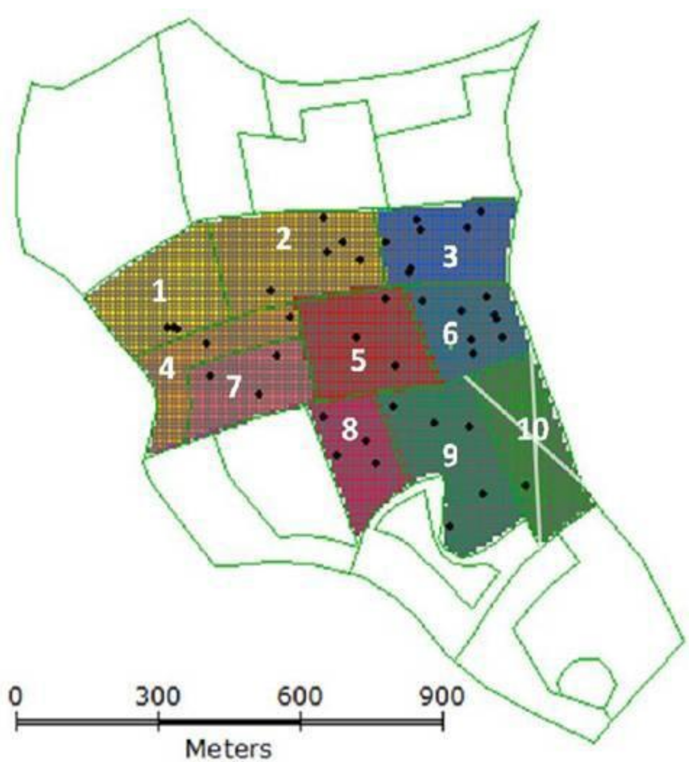
We use the kernel estimator with aggregated value for this task...

But the question remains: How to use the 78 maps?

Census tract scale

The ovitrap data was aggregated by census tract.

Linear regression applied: *C = 37.48 + 5.387*mean (Eggs), with* $r^2 = 96.5\%$.



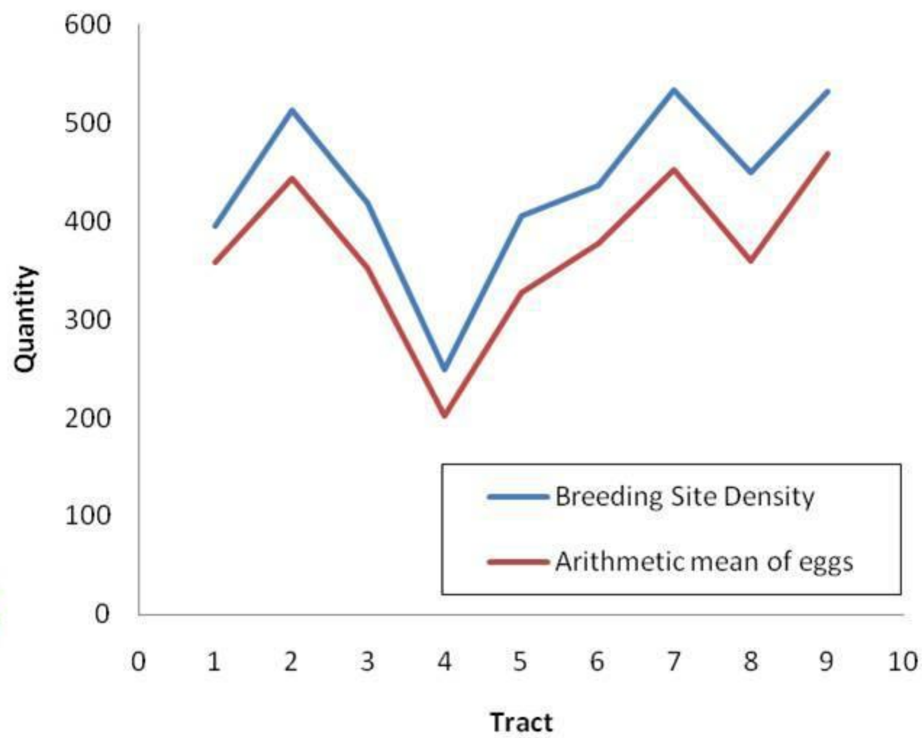


Figure 5. (a) The Higienópolis district divided in census tracts. (b) Comparison between the estimated carrying capacity per census tract and the mean number of eggs.

Steps for Lot Scale

Kernel Estimator

Estimation of a continuous surface of egg density

78 weekly maps

↓

Average map of egg density

↓

Input to the spatial model

Why average maps?

An **arithmetic average** of samples for each census tract has the same information obtained when the model was calibrated separately for each census tract.

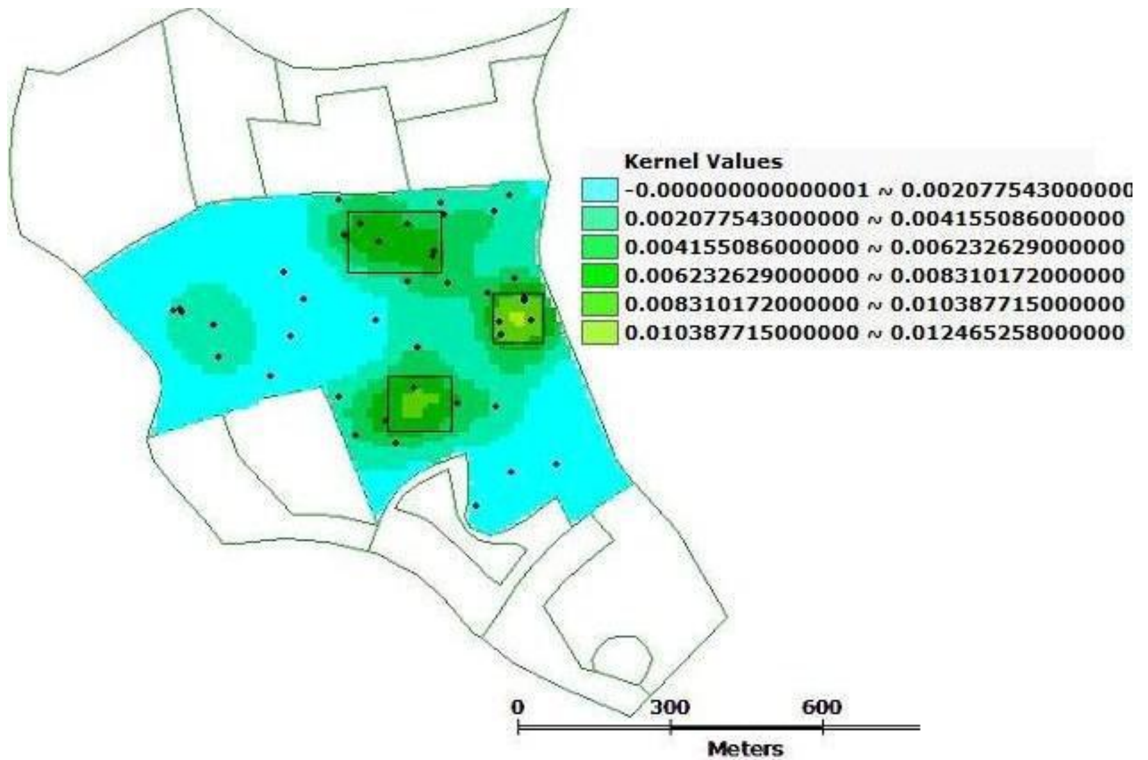


Figure 6: Average kernel map of egg density.

Allocation model for spatialization of the *Aedes aegypti* population

Considerations to develop an *Aedes aegypti* population allocation procedure.

Cells of 10 by 10 meters were generated and adopted as the spatial scale.

The estimated egg population is distributed through space according to the kernel map of egg density.

The carrying capacity is proportional to the mean egg density

Algorithm of allocation

```
for each time step t do
    estimatedPop = DynamicModel (t)
    allocatedPop = 0
    while (allocatedPop < popEstimated) do
        for each cell in decresingOrder ( 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 7. *Aedes aegypti* population dynamic allocation algorithm

Algorithm

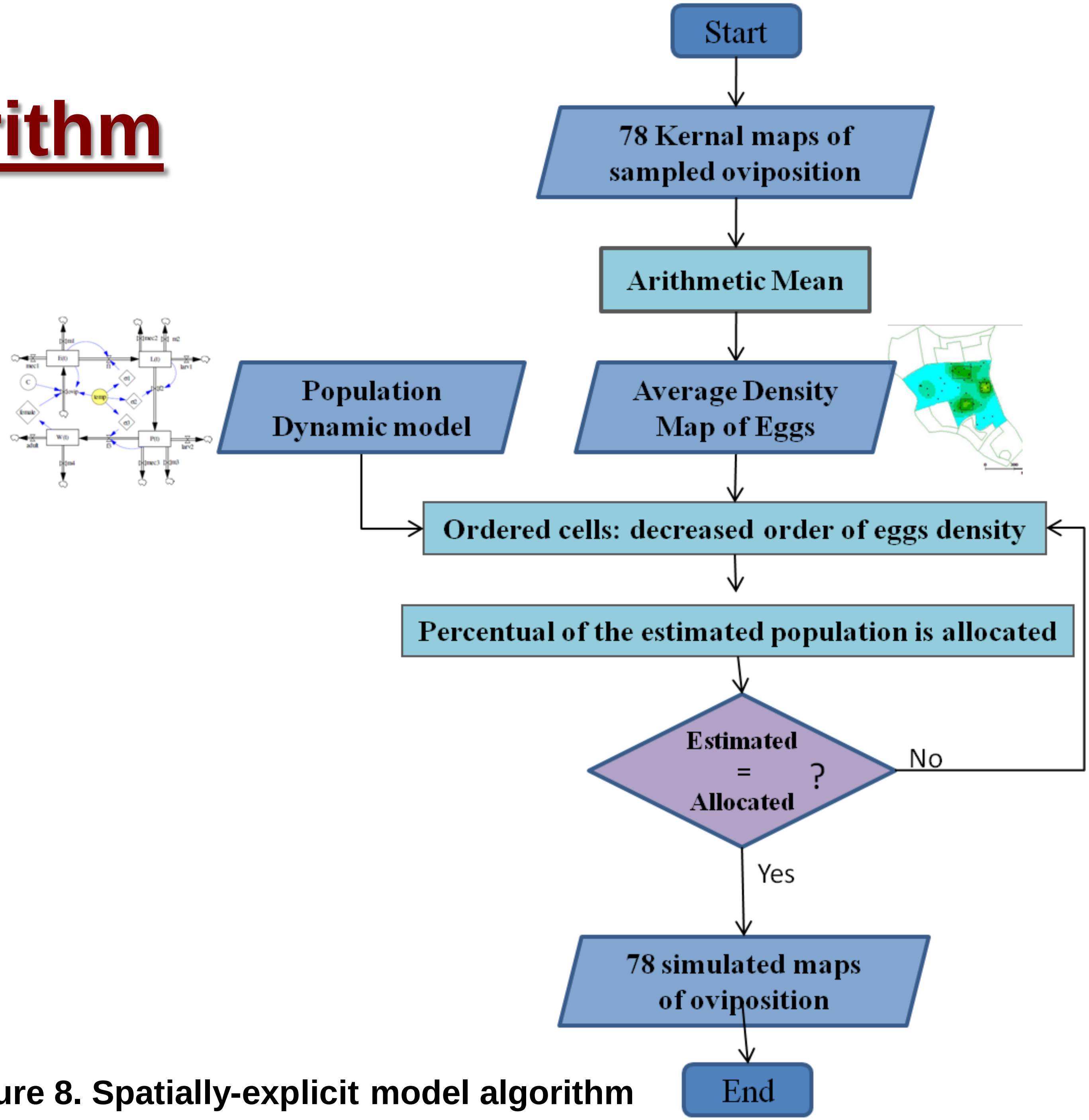


Figure 8. Spatially-explicit model algorithm

Results and Future Works

An approach to **allocate** the *Aedes aegypti* population on the **real space**.

The allocation algorithm based on **Kernel** estimator map.

Parameterizing and integrating to a **geographical database** for the Higienópolis district from Rio de Janeiro city, RJ, Brazil.

- Temperature: **less** responsive to control the model.
- Winter: **largest** discrepancy.
- **Underestimating** the quantity of weekly deposited eggs.

Figure 9. Graph of comparing between Observed oviposition (OO) and Simulated oviposition (SO) in Population Dynamic Model. The blue line, *temp, is the temperature time series.*

Several factors can be contributed for this **imperfection**:

- Just on 1.5 years of sampling

- The Higienópolis neighborhood is not an isolated place

Despite the **simplifications** introduced in the **spatialization** of the model, the model was **capable** of capturing the **spatial pattern** of eggs density.

Despite this spatial similarity, though, simulated and observed maps **differ** in the intensity of the mosquito abundance.

Filme

Neglecting the interactions between **spatial heterogeneity** and the **growth of the mosquito population**.

- Whole district as a **homogeneous** area.
- It does not consider the **spread** of mosquito by flight.

Other simplification: 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

Investigating **integrated methods** to develop spatial dynamic models for the *Aedes aegypti* life cycle.

Evaluating each **improvement** of *Aedes aegypti* population dynamic model.

The spatial structure will be **dynamic** and population dynamics will be governed by **autonomous populations** located in **each cell**.

Dispersion of mosquitoes by flight will be also considered.

Simulation of control **strategies** to evaluate their efficiency.

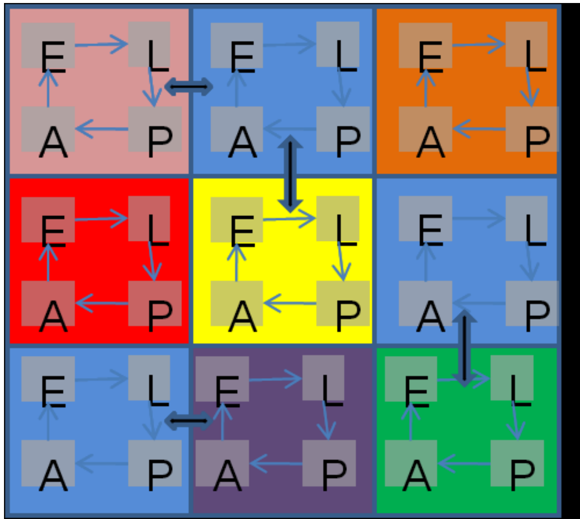


Figure 10. Autonomous *Aedes aegypti* populations occupy each space cell. Mosquitoes may fly to the neighbor cells indicated by blue arrows. E: egg, L: larva, P: pupa and A: adult.

Comparison of population dynamics models

(Preliminary Analysis)

Objectives

Real capacity of dynamic models to simulate the life cycle of *Aedes aegypti*.

Impact of these contributions on the conceptual complexity and representation of the model.

Methodology

Population dynamic models for *Aedes aegypti*

Sensitivity analysis

Calibration

Validation

Study Area and Sampled Design

The data used in this work (eggs collection) was collected by Honório et al., (2009).

1.5 years of weekly collections with ovitraps (Honório et al. 2009) for three neighborhoods of Rio de Janeiro:

- Higienópolis
- Tubiacanga
- Palmares

Temperature was collected from Rio de Janeiro's international airport.

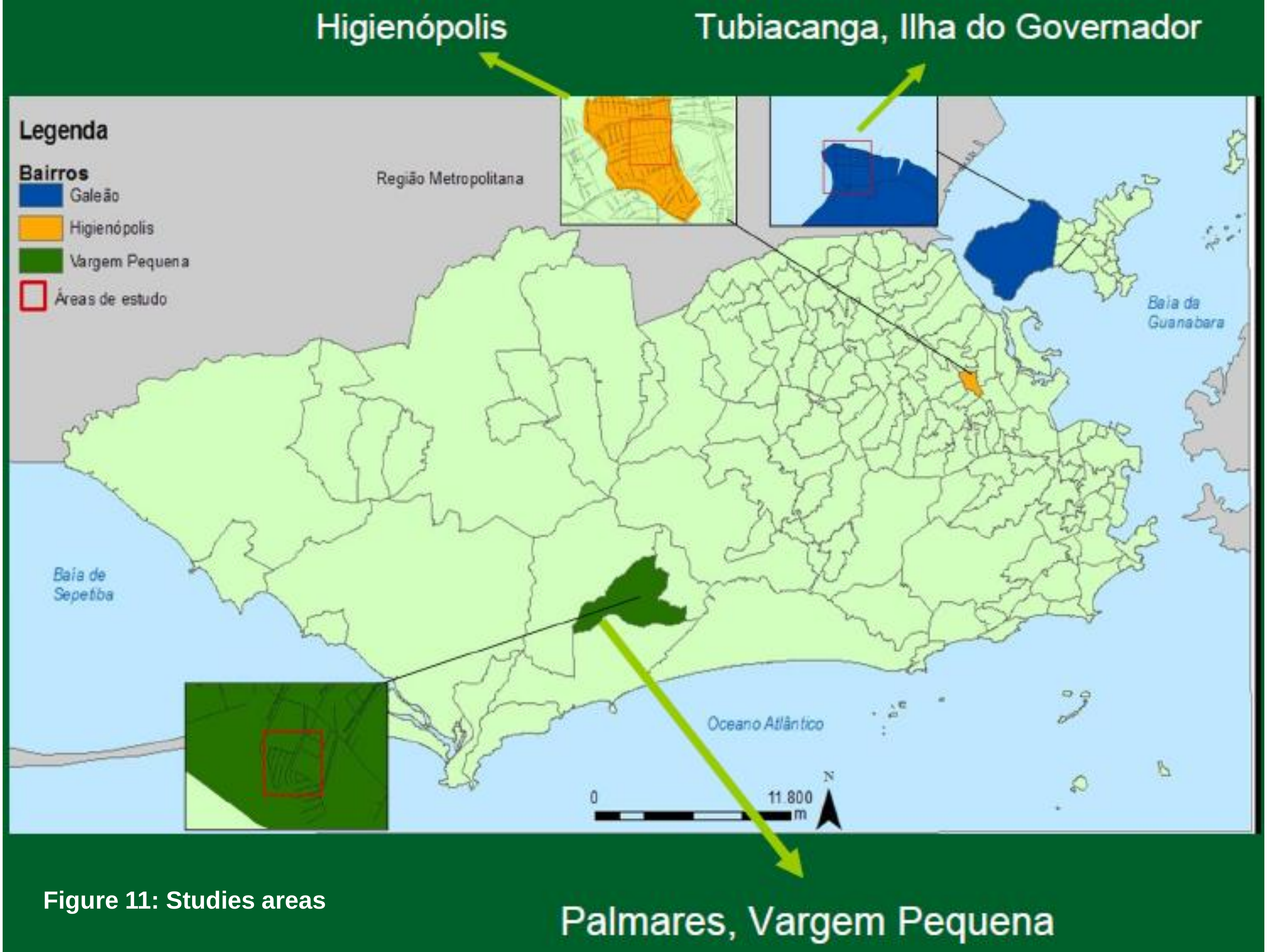
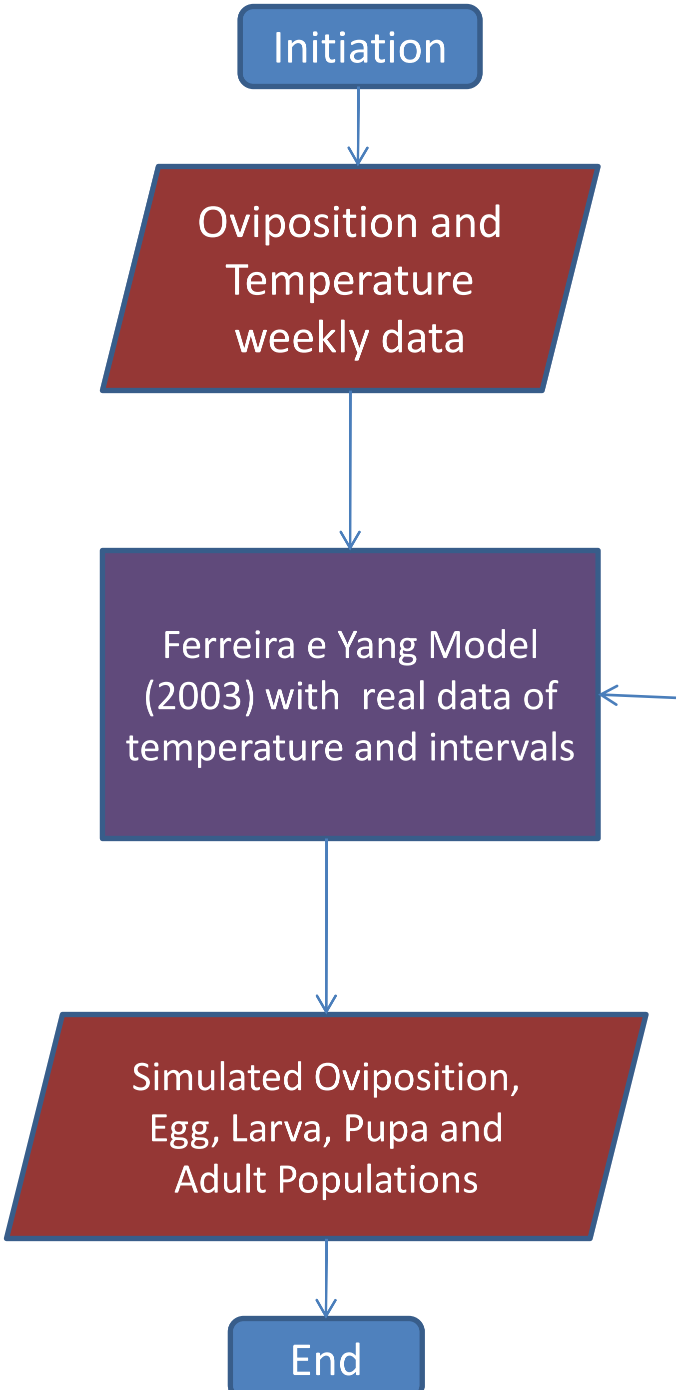
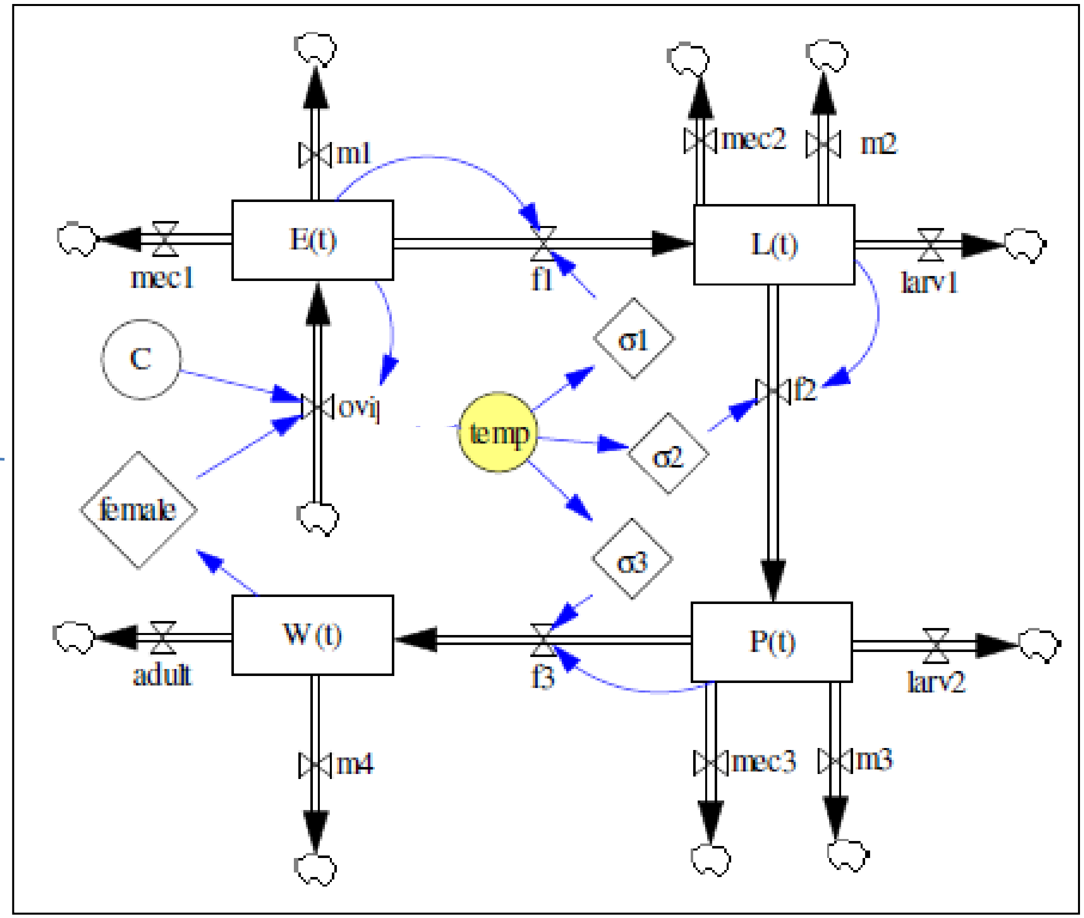


Figure 11: Studies areas

Model 1

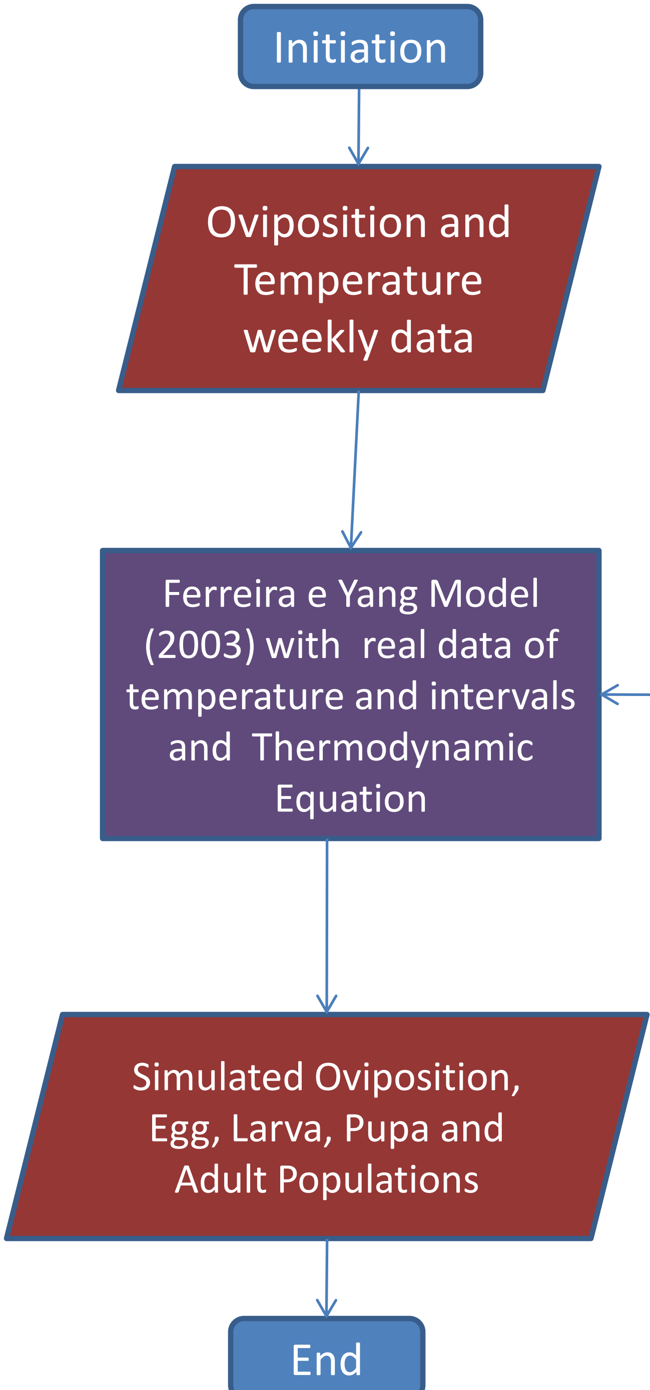


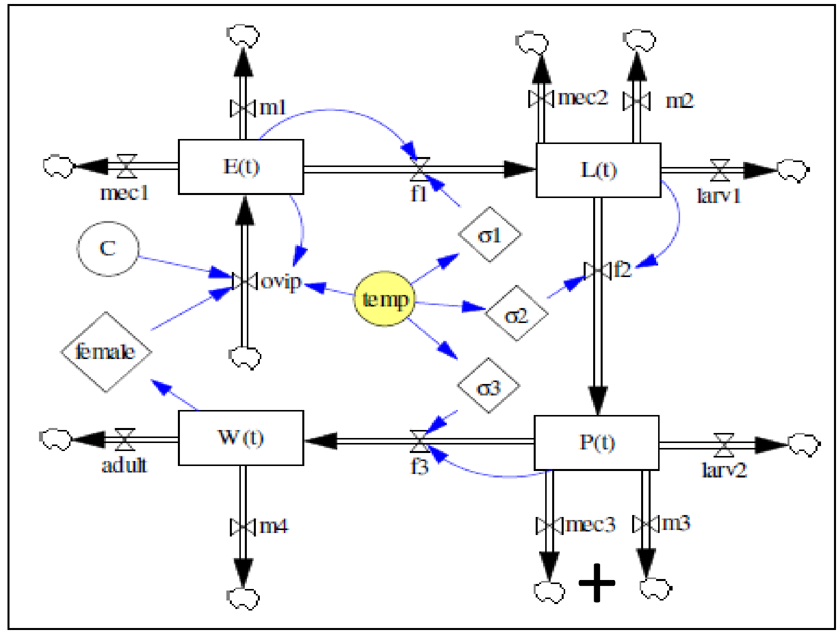
Initiation
Oviposition and Temperature weekly data
Ferreira e Yang Model (2003) with real data of temperature and intervals
Simulated Oviposition, Egg, Larva, Pupa and Adult Populations
End



E(t)
L(t)
P(t)
W(t)
m1
mec1
f1
mec2
m2
larv1
σ1
C
ovi
temp
σ2
f2
female
σ3
adult
f3
larv2
m4
mec3
m3

Model 2





$$R_D(T) = R_D(298^{\circ}K)\frac{(T/298^{\circ}K)\exp((\Delta H_A/R)(1/298^{\circ}K - 1/T))}{1+\exp(\Delta H_H/R)(1/T_{1/2} - 1/T))}$$

Model 3

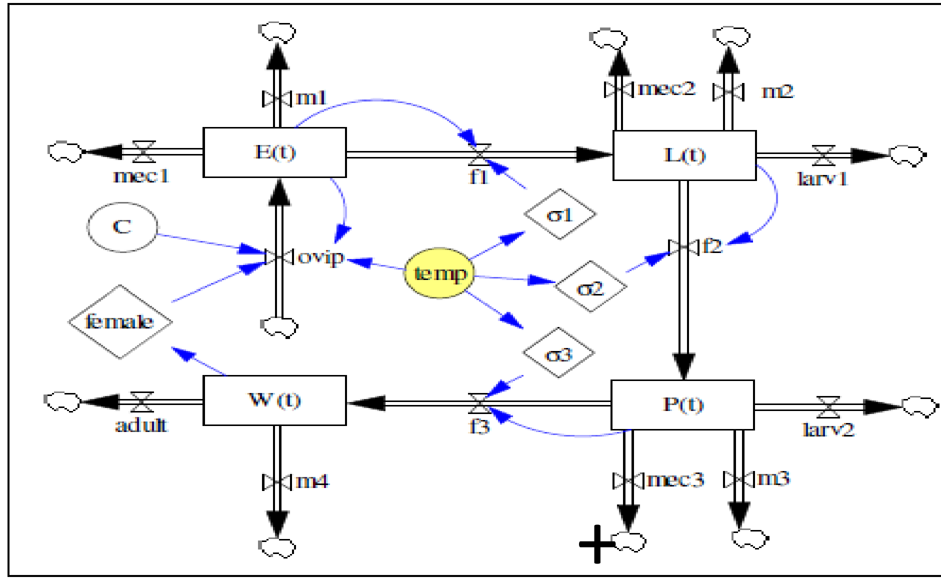
Initiation

Oviposition and Temperature weekly data

Ferreira e Yang Model (2003) with real data of temperature and intervals and Carrying Capacity limited by larvae populations

Simulated Oviposition, Egg, Larva, Pupa and Adult Populations

End



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

Model 4

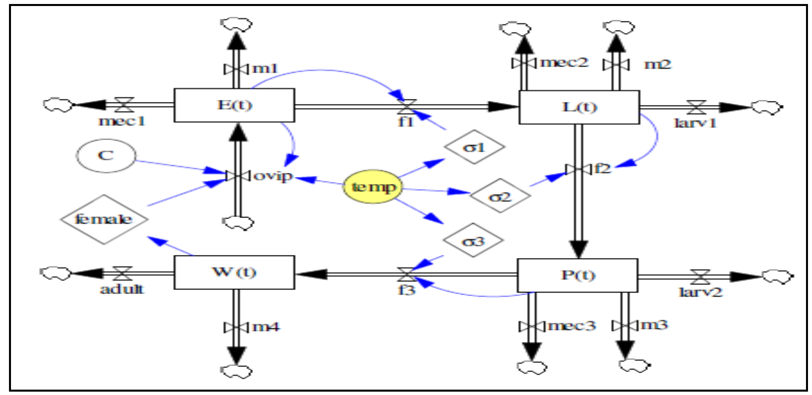
Initiation

Oviposition and Temperature weekly data

Ferreira e Yang Model (2003) with real data of temperature and intervals and Oviposition Equation

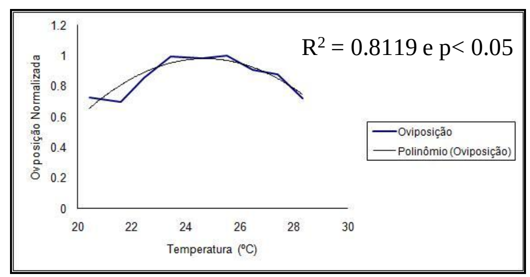
Simulated Oviposition, Egg, Larva, Pupa and Adult Populations

End



+

$$TxOvip = -0.0176*(Temp)^2 + 0.8714*Temp - 9.7903$$



Model 5

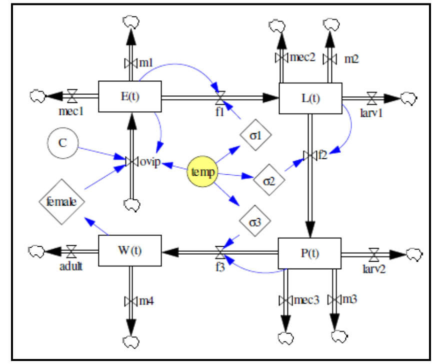
Initiation

Oviposition and Temperature weekly data

Ferreira e Yang Model (2003) with real data of temperature, Thermodynamic Equation and Carrying Capacity limited by larvae populations

Simulated Oviposition, Egg, Larva, Pupa and Adult Populations

End



+

$$R_D(T) = R_D(298^{\circ}K)\frac{(T/298^{\circ}K)\exp((\Delta H_A/R)(1/298^{\circ}K - 1/T))}{1+\exp(\Delta H_H/R)(1/T_{1/2} - 1/T))}$$

+

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

Model 6

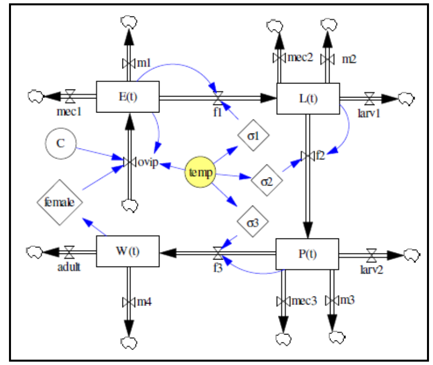
Initiation

Oviposition and Temperature weekly data

Ferreira e Yang Model (2003) with real data of temperature, Thermodynamic Equation and Oviposition Equation

Simulated Oviposition, Egg, Larva, Pupa and Adult Populations

End



+

$$R_D(T) = R_D(298^\circ K)\frac{(T/298^\circ K)\exp((\Delta H_A/R)(1/298^\circ K - 1/T))}{1+\exp(\Delta H_H/R)(1/T_{1/2} - 1/T))}$$

+

$$TxOvip = -0.0176*(Temp)^2 + 0.8714*Temp - 9.7903$$

Initiation

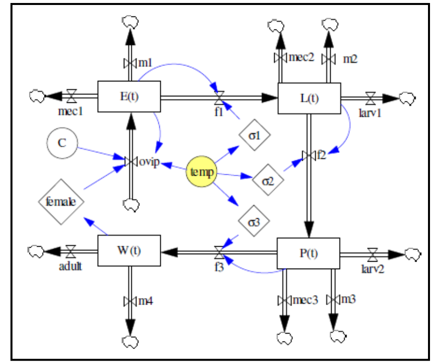
Oviposition and Temperature weekly data

Ferreira e Yang Model (2003) with real data of temperature, Carrying Capacity limited by larvae populations and Oviposition Equation

Simulated Oviposition, Egg, Larva, Pupa and Adult Populations

End

Model 7



+

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

+

$$TxOvip = -0.0176*(Temp)^2 + 0.8714*Temp - 9.7903$$

Initiation

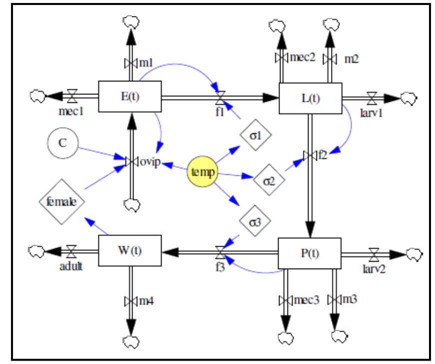
Oviposition and Temperature weekly data

Ferreira e Yang Model (2003) with real data of temperature, Thermodynamic Equation, Carrying Capacity limited by larvae populations and Oviposition Equation

Simulated Oviposition, Egg, Larva, Pupa and Adult Populations

End

Model 8



+

$$R_D(T) = R_D(298^\circ K)\frac{(T/298^\circ K)\exp((\Delta H_A/R)(1/298^\circ K - 1/T))}{1+\exp(\Delta H_H/R)(1/T_{1/2} - 1/T))}$$

+

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

+

$$TxOvip = -0.0176*(Temp)^2 + 0.8714*Temp - 9.7903$$

Sensitivity Analysis

Models Behavior

Free parameter: Carrying Capacity, C

Values: 100, 500, 1000

Calibration

Estimative of Carrying Capacity

Dividing into two subsets

First group of data:

- Monte Carlo method to minimize the quadratic average error
- 2000 iterations to 10000 MC experiments

Validation

Second group of data

- Provided as models input
- Comparison between the errors of calibration and validation

Results

Table 2: Average errors for model calibration and coefficient of variation

Model	Mean	SD	Variance	Coef Variation
Model 1	0.916077	0.097116	0.009432	10.6013
Model 2	0.497158	0.063467	0.004028	12.766
Model 3	0.599687	0.073435	0.005393	12.2455
Model 4	0.964621	0.060785	0.003695	6.30145
Model 5	0.43626	0.076079	0.005788	17.4388
Model 6	0.489825	0.063655	0.004052	12.9954
Model 7	0.734259	0.242422	0.058768	33.0158
Model 8	0.440975	0.07355	0.00541	16.6789

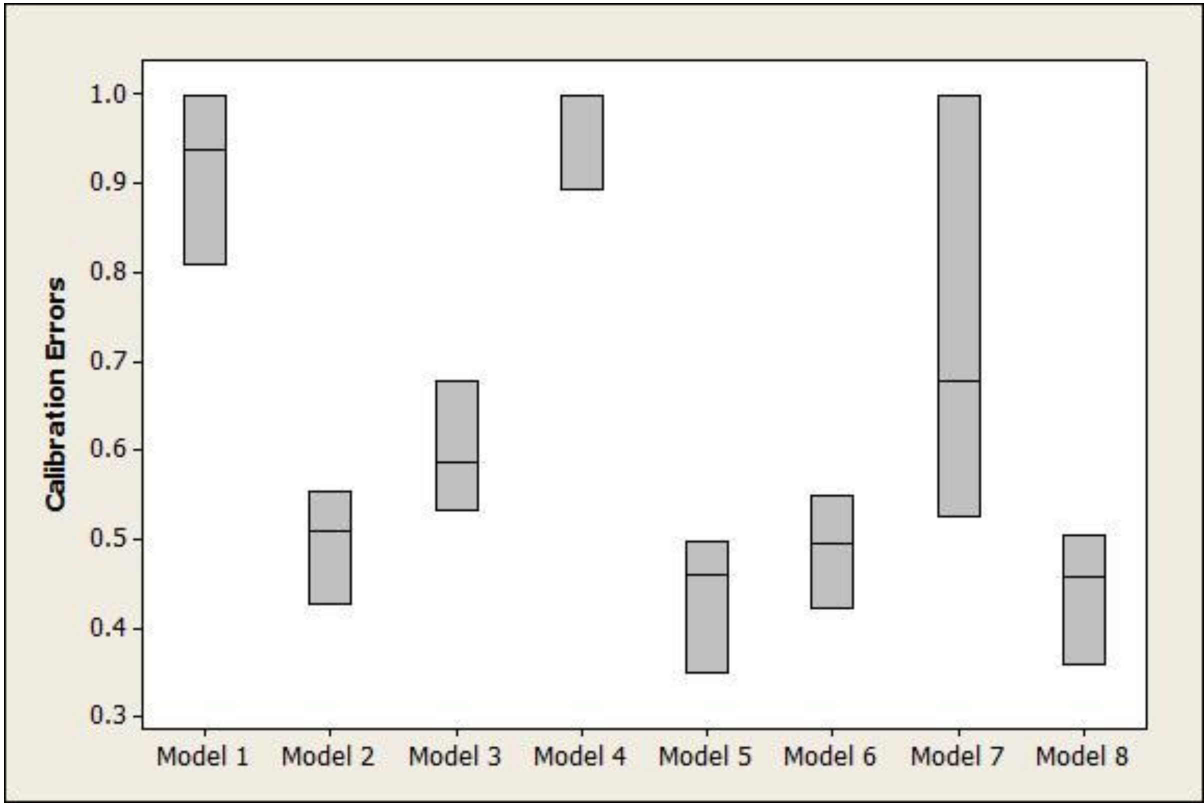


Figure 12 : Average errors for model calibration

Results

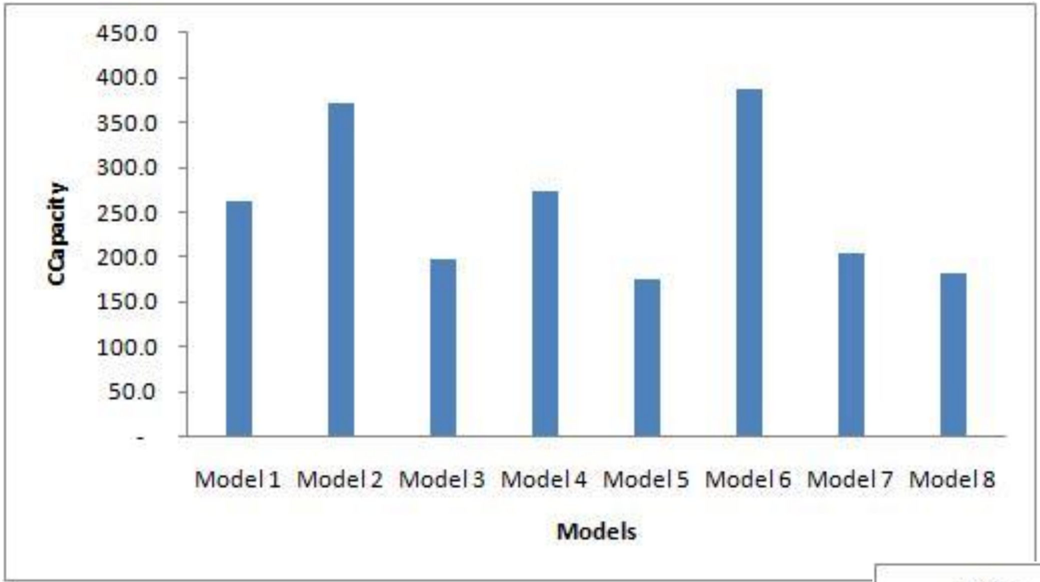


Figure 13 : Average CCapacity for model

Table 3: Average CCapacity for model and coefficient of variation

Model	CCapacity Average	Coef Var
Model 1	261	42.1508
Model 2	370.333	41.6335
Model 3	196.667	41.4846
Model 4	272.667	41.8179
Model 5	176	41.5239
Model 6	387	41.2151
Model 7	204.333	45.5279
Model 8	181.333	41.0849

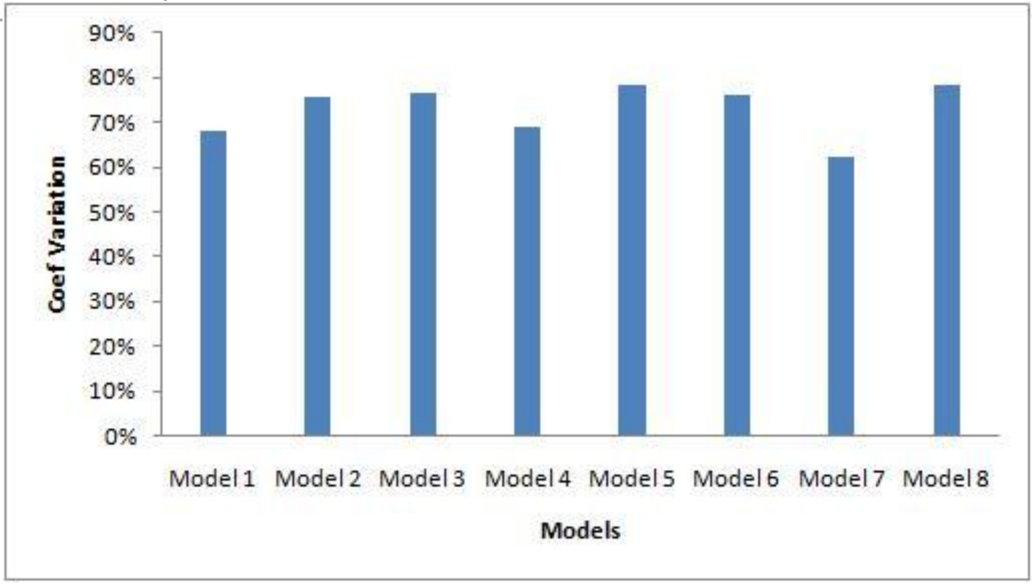


Figure 14 : Coefficient of Variation of Average CCapacity

Results

Table 4: Comparison between Calibration and Validation Errors

Model	Higienópolis	Palmares	Tubiacanga
Model 1	0%	8%	1%
Model 2	14%	20%	2%
Model 3	9%	11%	6%
Model 4	0%	11%	0%
Model 5	12%	29%	1%
Model 6	14%	22%	1%
Model 7	10%	43%	2%
Model 8	13%	27%	1%

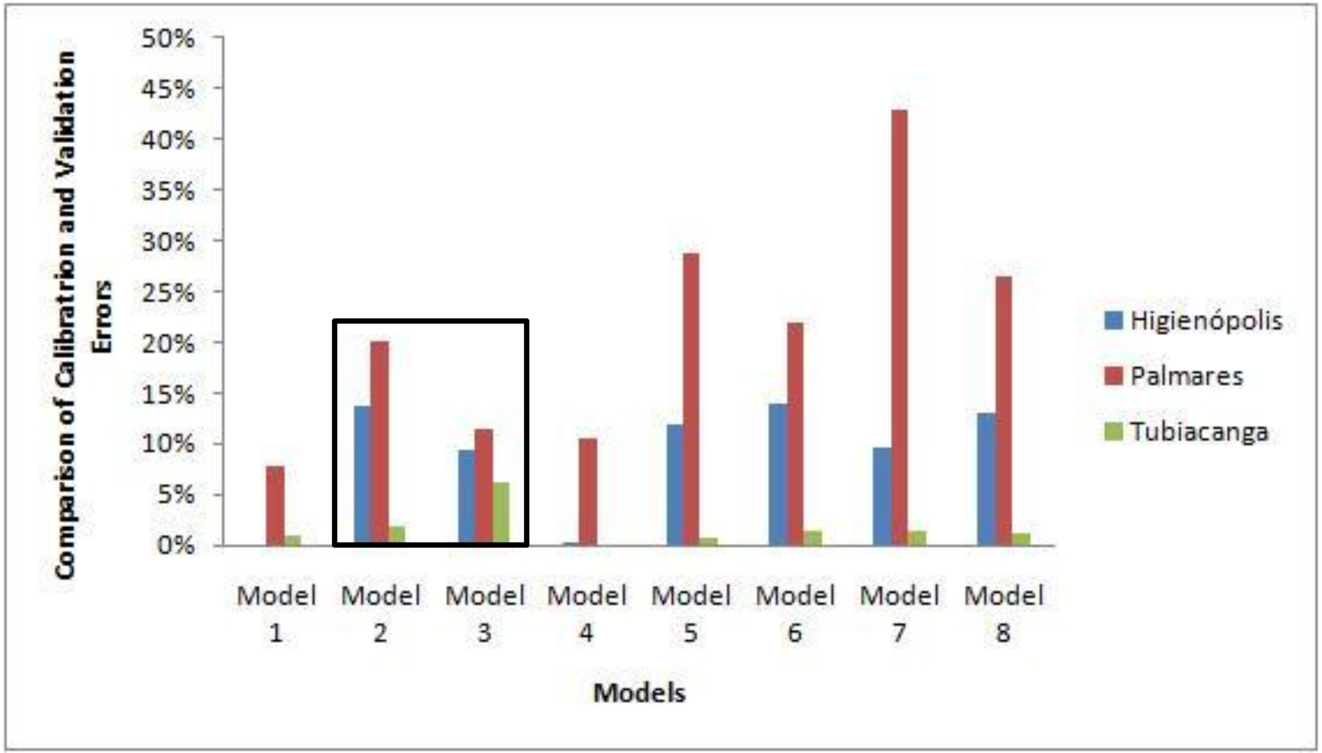


Figure 15: Comparison between Calibration and Validation errors

Conclusion

Models were parameterized, calibrated and validated for all neighborhoods.

However, calibration and validation for some models were not great.

The model of highest complexity no obtains the best fit, in contrary of expectations.

Conclusion

Models with one improvement showed lowest errors.

Factors that can have contributed for imperfections:

- Less than 2 cycles of temporal series data
- External influences

Future Works

Investigating problems on the models that causes big errors.

Improving mathematics and statistics.

Testing and comparing stochastic models.

Chronogram

Steps

First step:
Training student's scientific initiation

Second step:
Evaluation of Deterministic Models for Population Dynamics of Aedes aegypti

Third step:
Evaluation of Stochastic Models for Population Dynamics of Aedes aegypti

Fourth step:
Evaluation of Spatially-Explicit Models for Population Dynamics of Aedes aegypti

Fifth step:
Spatially-Explicit Population Control

Sixth step:
Construction of the Software for Identifying Priority Areas for Control

Working Partnerships

Multidisciplinary Project

Interaction between different types of professionals

TerraLab example:

- Biologist: define and understand the model
- Computer Scientist: simplicity of implementation
- Current problem of this partnership: difficulties related to advanced mathematics

Acknowledgments

UFOP
Universidade Federal de Ouro Preto

Master Program in Ecology of Tropical Biomes

TerraLAB

CNPq
Conselho Nacional de Desenvolvimento Científico e Tecnológico

Pronex Rede Dengue

tiagogsc@gmail.com
raquelmlana@gmail.com
fernando.filipereis@gmail.com

www.terralab.ufop.br