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Review

Multi-agent modeling and simulation of an *Aedes aegypti* mosquito population

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ABSTRACT

The present work deals with the simulation of a mosquito *Aedes aegypti* population. The mosquito population was modeled using an individual-based approach. The model consists of agents representing *A. aegypti* mosquitoes, human beings, some mammals and objects found in urban environments such as walls and water containers. We describe the model which was implemented by multi-agent systems in the Repast framework. Simulations were performed and the results were compared with those obtained in a biological experiment, and data obtained from a local Zoonozes control center. Comparisons between real and simulated data showed high correlation indices. We simulated cases to study whether or not an artificial trap can be effectively used as an active based population control measure. We studied how the number of traps and their localization can affect the population dynamics.

1. Introduction

Dengue virus, an arthropod-borne viral agent causes two types of diseases, classic dengue fever and dengue hemorrhagic fever. Regarded as a major public health concern, the disease is transmitted by infected female mosquitoes of the genus *Aedes* while blood feeding. Dengue is endemic in several countries worldwide, and public expenses to cover treatment have risen significantly. Global warming will certainly affect the abundance and distribution of the disease vector. The mosquito population has expanded into new geographical areas and increasingly higher latitudes (Houghton et al., 1997; Peterson, 1998).

Currently, dengue can only be reduced by mosquito control as no antiviral drugs and vaccines are available. The main insect vector control measure consists of eliminating open water storage containers to prevent adult insects from reproducing (World Health Organization, 2002). The problem with eliminating water storage in an urban environment is that it is dependent upon population engagement and education. Since the main problem regarding control measures of mosquito-borne diseases is related to insect infestation control, some of the main questions raised are 'what is the size of a mosquito population in a particular area?' 'what is the spatial and temporal dynamics of such population?' which leads to 'what can be done to control such a population?' The answers to these questions are determining factors in the decision-making processes for designing efficient control measures.

Nowadays, estimates of a mosquito population size may be calculated by the number of mosquito larvae found in a particular surveyed area. However, the larval survey is not accurate and it does not provide a reliable estimate of the population, or tips about its dynamics. Methods to estimate the mosquito population size are based on the direct counting of individuals in an area, using adult traps, backpack aspirators, or human landing counts.

Computational simulation has been employed to support decision-making processes. A computer-based simulation works as a virtual laboratory where a what-if statement is raised and answered and is used in order to increase the overall knowledge and understanding of a specific subject (Chung, 2003). Computational simulation may provide answers to difficult questions limited by economical, environmental, ethical, technological and scientific matters (Peck, 2004).

Population dynamics models found in literature can be analytical models (Dye, 1984), models based on systems of differential equations (Dye, 1984; Williams et al., 2008) or individual-based

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models (Ferguson et al., 2003). Some of the principal differences among these model types are based on questions about aggregation assumptions. They can be represented by closed mathematical expressions, systems of differential equations, or by individual computational descriptions (Rahmandad and Sterman, 2008; Fahse et al., 1998; Parunak et al., 1998). These models are not incompatible but complementary and each has strengths and weaknesses. Differential equation based models assume homogeneity and mixing compartments (Rahmandad and Sterman, 2008). Agent-based models can represent the agent heterogeneity and the agent interrelationships network.

Investigations have been undertaken to assess population dynamics of mosquitoes (Focks et al., 1993a, b; Yang et al., 2002; Ferreira and Yang, 2003; Yang, 2003), as well as dengue transmission dynamics (Derouich et al., 2003; Leonel and Yoneyama, 2000; Focks et al., 1995; Williams et al., 2008).

The simulation models of mosquito populations reported in literature are not aimed at simulating the behavior of individuals or small groups of mosquitoes. Nevertheless, the control of mosquito populations is actually carried out from house-to-house, street-to-street, always based on small areas, whose infestation is affected by both geographical and social characteristics (Grand Challenges in Global Health, 2009).

An *A. aegypti* population simulator was proposed by Focks et al. (1993b) for which CIMSiM, a site-specific model, was used. It is a dynamic life table simulation entomological model which produces mean-value estimates of various parameters for all cohorts of a single species of *Aedes* mosquito within a representative area of one *hectare*. This dynamic life table simulation entomological model maintains information about a mosquito group throughout its environment, such as temperature and humidity.

Computational monolitical mathematical models fail to simulate environmental features and mathematical equation representations of qualitative characteristics, such as preferences and behaviors, may differ between individuals of the same species (Parunak et al., 1998). To overcome limitations of classical mathematical models, several investigations have used the individual-based modeling (IBM) approach. Grimm (1999) defines IBM as a computational model for simulating the actions and interactions of autonomous individuals in a network, and the characteristics of each individual are tracked through time. Individual-based models are also known as entity or agent-based models, and as individual/entity/agent-based simulations. Each individual is seen as a single entity with attributes such as age, weight and social status. As a result, these models typically consist of an environment or framework in which the interactions occur and individuals are defined by their emerging behaviors. These are not pre-programmed behaviors, but they emerge from local interactions (Grimm and Railsback, 2005). An important example of how an individual-based model can be used to lead with complex problems is described in (Barrett et al., 2005). There are many other recent works (Athanasiadis et al., 2009; Bithell and Brasington, 2009; Bomblies et al., 2008; Perez and Dragicevic, 2009; Rao et al., 2008;).

This paper provides a model and a computational tool for simulating the dynamics of *A. aegypti* population, *SimPopMosq*. Our aim is to simulate mosquito population, which present in small geographical area such as: a single home, a group of houses, or a city block. The simulator uses a multi-agent system (MAS), in which each individual is modeled and the model is carried out by a computational agent capable of interacting with the environment and with other agents using sensors and actors (Sandholm, 1999; Wooldridge, 2002; Vlassis, 2003). The developed simulator can, for example, simulate a house and its inhabitants, objects and mosquitoes flying within its limits. It is possible to simulate the dynamics of an *A. aegypti* mosquito population in a controlled environment in order to observe the group dynamics of mosquitoes under particular constraints, such as lack of water or blood for feeding. The degree of detail in the simulated environment can be increased. For example, it is possible to model and simulate a house, a city block, or a neighborhood. One objective of the proposed model is to explore how the mosquito population can be affected by small-scale distributed actions: how can people in their living environment change the mosquito population dynamics? The *SimPopMosq* model can provide spatial, temporal, and state details of each agent in the simulation. The model can also specify special behaviors for each agent. We want to use the model to study how these behaviors could affect the mosquito population (Anholt, 1997). An agent-based model can define specifications for each agent, group of agents, and objects without modeling overhead (the environment can be specified in detail: position of walls, windows, doors, and when they are opened or closed and the spatial and temporal distribution of agents and objects in the environment). People living in infestation areas implement simple practices such as keeping windows closed during the day, and the keeping the lights off at night can help to keep home infestations to a minimum. The proposed model can be used to evaluate the effectiveness of this kind of popular knowledge. This kind of bottom-up simulation modeling is not very suitable for equation based models, unless you do not have problems with solving rather large differential equation systems with deeply detailed boundary conditions (Parunak et al., 1998).

We manually calibrated the parameters of the proposed model and performed several oriented simulations. Two real experimental databases were used to calibrate and validate the model. The first data base was obtained with an experiment conducted in a greenhouse, which was used as controlled environment. The second data base was obtained from the Zoonoses department of Belo Horizonte, Brazil. This second data base was developed using real infestation data gathered while using in-practice techniques to control the mosquito population. The simulation model was used to test the effectiveness of a trap applied (BG-Sentinel trap) (Kröckel et al., 2006) for active mosquito population control. Some "what-if" simulation cases were tested to verify how the localization and/or the number of traps affect a mosquito population within a city block.

We consider that the structured definition of a decision-making model for *A. aegypti* as being a significant contribution of the simulation model proposed. We did not find a similar model in literature. A decision-making model is useful for understanding how the behavior of the mosquito can affect its population development.

The following sections are organized as follows: in section two, the simulator conceptual model, the proposed simulator and its components are described in technical terms and in terms of implementation; section three presents the results of the computer experiments and relates them to the construction and validation processes of the proposed models. Comments and conclusions are presented in section four.

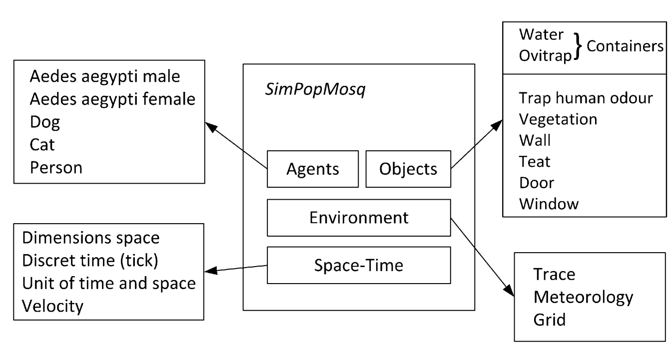

Fig. 1. Elements of the simulation model.

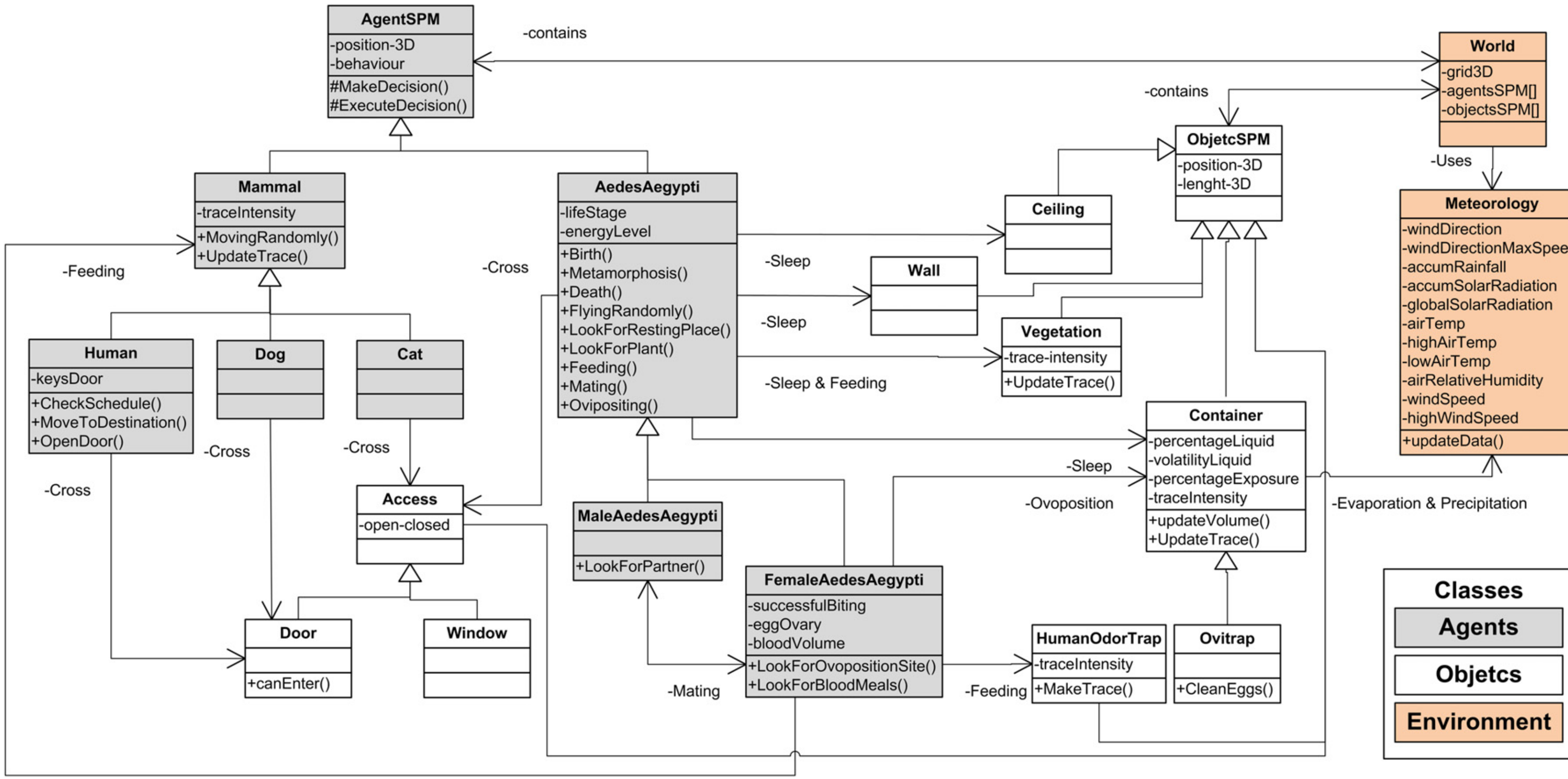

Fig. 2. UML class diagram of the agents, objects and the environment that composes the model.

2. Conceptual model

The simulation model proposed, *SimPopMosq*, is described using the ODD protocol (Overview, Design concepts and Details) proposed by Grimm et al. (2006). The ODD protocol was proposed to describe individual-based modeling (IBM). It consists of three main blocks – overview, design concepts and details.

The simulator was developed using Recursive Porous Agent Simulation Toolkit (Repast), version 3.0 (North et al., 2006). Several factors have contributed to this choice, including the structure of object orientation offered by this framework. The programming language used for developing the simulator was Java. Therefore, it can run in any operational system equipped with a Java virtual machine.

The simulation model is divided into layers, Fig. 1 illustrates the set elements which comprise the simulation model.

If we observe the levels presented in Fig. 1 in an ascending way, we notice the definitions of some basic properties of the system, such as: timescale, definition of the space, definition of shifts and speeds. The "environment" layer contains elements that can be inserted into simulation settings, such as: diffusion trace, weather variables (rain, solar radiation, wind, etc.) and the geo-referenced space where other elements such as agents and objects can be inserted. And above the other levels objects and agents, which depend on lower layers to function, which may be used in computer simulations. Next, the layers presented in Fig. 1 are described along with their elements and properties.

2.1. Overview

2.1.1. Purpose

An understanding of the population dynamics of *A. aegypti* populations is necessary for adopting policies to implement efficient control measures. In order to access estimates of the population dynamics, a simulation model for *A. aegypti* populations has been proposed. The aim of the computational model is to allow analysis of the population dynamics of *A. aegypti* in order to estimate the population size under different environmental conditions. This analysis was made by considering the mosquito population during the egg and adult life stages, availability of water-holding containers and food in environments in which size may range from tens to hundreds of square meters. To date, there are few strategies for directly estimating the population *of A. aegypti* mosquitoes in a given region. For example, it is possible by using BG-Sentinel traps (Kröckel et al., 2006) for host-seeking females and MosquiTRAP (Maciel-de-Freitas et al., 2008) for gravid females.

2.1.2. State variables and scales

The *SimPopMosq* model comprises agents (mosquitoes, humans, dogs, and cats), objects (vegetation, water containers, traps, ceilings and walls) and their physical environment. Fig. 2 presents the UML class diagram of the agents, objects and the environment that composes the model.

The spatial reference of agents and objects indicates their location at a particular time in the setting for the simulation (world). Location is given by combining three coordinate points, *x, y* and *z* (length, width and height). Length and width are discrete, whereas the *z* dimension is continuous. It was established that one discrete unit of simulated space would correspond with *50* centimeters in the real world. One or more elements (agents and/or objects) can occupy the same cell. Each cell has a linked list of elements which stores the elements sequentially.

Time is modeled by discrete execution units called *ticks,* which constitute one unit of artificial time adopted by the framework Repast, corresponding to 1-second. The notion of time is converted to standard units of date and time. The standardized units of time, space and speed are seconds (s), meters (m) and meters/second (m/s).

Traces are left by agents and objects, such as: *A. aegypti, mammals, traps with human odor, water* and *vegetation.* Such traces are used for modeling the visual field and the dispersion fields of chemicals. Each element has parameters pointing out the lowest and the highest trace levels that can be emitted. The trace intensity emitted by an element is defined by producing a random number defined between these parameters. The diffusion model for estimating traces was inspired by the model available in the multi-agent framework Swarm (Swarm Development Group, 2004; Minar et al., 1996).

The main computational agents of the simulation tool are the *A. aegypti* mosquitoes. The purpose of the system is related to *A. aegypti* mosquitoes. Male and female mosquitoes have some variables in common and some gender related traits. Each mosquito has the following state variables:

(i) *Energy level (seconds)* – energy level will affect decision making by the agent. This is a variable property and its values range from 0 to 259,200 s. The mosquito maximum energy is calculated considering the number of days that a mosquito can survive without feeding 3 days = 259,200 s (Costero et al., 1999), so the energy level measures the number of seconds that a mosquito may stay alive without feeding.
(ii) *Stage* – the stages, which the *A. aegypti* agent may undergo: *egg, larva, pupa, adult* and *dead*. The stage defines the mosquito's behavior. This variable can assume four possible values, programmed as enumerable types.
(iii) *Behavior/current status* – mosquitoes behave in different ways. Their behaviors are defined by variables which can assume some different values (enumerable types). They may, for instance, display the following behaviors:
  (a) Common – flying randomly, looking for a resting place, looking for a sap-based meal, feeding, mating,
  (b) Male – looking for a female,
  (c) Female – looking for an oviposition place, looking for blood feeding, ovipositing, copulated, trying to bite a mammal normal, trying to bite a mammal fast;
  (iv) Other female mosquitoes variables are:
  (a) number of eggs in the ovary (integer),
  (b) *Trace intensity* – every mosquito owns a trace intensity that can be perceived by other agents. This is a variable property and its values range randomly between 3000 and 10,000 *trace units*,
  (c) *Energy level related with blood feeding* – female mosquitoes need a "*specific*" sort of energy to mature their eggs. This energy is provided by blood feeding. The higher the amount of blood consumed, the more likely are the eggs to hatch;

The mammals agents: human, dogs and cats present in the simulation will be the blood source for the *A. aegypti* females. They have common state variables:

(a) *ongoing behavior* – which can affect the agent's speed (moving or stopped) – Boolean variable;
(b) *trace intensity* – which can affect attraction of the mosquito female

The human agents have a task schedule that may be programmed. If the task is not informed they follow random movements.

The objects present in the model are: vegetation, water-holding containers, ovitrap, human odor trap (BG-Sentinel trap) (Kröckel et al., 2006), ceilings and walls. Water-holding containers and object ovitrap (a trap for capturing eggs) are liquid containers which have the following state variables, p*ercentage of liquid, volatility of liquid* and *percentage of exposure.* The difference between water-holding container and ovitrap is the intensity of the trace emitted.

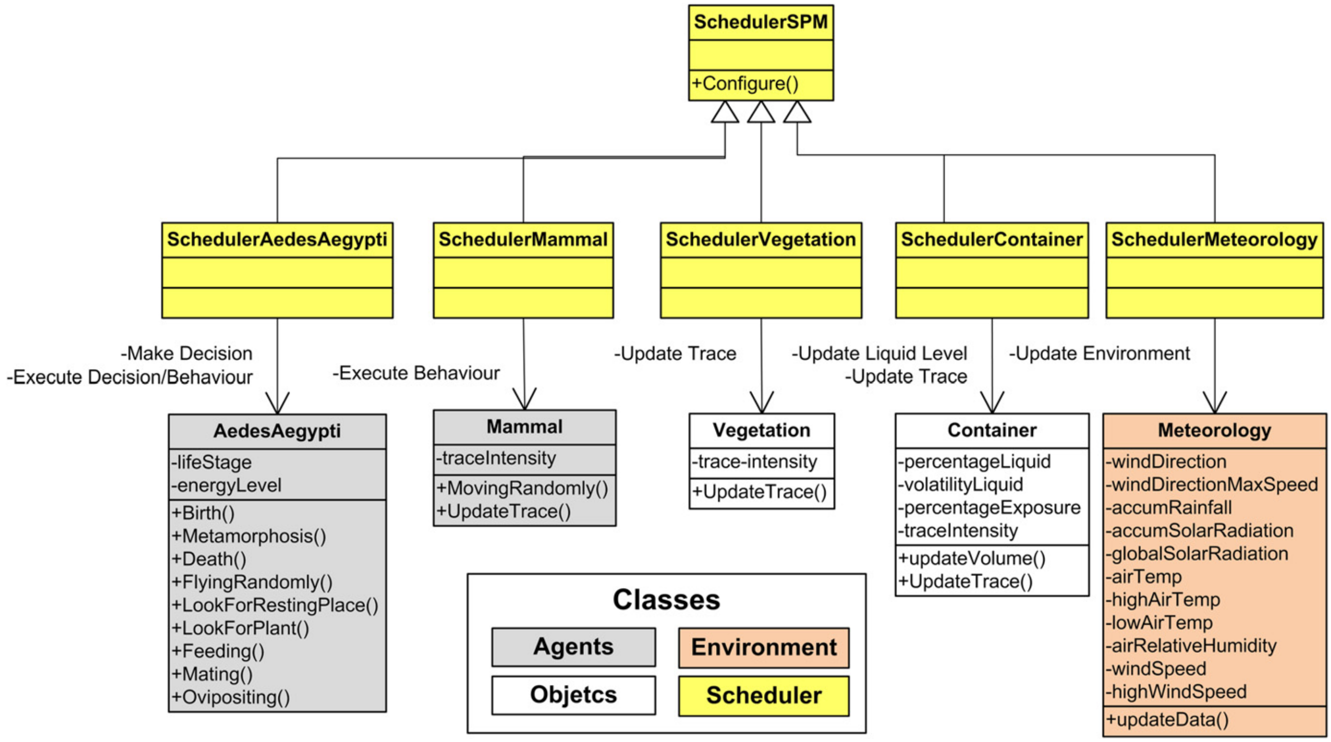

Fig. 3. UML class diagram of the schedules classes.

Furthermore, eggs laid onto the ovitrap are eliminated. The second type of trap called "human odor trap" emits traces similar to those of mammal agents and attracts adult female mosquito. Upon entering the trap, the mosquitoes are captured and eliminated.

Each vegetation object has its own trace, capable of attracting mosquitoes searching for sap-based feeding or for a place to rest. They have position state variables and *trace intensity*.

The objects representing ceilings and walls are used for defining the geographic scenery to be simulated (houses, walls and plots of land). Access to restricted spaces can also be represented in the simulation sceneries. The forms of access that can be represented are doors and windows. The state variables for such objects are location, dimensions and whether they are open or closed.

2.1.2.1. Environment. The environment layer of the computational tool comprises elements that can be incorporated into simulations that may interact with agents and objects from upper layers. Some state variables set up the environment conditions: d*aylight period*, and weather variables. Weather conditions of the simulated environment are defined by global variables. The effects caused by such variables are used to calculate the water evaporation and rain which control the water level in the water containers. The weather variables used are: *accumulated rainfall (mm), air temperature (C), air relative humidity (%).*

2.1.3. Process overview and scheduling

Agent-related processes are performed based on the decisions made by each agent (decision-making process). Agents are autonomous and manage their own activities. In asynchronous updating, agent and object processes are performed at time intervals previously defined in the parameters of the simulation model. The asynchronous method randomly takes agents, objects and the environment processes one after another and updates all their individual schedules (North et al., 2006). Fig. 3 presents the UML class diagram of the schedules classes related to the agents, objects and environment that compose the model. The schedulers manage the sequence of actions in the simulation. Actions are individual events that occur in a simulation, and they are dependent on agent and object behaviors. Agent behavior causes actions to occur by registering them with a scheduler. The scheduler implemented is preemptive.

2.2. Design concepts

2.2.1. Emerging phenomena

The dynamics related to the *A. aegypti* population size may be seen as an emerging property of the simulation model.

2.2.2. Adaptability

The only agents whose behavior may be adapted according to their internal conditions or to those of their surrounding environment are female and male mosquitoes.

Female *A. aegypti* mosquitoes are able to adapt their behavior according to the following conditions:

1. Daylight period – behavior of female mosquitoes at night is different during day night. Females usually lay eggs at night; if it is not the oviposition period of a female, it will rest at night.
2. Energy level – daylight behavior of females depends on their current energy level. Chances are that if the female has a low (0 s) or medium (129,600 s) energy level, it will look for more food for their own nourishment. Fertilized females will look for blood meals.

Although the male is less complex than the female, its adaptation behaviors include:

1. *Daylight period* – male mosquitoes behave differently during daylight and at night. They usually rest at night.
2. *Energy level* – daylight behavior of males depends on their current energy level. If the male has a low or medium energy level, it will look for plant-based meals for its own nourishment.

3. *Female closeness level* – as the male mosquito notices the presence of a female, it changes to mating behavior.

2.2.3. Fitness

Grimm et al. (2006) define *Fitness* as the outcome of a certain behavior and *fitness-seeking* as a phenomenon searching for better behavior options, to improve the agent's conditions of survival.

The *fitness-seeking* process of modeled computational agents is implicit in the current work. Although agents are not capable of finding out how a decision can be more effective than another: they implicitly choose the behaviors that better fit their conditions (e.g. lack of water and blood feeding, etc.). They obey pre-defined behaviors pre-programmed in decision diagrams. They decide what to do based on their state and in the environment variables (see Subsection 2.3.2.3).

During oviposition periods, female lay their eggs randomly: different numbers and different times. This nonuniform distribution strategy minimizes the effects of a possible destruction of oviposition sites. The distribution adopted was based on the model proposed by Gomes et al. (2006).

A. aegypti mosquitoes adopt strategies taking advantage of their current situation. For instance, if a male notices a female approaching, the mating behavior is favored. Occasionally, if the female has eggs in its ovary and notices the presence of mammals around, it will take advantage of the situation by blood feeding, even if its energy level is plenty. The behavioral choices are based on rules codified as IF–THEN statements.

2.2.4. Sensing

The best way by which agents can detect the presence of a certain agent or object is by noticing the trace emitted by the explored element.

2.2.5. Interaction

Agents, objects, and environments interact in the simulated world since they are georeferred in this world and fulfill some physical space. Major interactions include:

1. Objects and environment – objects existing in the simulated world may interact with the environment as they emit traces. Water-holding containers leave humidity traces in the surrounding environment and vegetation emit sap traces. Water-holding containers can also collect water from rain falls.
2. Agents and environment – agents interact with the environment by emitting traces, as well as objects.
3. Agents and objects – agents interact with objects. This interaction takes place by physical contact among them. *A. aegypti* mosquitoes interact with vegetation as they land on it for either feeding or resting; as they do with water-holding containers during oviposition and larval development, as well as with objects such as walls, ceilings, doors and windows. In the experiments, only Human agents have access to some particular spaces. For example, a human agent can arrive at the front door of his house, open the door, enter the house, close the door. He or she can keep the windows and the doors closed do not allowing mosquitoes to enter his or her house.
4. Male and female *A. aegypti* – male and female mosquitoes interact by mating. When the male detects a female's trace, it gets closer and tries to mate. If the female is willing to mate, the agents remain together until the mating process is over.
5. Female *A. aegypti* and mammals – the female needs blood to provide enough nourishment for its eggs. It is guided by the mammal's trace (which emits an odor trace) and tries to bite it. If the attempt is successful, the mosquito will remain feeding for some time.

2.2.6. Stochastic model

The simulation model proposed in this work presents a stochastic behavior due to the several probabilistic transitions defined and configured based on pseudo-random numbers that are generated. The following elements are randomly produced:

1. Trace intensity of elements – trace are emitted at different intensities. This intensity is randomly chosen within a range determined for each element (agent, object).
2. Random displacement – *A. aegypti* and mammal agents can move randomly. Mosquitoes can also move along the *z*-axis.
3. Life cycle of *A. aegypti* – as the mosquitoes undergo changes at different stages, probabilities that can increase or decrease the length of each stage are associated.
4. *Aedes* female – there is an element of randomness for female *A. aegypti* regarding: reproduction (the number of eggs to be nourished); oviposition (the gender of born-to-be mosquitoes) and; blood feeding (successfulness of a blood feeding and death probability in a failed bite attempt).

2.2.7. Observations

One of the main issues raised and intended to be answered by the present simulation model is *How large is the mosquito population at a certain moment*? Population sizes of mosquitoes at different stages are recorded, as well as other variables that may contribute to analyzes of mosquito population dynamics. The main variables that can be observed and recorded in the model proposed are *the number of A. aegypti* mosquitoes at the stages: egg, larva, pupae and adult; the number of female and male; the number of *A. aegypti* at the stage egg and adult born in the last 24 h; biting rate; *ovitrap* positivity index; *ovitrap* density index; and positivity index of larvae and pupae inside *ovitrap* containers.

2.3. Details

2.3.1. Simulation control: initialization and input

Starting the simulation model needs formal specification of data and information such as:

1. Simulation setting – it includes configuring agents and objects to be added to the environment and the simulation sceneries

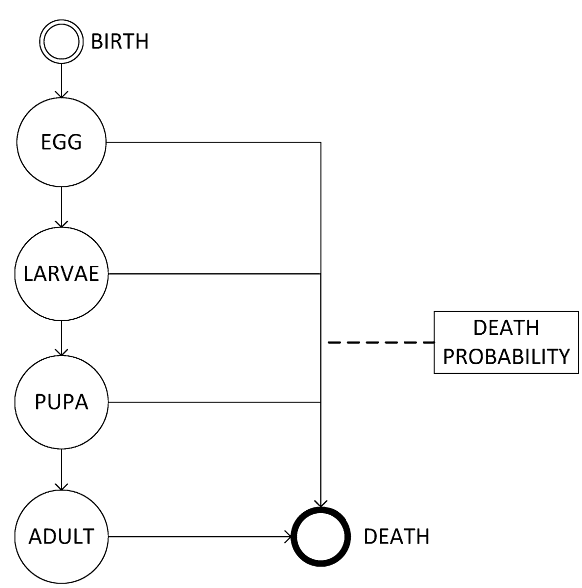

Fig. 4. Life cycle of mosquito agent *Aedes aegypti*.

must be defined. Simulation sceneries can be defined and stored into a repository. The following operations should be defined to build the simulation scenery:

(a) Space definition – width, length and height of *the virtual world* are defined. Height values for the *z* dimension are continuous and, if this dimension is not defined, it can have any value.
(b) Time definition – defining time in the simulation scenery means associating virtual time and date to the simulation. The main dates/times in the virtual world are: beginning of simulation, end of simulation and the current date and time.
(c) Object creation – configuring object installation in the simulation scenery is an important aspect. The positions of objects *in the virtual world* as well as their particular properties are defined.
(d) *Agent creation* – the agents participating in the simulation have to be defined, such as mosquitoes, mammals. For the *human* agents, the path and dynamics of displacement must be previously defined.

2. *Meteorological data* – environment variables are updated by data imported from weather databases and adapted to a previously defined pattern. The meteorological data used in the simulations follow the same data pattern from CPTEC-INPE (2009). Although extensive data are available in the simulation scenery, the current models for objects and agents do not make full use of them. The main data used in the present model are: air temperature, accumulated rainfall, and air relative humidity.
3. *Expected output* – the user can follow the evolution of each variable throughout the simulation. It is possible to point out the variable to be observed by a formal specification (XML file). Model parameters – the simulation model proposed is provided with a set of control parameters. The main parameters of the simulation model are shown in Subsection 2.3.2.

2.3.2. Submodels

The simulation model *SimPopMosq* comprises several submodels.

2.3.2.1. Diffusion model for estimating traces. Traces are left by agents and objects, such as: *A. aegypti, mammals, traps with human odor, water* and *vegetation.* Such traces are used for modeling the visual field and the dispersion fields of chemicals.

Trace emitting elements (agents and objects) have a property indicating the intensity of emitted traces. Each element has parameters indicating the lowest and the highest trace levels that can be emitted. The trace intensity emitted by an element is defined by generating a random number defined between these limits. The diffusion model for estimating traces was inspired in the model Cellular Automata model available in the multi-agent simulating framework Swarm (Swarm Development Group, 2004). The adopted equation for each cell is $i_n = t_e \times (i_a + c_d \times (m_v - i_a))$ where i_n is the new trace intensity, i_a is the actual cell trace intensity, t_e is a evaporation constant, c_d is a diffusion constant, m_v is the average of the eight neighborhood cells trace intensity. We adopted $c_d = 1$ and $t_e = 0.99$ as in Minar et al. (1996).

When we use these Diffusion model for modeling the visual field or dispersion fields of chemicals. The intensity values calculated represent points into a potential field (Hagelbäck and Johansson, 2008). The major intensity implies that the cell is localized nearest the element (which has emitted the trace).

2.3.2.2. Water level variation in water-holding containers. The water-holding containers in the simulation model show varying liquid levels because of weather changes, such as increased volume due to rainfall or decreased volume due to evaporation.

Liquid volume increase comprises a value increase of the liquid percentage variable in the container, according to the weather variable related to accumulated rainfall.

Liquid volume drop because of evaporation in the containers is a more complex process than that of rain. The evaporation model presented by Focks et al. (1993a) was adopted.

2.3.2.3. Agents. The processes related to the computer agents representing *A. aegypti* are basically the following:

1. Birth – initializing process of the agent and its basic characteristics.
2. Metamorphosis – process responsible for the agent stage transition. The agent's life cycle is shown in Fig. 4.
3. Death – this process finishes any other processes performed by the agent and removes it from the simulation scenery.

One of the main contributions of this work is to provide computational models for decision-making processes and behavior of *A. aegypti*. The female agent is more complex than its male counterpart, since it takes blood meals for egg maturation during gestation, and then searches for oviposition sites to ensure eggs survival. Every mosquito agent can decide through a process that evaluates a series of predetermined statuses and decisions. This process is performed at previously defined time intervals. The following processes can take place according to the female's decisions:

(a) Flying randomly – allows the agent to fly randomly, respecting the space occupied by other elements.
(b) Looking for a resting place – this process is usually performed when the daylight period is over.
(c) Looking for blood meals – the female needs blood feeding for egg maturation.
(d) Looking for plant phloem sap – this feeding will be favored if the female is not fertilized or if it needs urgent feeding.
(e) Feeding – after finding food, the mosquito starts to feed.
(f) Mating – mating process takes place if a male mosquito finds a female.
(g) Looking for an oviposition site. The female model differs from the male model regarding gestation. Therefore it is necessary to define a process by which the female looks for an oviposition site.
(h) Ovipositing – after finding a site, the female starts it.

The conditions under which such processes occur, as well as the order in which they take place are defined by the decision-making process of the agents. Fig. 5 depicts the decision-making process for female.

One of the major differences between male and female mosquitoes is the oviposition-linked response behavior. If the female is laying eggs and has not finished the process, it must remain performing this action. In continuing oviposition standing, the female will look for a new oviposition site. When oviposition is concluded, the mosquito is free for adopting new behaviors.

If the mosquito is not performing any of the activities mentioned above (feeding, mating, and oviposition) and is not dead, answers concerning the following items must be answered: current daylight period, mating state, oviposition starting point, checking oviposition moment/time, current energy level, and presence of humans or vegetation in the surrounding area. Depending on how these questions are answered, the following states of behavior may be selected: *looking for a resting place, looking for an oviposition location, flying randomly, dying, looking for sap-based meals, looking for a mammal for blood feeding, trying to bite a mammal.*

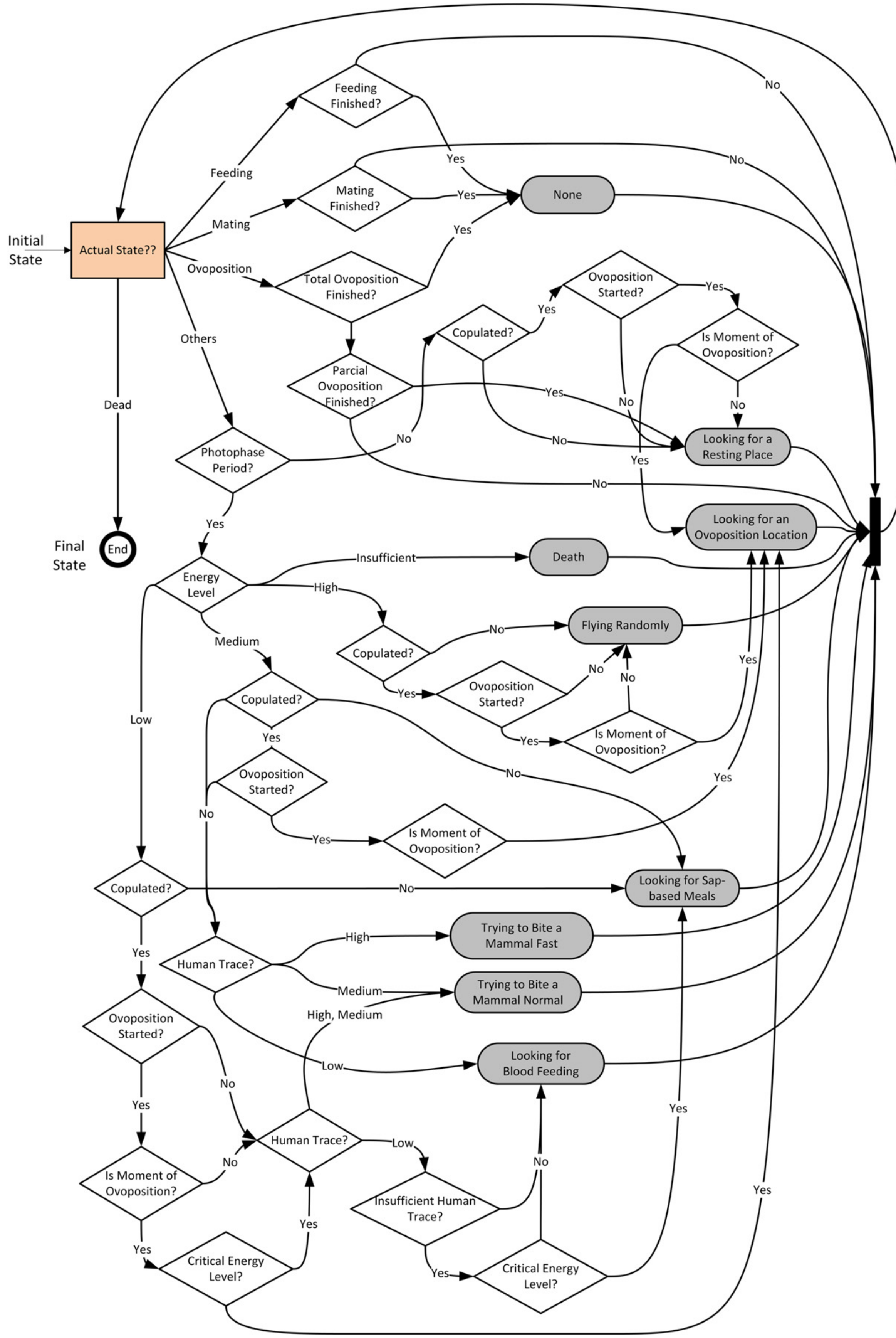

Fig. 5. Female *Aedes aegypti*'s decision diagram of behavior model.

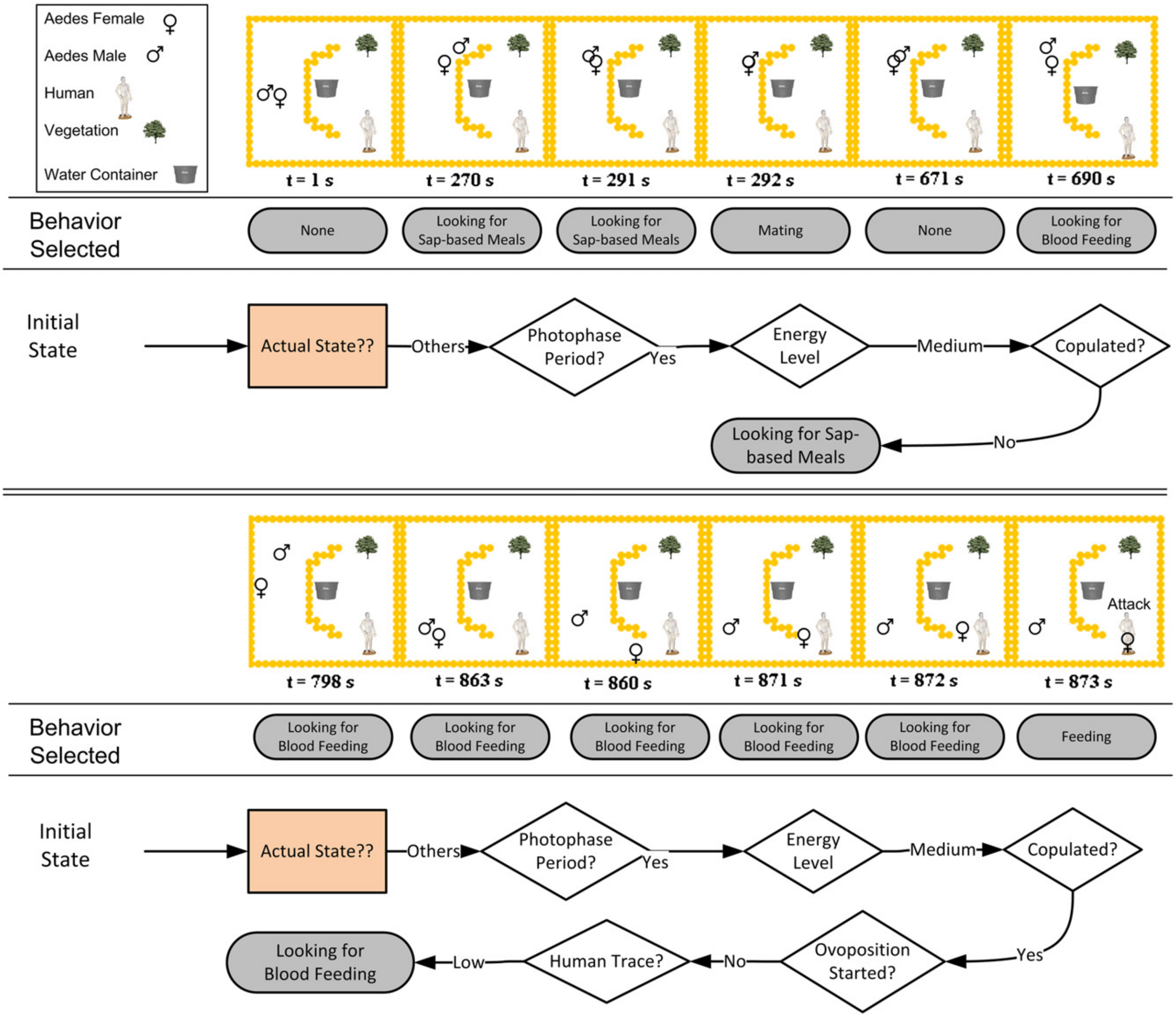

Fig. 6. Female *A. aegypti* making decisions in a controlled environment.

An important instant is present in the decision diagram, the First Question. It is associated with the decision-making stage of the model (grey box). At this moment, a question is asked about the current behavior of the mosquito. Depending on the answer, further questions are asked (lozenge).

Once such questions have been answered, a behavior status is defined (grey ellipse). The mosquito then performs actions according to the selected status. The decision-making process is iterative (re-starts at the initial question). Such iterations are performed at pre-defined time intervals. In the case of the *A. aegypti* agent, this decision-making interval was defined as 10 s (or 10 ticks).

Five possible answers are associated with the initial question concerning the following behaviors: feeding, mating, death, oviposition and remaining states. If the mosquitoes are ongoing feeding or mating, they must keep performing these activities. On the other hand, if feeding or mating is concluded, the mosquito is free to make new choices. One of the questions concerns the death of a mosquito agent, based on which, the decision-making process is terminated.

Fig. 6 illustrates how the decision diagram is used by a mosquito female. In the first sequence the female was searching by a sap-based meal, but at the instant $t = 292$ s, she is founded by a male

Table 1
Computer simulations.

Experiment	Evaluated data	Results
Greenhouse pre-trap Objective: calibration	Accumulated production of eggs	Fig. 8
	Fortnightly production of eggs – sliding window	Fig. 9
	Accumulated adults mosquito production	Fig. 10
	Fortnightly adults mosquito production (sliding window)	Fig. 11
Greenhouse pos-trap Objective: calibration and *what–if cases*	Accumulated adults mosquito production	Fig. 12
	Fortnightly adults mosquito production (sliding window)	Fig. 13
2004–2005 City block Objective: validation	Ovitrap captured eggs versus simulation results	Fig. 14
2004–2005 City block Objective: what–if cases (effect of traps)	Number of traps influence	Fig. 15
	Effect of Trap location: closer water containers versus distributed randomly	Fig. 16
	Effect of trap location: house inside versus outside	Fig. 17

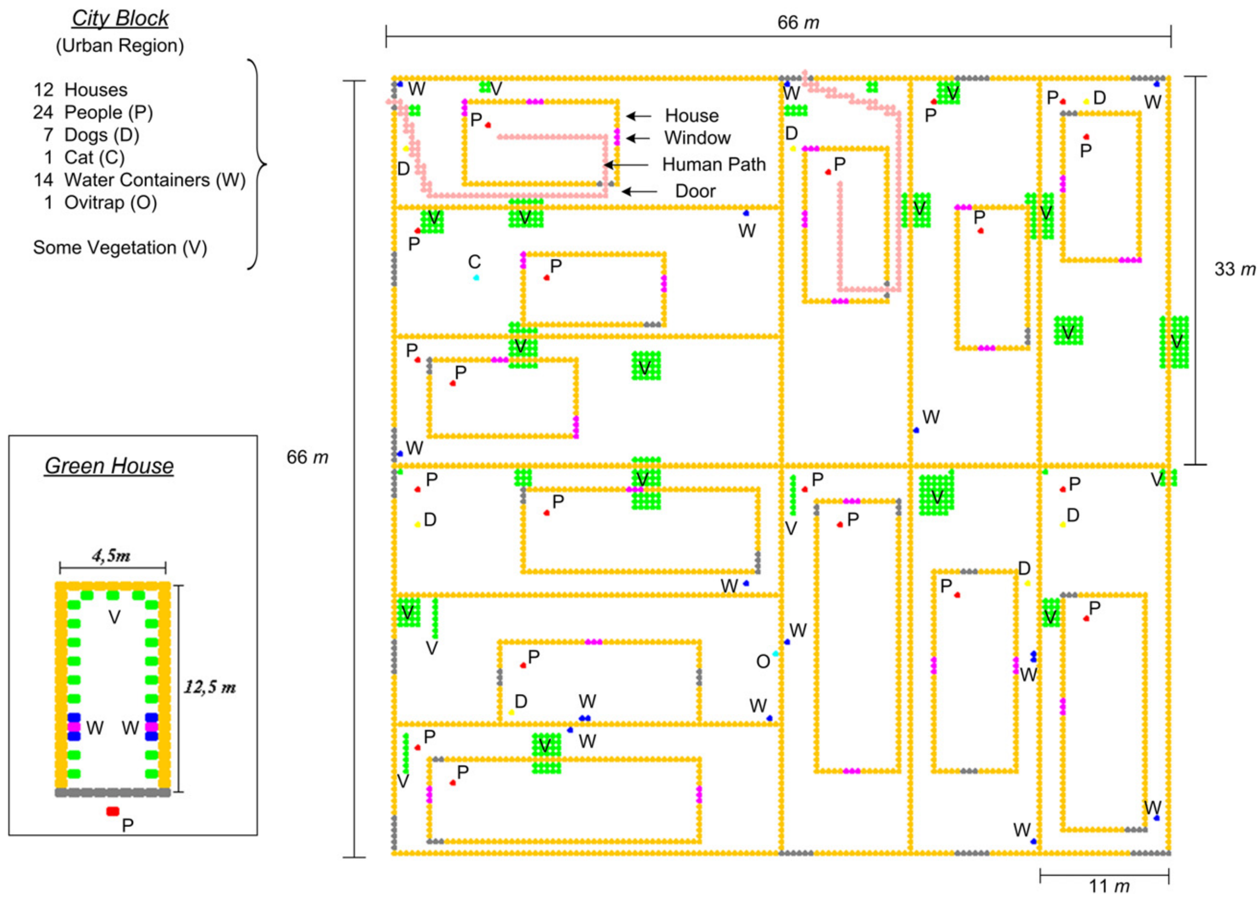

Fig. 7. Simulated cases.

Table 2
Correlation analysis in the pre-trap period.

ID.	Compared data	Correlation coefficient
EP	Correlation of egg production	
EP.1	Daily production of egg	0.20
EP.2	Daily production of egg – irregular sampling	0.37
EP.3	Accumulated daily production of eggs	0.97
EP.4	Accumulated daily production of eggs – irregular sampling	0.98
EP.5	Weekly production of eggs – fixed window	0.65
EP.6	Weekly production of eggs – sliding window	0.63
EP.7	Fortnightly production of eggs – fixed window	0.74
EP.8	Fortnightly production of eggs – sliding window	0.80
AP	Correlation of adults mosquito production	
AP.1	Daily adults mosquito production	0.51
AP.2	Daily adults mosquito production – irregular sampling	0.51
AP.3	Accumulated daily adults mosquito production	0.98
AP.4	Accumulated daily adults mosquito production – total data	0.97
AP.5	Weekly adults mosquito production – fixed window	0.60
AP.6	Weekly adults mosquito production – sliding window	0.56
AP.7	Fortnightly adults mosquito production – fixed window	0.54
AP.8	Fortnightly adults mosquito production – sliding window	0.70
BR	Correlation of biting rate	
BR.1	Biting rate	0.31
BR.2	Biting rate (10 days before setup of trap)	0.77

and copulated. After this moment she changed her behavior and began to search a blood meal. Finally, she has started feeding at the instant $t = 873$ s.

This experiment showed in Fig. 6 was presented to biologist specialists. The biologists validated the mosquito behaviors. They judge that the behavior of mosquito in the experiment and the decision model presented in Fig. 5 are coherent with the reality. This opinion was very important to help us validate the model *SimPopMosq*. In Section 3, we complement the process of validation of the *SimPopMosq*.

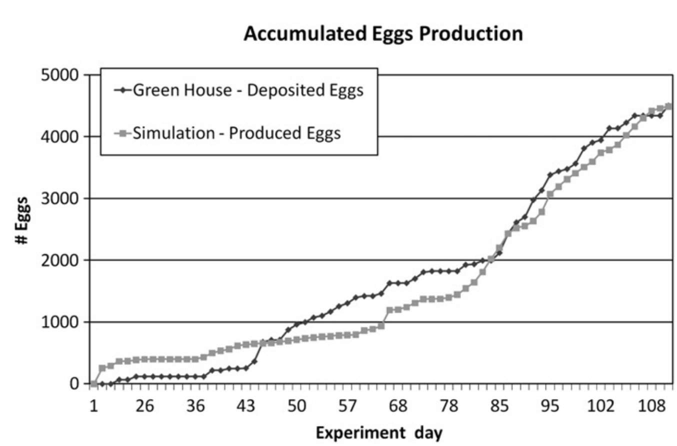

Fig. 8. Accumulated production of eggs in pre-trap period.

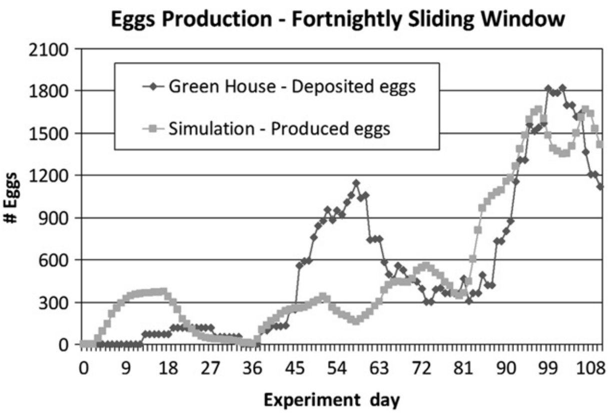

Fig. 9. Fortnightly production of eggs in pre-trap period – sliding widow.

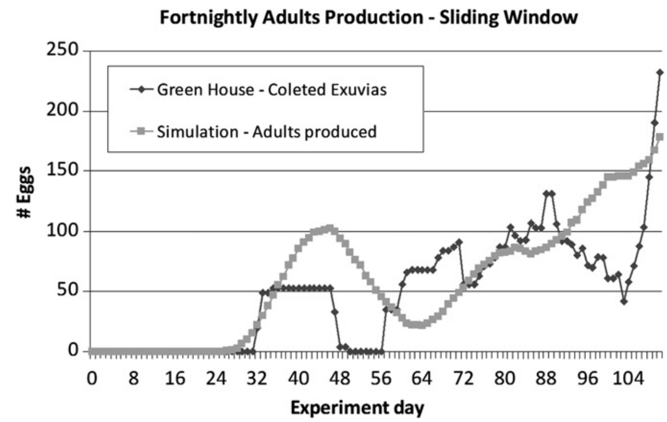

Fig. 11. Fortnightly adults production in pre-trap period – sliding window.

Various mosquito parameters affect its behavior and its variables, defining its status. Next, we show the main parameters:

(i) *Duration of stages* – each stage has an average duration, therefore, every agent has a different life span. The duration of each stage is calculated based on equations, parameters and random numbers. Biological parameters were defined accounting to Consoli and Oliveira (1994) and Eiras (2000).

(a) *Duration of the egg stage*: $f_o = l_o + (l_o + \text{RandomNormalDist}(\mu, \sigma))$ (days).

Parameter l_o corresponds to the average duration value of the egg stage according to literature. Duration of the egg stage is calculated by adding l_o to a random number obtained from the normal distribution set by the average μ and by the standard deviation σ. The values adopted for l_o, μ and σ were 3, 0 and 10 days.

(b) *Duration of the larva stage:* $f_l = l_l + (l_l \times \text{RandomUniformDist}(\text{min}, \text{max}))$ (days).

The parameter l_l corresponds to the average duration value of the larva stage according to literature data; min and max are the limit values (lowest and highest) for generating the number based on the uniform distribution. The values adopted for l_l, min and max were 15, −0.2 and 0.2 days.

(c) *Duration of the pupa stage*: $f_p = l_p + (l_p \times \text{RandomUniformDist}(\text{min}, \text{max}))$.

The pupa stage is calculated in an identical way as the larval stage. The values adopted for l_p, min and max were 3, −0.1 and 0.1 days, respectively.

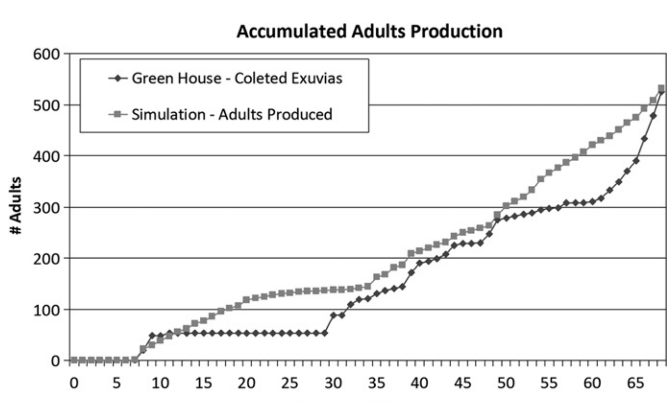

Fig. 10. Accumulated production of adults in pre-trap period.

(d) *Duration of the adult stage*: $f_a = \text{RandomNormalDist}(\mu, \sigma)$.

If RandomNormalDist (μ, σ) has a negative value, the equation used is:

$f_a = l_a - \text{RandomNormalDist}(\mu, \sigma)$

The parameter l_a corresponds to the average duration value of the adult stage according to literature data. The stage duration is calculated using a random number obtained from the normal distribution set by the average μ and by the standard deviation σ. The values adopted for l_a, μ and σ min and max were 15, 15 and 15 days, respectively.

(ii) *Risk of death during stage transition* – a mosquito may die while undergoing different stages. The model developed adopts survival odds in each stage transition. The parameters adopted are *risk of death during egg–larva transition 30%, risk of death during larva–pupa transition 30%, risk of death during pupa–adult transition 30%, risk of death after reaching the end of the adult age 90%.* These parameters were calibrated based on literature references (Bellows et al., 1992; Hawkins et al., 1997; Mwangi and Rembold, 1988; Peters and Barbosa, 1977) and submitted to expert judgment.

(iii) *Power consumption* – power consumption is determined by the amount of energy the agent needs to undertake a certain task. Each sort of activity has a power consumption value as a parameter. The average value adopted for this parameter was 0.75 energy units (seconds) per second. For example,

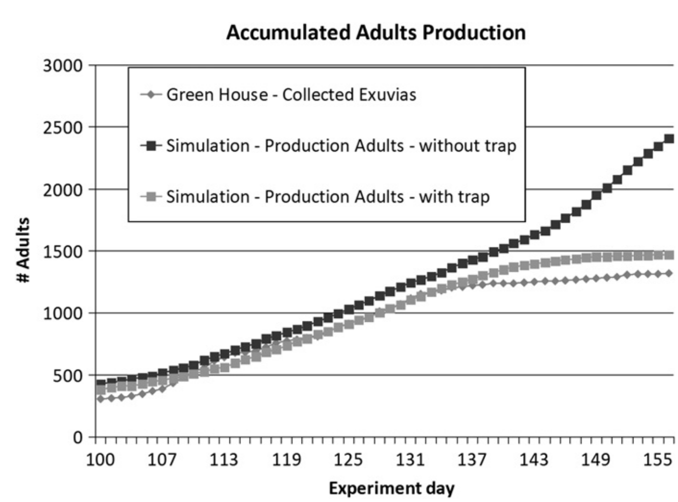

Fig. 12. Accumulated adults production in period with trap.

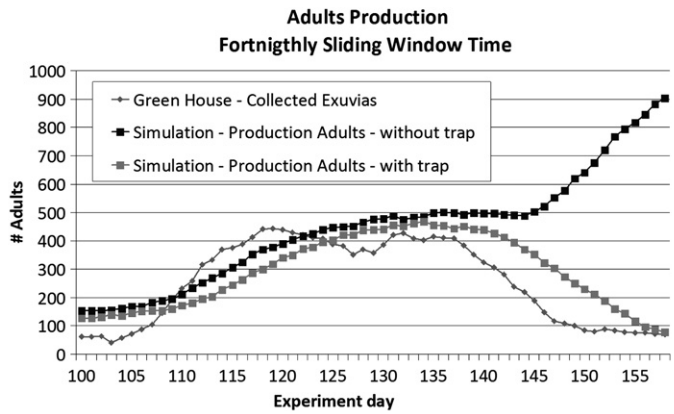

Fig. 13. Fortnightly adults production in period with trap – sliding window.

a mosquito flying at 1 m/s uses 20 W/kg in our model 1.00 energy units (seconds) per second (Templin, 2000).

(iv) *Standard flying height* – the standard flying height parameter is defined as one meter. This value is related to the thickness of the boundary layer of a flow caused by a moderate wind (Templin, 2000).

(v) *Perception of vegetation proximity* – it is important for an agent to notice the proximity of vegetation. The parameters *high*, *medium* and *low* vegetation trace intensity were defined, so that the agents can verify if the trace intensity at their location is high, medium or low. According to that specification, the mosquito will choose the behavior to perform. The values adopted for *high* and *medium* vegetation trace intensity were 6000 and 8000 trace units, respectively.

(vi) *Feeding time* – the parameter adopted for the mosquito feeding time to was 1200 s.

(vii) *Displacement speed* – the average value adopted for this parameter was 0.6 m/s (Consoli and Oliveira, 1994).

(viii) *Vertical displacement speed* – this parameter has a value of 0.8 m/s. We estimate this value considering that the mosquito climbing speed is equal to the *displacement speed* is 0.6 m/s, but we consider its diving speed as 1.0 m/s, the vertical displacement speed is the average.

Female *A. aegypti* mosquitoes, when compared to the males, have several differences in terms of species reproduction. Activities such as blood feeding, fertilization and oviposition are performed only by female individuals. The variables that complement the computational model of the female defining its status are the following:

(i) *Energy level related with blood feeding* – female mosquitoes need a "*specific*" sort of energy to mature their eggs. This energy is provided by blood feeding. The higher the amount of blood consumed, the more likely are the eggs to hatch.

(ii) *Number of eggs in the ovary* – the number of eggs laid varies according to each gestational event. This variable can assume values ranging from 80 to 120 eggs (Consoli and Oliveira, 1994; Eiras, 2000). However, the number of hatching eggs will proportionally depend on the variable *Energy level as a function of blood consumed.*

(iii) *Mating time* – its ranges between 300 and 600 s (expert defined).

(iv) *Successful biting* – this variable is calculated by dividing the number of bites by the total number of bite attempts, for which the value of 80% was adopted. This probabilistic parameter is used to calculate how many attempts of the female to bite will be successful to feed blood.

(v) *Risk of death due to bite attempt* – the probability of a mosquito being killed when trying to bite is 2% (calibrated).

(vi) *Blood feeding length* – the blood feeding is undertaken within 900 s (calibrated).

(vii) *Maximum amount of blood intake per bite* – percentage determining the maximum amount of blood that can be ingested per bite. The value adopted was 90% (calibrated).

(viii) *Perception level for approaching mammals* – female individuals notice the closeness of mammals trace intensity adopted were 8000 and 6000 trace units, respectively.

(ix) *Oviposition speed* – oviposition speed indicates the number of eggs laid per time unit. A value of 0.02 eggs/s was adopted (calibrated).

(x) *Spatial oviposition pattern* – the eggs deposited on each substrate is an important factor for the survival of mosquito species. According to the distribution pattern adopted, a female tends to lay its eggs randomly in environment at different times and amounts. The distribution adopted is based on the model proposed by Gomes et al. (2006).

2.3.3. Male Aedes aegypti agent

The decision-making model of the male mosquito is a simplified version of the female. The computational model for the male mosquito contains parameters allowing perception of the trace intensity level of female mosquitoes. Such parameters are the *high* and *low* trace intensities with a goal similar to that related to perception of vegetation: the mosquito chooses what kind of behavior to adopt when a female individual gets closer. The values adopted for a *high* and *medium* female trace intensity were 8000 and 6000 trace units, respectively.

2.3.4. Mammal agents

The mammals – dogs and cats – available in the simulation model *SimPopMosq* are agents capable of moving *randomly*, according to the physical conditions imposed by the environment, when inserted into particular simulation scenery. The only process associated with mammal agents is that of movement. Such agents move without invading previously occupied locations.

2.3.5. The human agent

Besides their random movement behavior, the human agent also poses a schedule in this model that can determine activities to be performed by them. The human agent follows tasks in its

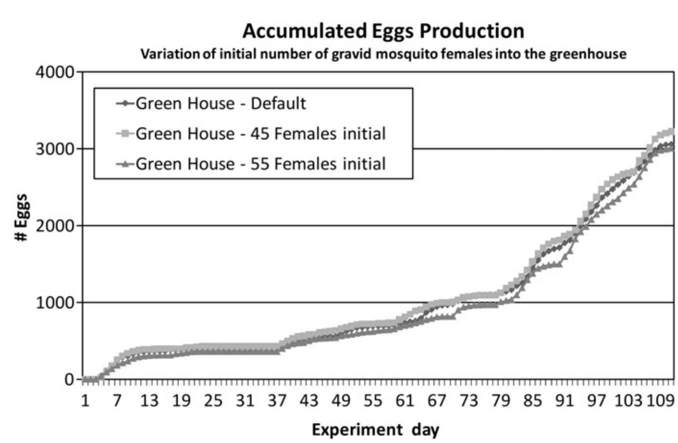

Fig. 14. Variation of initial number of gravid mosquito females into the greenhouse.

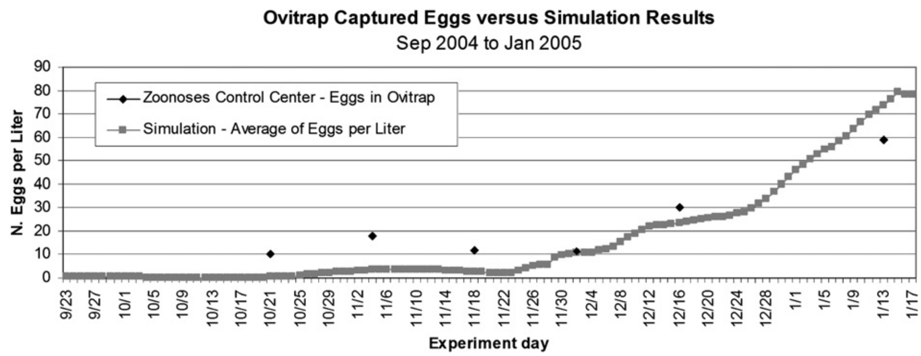

Fig. 15. Ovitrap captured eggs versus simulation results.

schedule. The human agent schedule defines where it should be or where it should be going at each moment..

A shift submodel based on the graph theory and shortest-path algorithms is adopted in the simulation model proposed. It allows the human agent to move between two points using the shortest way.

2.3.6. Transposition model

A transposition model has been developed to be used in the simulation model proposed. By means of a centralized matrix – the transposition matrix determines which elements may be transposed. When an agent attempts to move in a certain direction, verification is performed to check if the agent may occupy the expected space. This also includes analyzing the transposition possibility of elements that might be occupying the expected space. In case the agent is not able to move into the expected space, its surrounding cells must be analyzed until a possibility of position shift is found (Millington, 2006; Ericson, 2004).

3. Experiments

Trials were aimed at adjusting parameters, validating the simulation model and to answer "what–if" questions. They were based on situations obtained from an actual biological experiment undertaken in a greenhouse at the University of Regensburg, Germany, in a partnership with the Institute for Biological Sciences (ICB) of the Federal University of Minas Gerais (UFMG) and on data obtained with the Center for Zoonoses Control of the Municipality of Belo Horizonte, Minas Gerais, Brazil. "What–if" case experiments were carried out to study how the localization and the number of traps can affect a mosquito population in a city block. Table 1 summarizes all computer simulations done.

We calibrated by hand the parameters of the proposed model undertaken several oriented simulations. Two real experimental databases were used to calibrate and validate the model. The first base was obtained with an experiment made in a greenhouse controlled environment. The second base was obtained with the Zoonoses Control center of Belo Horizonte, Brazil, and is real infestation data used to control in practice the mosquito population. The simulation model was used to test the effectiveness of a trap applied for active mosquito population control. Some "what–if" simulation cases were tested to verify how the localization and or the number of traps affect a mosquito population in a city block. The result obtained was based on the mean from five different simulations.

3.1. Practical experimental data description

Fig. 7 presents two graphs which represents the environments that were simulated: the greenhouse experiment (left), and the city block experiment (right). In the next subsections the cases are better explained and the results got are presented.

3.1.1. Greenhouse practical experiment

The greenhouse experiment was undertaken within a period of 159 days, from December 15, 2005 to May 22, 2006, in a plant greenhouse, including water-holding containers and *A. aegypti* mosquitoes. The greenhouse was configured to reproduce the characteristics of a tropical environment. The greenhouse used in the experiment was 11 m long and 3.8 m wide. The height in the greenhouse ranged from 2.8 m to 3.8 m. Temperature ranged between 22 °C and 30 °C, and air relative humidity from 58% to 79%. About five water-holding containers were installed in the greenhouse. Several plants were installed inside the greenhouse.

The experimenter volunteered to blood feed female *A. aegypti*, by allowing them to bite him throughout the experiment.[1] During the experiment period, data were collected concerning the development of the mosquito population as well as the effectiveness of a BG-Sentinel trap (Biogents AG, Germany, www.bg-sentinel.com) for controlling it. One trap was placed in the middle of the greenhouse after the biting rate was higher than 50 bites per min for three consecutive days. The pre-trap period of the experiment began on December 15, 2005, and continued to April 5, 2006, totaling 112 days. The post-trap period began when a trap was installed, on April 6, 2006, until the end of the experiment, on May 22, 2006, in 47 days.

Initially, 50 female *A. aegypti* were released into the greenhouse. The mosquitoes were 5 days old and seeking a blood meal. The experimenter visited the greenhouse almost daily:

1. Between 9 and 11 a.m., the experimenter offered the females to feed on his exposed arm. The rest of his body was covered with protective clothes. He stayed in the greenhouse from 5 to 30 min, depending on the number of bites he could stand each time. A maximum of 15 mosquitoes fed on his arm per day.
2. Between 3 and 7 p.m., the experimenter entered the greenhouse to measure the biting rate[2] for a period from 5 to 30 min. The females that landed onto the human arm were immediately collected (before biting him) and afterwards they were released into the greenhouse again. In this way, it was possible to calculate the biting rate from the landing rate with no need for new bites. After such values had been calculated, the water-holding containers (oviposition sites) were analyzed and the

[1] The mosquitoes were reared from a laboratory colony free of any viruses, which could be potentially transferred by *Aedes aegypti*.

[2] In this experiment, the biting rate corresponds to the number of bites taken within 1 min.

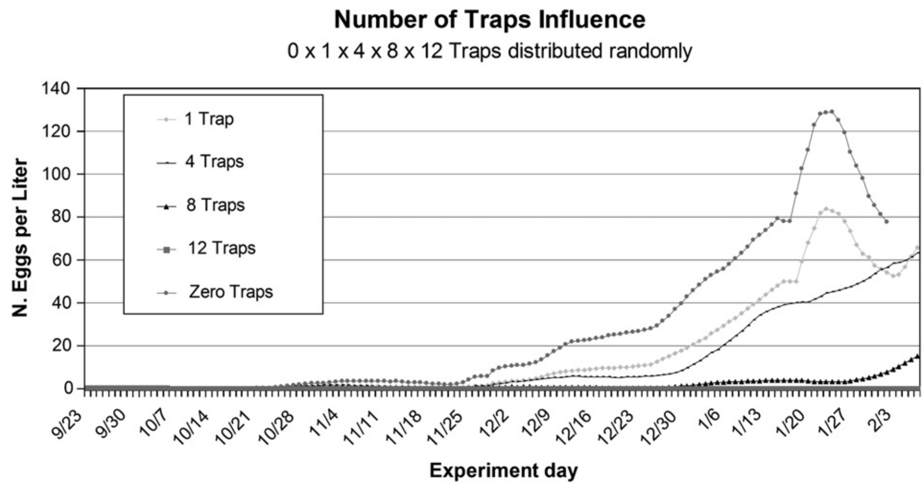

Fig. 16. Number of traps influence.

eggs and exuvias[3] were counted and then removed from the greenhouse. The eggs were re-introduced into the greenhouse one week later and placed into a container with water. In the afternoon, the *A. aegypti* larvae were fed with fish food.

Data collected provided information concerning egg production, adult production, biting rate and the number of daily blood meals.[4] These data were used as a reference for calibrating the simulation model proposed.

3.1.2. Data from the Belo Horizonte block experiment

Some experiments simulated a city block. The block was modeled from data released by the Center for Zoonoses Control of the Municipality of Belo Horizonte, Brazil. Meteorological data were obtained from CPTEC-INPE (2009). The Zoonoses Control Center provided data as "profile" and number of inhabitants of the region, number of residences, businesses and animals in each block, number of eggs of Aedes aegypti mosquitoes caught in each 15 days in Ovitrap (traps) from September 2004 to January 2005. They also provided the locations where they installed the traps.

We chose a block, called 3545, which is located in the Vista Alegre neighborhood, west of the city of Belo Horizonte. (You can see the Vista Alegre neighborhood using Google Earth, 19° 57′ 03.80″ S, 43° 59′ 13.02″ W).

3.2. Computer simulations results – greenhouse experiment

The computational simulation display of the greenhouse experiment was divided into two parts according to the periods previously mentioned: pre-trap and post-trap. Data from the actual trial related to such simulation periods were employed for adjustment of parameters and validation of the simulation model.

Results from computer simulations showed in the graphics of this section correspond to mean values from five different simulations. The main data compared between the greenhouse experiment and the computer simulation were egg production, adult production[5] and biting rate.

3.2.1. Parameter calibration – pre-trap period – greenhouse experiment

Parameter values of the simulation model were either obtained in literature data, calibrated or estimated by expert guess. The following parameters were adjusted:

1. Duration of *A. aegypti* stages: these values are described in Section 2.1.2.
2. Successful bites: 20%.
3. Risk of death in attempted bites: 2%.
4. Risk of death while undergoing stages: 30%.
5. Duration of sap-feedings: 1200 s.
6. Duration of blood-feedings on animals: 900 s.
7. Duration of mating: between 300 s and 600 s.
8. Maximum amount of blood ingested per bite: 90%.
9. Oviposition speed: 0.02 eggs/s.
10. Maximum energy level: 259,200 energy units.
11. High, medium and low energy: 259,200, 129,600 and 0 energy units, respectively.
12. High, medium and low of trace intensity: 8000, 6000 and 0 trace units, respectively.

These values were selected by hand by the manual version of the optimization method of descendent coordinates (Luenberger, 1989). The application procedure of this method consisted of fixing some parameter values and varying others within a region of feasible solutions by following an appropriate direction.

One weak points of our model is that we cannot assure interdependencies between parameter values. Most of the model parameters were estimated outside the model, so we do not consider interdependencies between the parameter values (Batty and Mackie, 1972; Lowry, 1965).

The results of the experiments performed in the pre-trap period are summarized in Table 2. The results shown in Table 2 are divided into three parts: correlation of egg production (EP), correlation of adult mosquito production (AP) and correlation of biting rates (BR).

Essentially, the experiments presented in Table 2are subdivided into:

1. Daily production – irregular sampling: indicates the number of eggs and adult mosquitoes produced per daily. The values obtained in the real experiment, the greenhouse trial, were not collected according to an uniform frequency (for instance, a day or a week), whereas data obtained from simulated trials in the greenhouse were collected daily. Such differences in data

[3] Exuvia is defined as the remaining parts of the mosquito while undergoing from pupa to the adult form, which permits to estimate the number of adults produced.

[4] Although the biting rate and the number of bites are available, the period of biting is not.

[5] The production of adult mosquitoes was measured by evaluating the number of exuvia found on filter paper placed into the greenhouse.

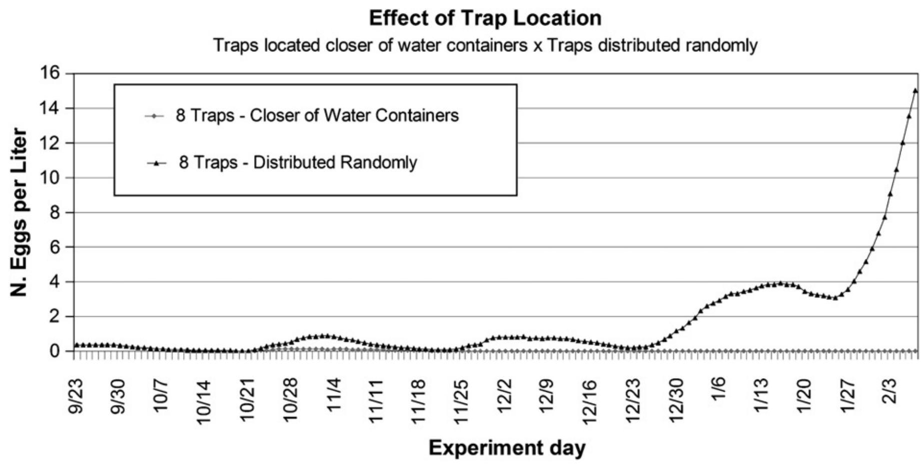

Fig. 17. Effect of trap location: closer water containers versus distributed randomly.

collection lead to behavior variations in comparative analysis. One of the approaches to dealing with such differences is to sum up the number of eggs produced in the computational simulation according to the days the human agent entered the greenhouse to collect eggs.

2. Production with sliding window – the concept of sliding window in this work is associated with the sum of the values got in the experiments in n days, where n is the size of the wanted window. For each day of experiment, the window "slides a position" and sums up the previous elements. The comparisons were made using 7- and 15-day sliding window.
3. Biting rate – the biting rate is the number of mosquitoes landed per min on the experimenter's arm trying to suck his blood.

Table 2 presents the accumulated and daily egg and adult production. The correlation coefficients of the daily egg productions suggests that simulation results are not similar to real data under this perspective. The highest correlation coefficient for this analysis was about 37%(EP.2). However, the accumulated data suggests that the simulation results are close to the real data found in real experiment. This analysis resulted in a 97% similarity (EP.4). Another result that should be considered is that of the comparison between egg productions from a fortnightly perspective with sliding window (identification comparison EP.8). This comparison resulted in a similarity higher than 80%.

The correlation coefficient of the daily egg production by adult mosquitoes (AP.2) shows that the simulation results are quite similar to the real data under this perspective. The simulation coefficient for this analysis was about 51%. However, in an accumulated perspective (AP.4), the simulation results are close to the results of the real experiment. This analysis resulted in a similarity index higher than 97%. The productions of adult mosquitoes in a fortnightly period, with sliding window (AP.8) resulted in a similarity higher than 70%.

The biting rates got from the real experiment and from the computer simulations did not behave in the same way during the pre-trap period. The correlation coefficient is approximately 31% (BR.1). However, the correlation coefficient between real and simulation data in the period between the beginning of the experiments and 10 days before the trap was placed into the greenhouse reveals a significant raise (identification comparison BR.2). If we consider this comparison, the correlation coefficient is about 77%.

Figs. 8–11 show how the experiments evolved. Fig. shows the curves concerning the number of eggs produced throughout the experiment and the simulation time. Fig. 6 shows a graphic with fortnightly egg production. The graphic shown in Fig. 8 is presents the collection of exuvias accumulated throughout time and the accumulated adult production in the computer experiment, in a similar way to what was presented previously concerning an cumulative evaluation of the egg production in the experiments. To complement the analysis of adult/exuvias production, Fig. 11 shows a graphic with fortnightly totalizations of the adult/exuvias productions.

Figs. 9 and 11 reveal a difference between the curve based on the real experiment and the one based on the simulation, between the 45th and the 65th day of experiment. We believe that this difference

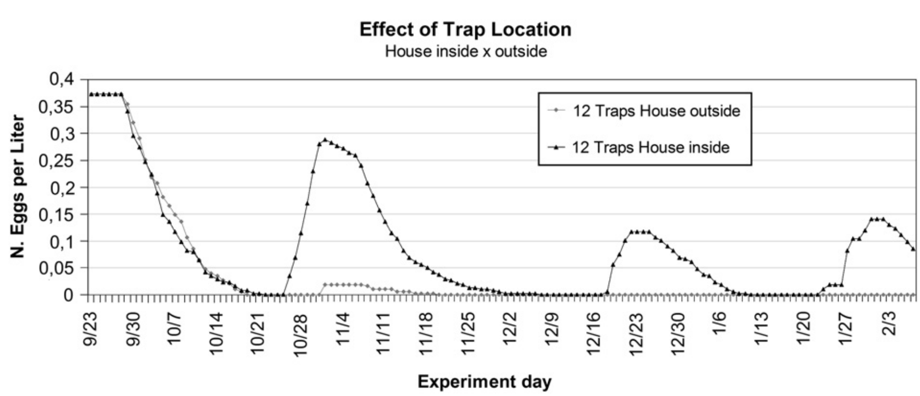

Fig. 18. Effect of trap location: house inside versus outside.

could be due to reasons related to details of the real experiment that are not considered by the simulation model proposed. Our hypothesis is associated with the time-distribution model adopted for the eggs, that is, the model adopted is more simple and deterministic than the real egg-distribution model of *A. aegypti* mosquitoes. Other possible hypothesis is related to the fact that on one hand the egg production increased but on the other hand the exuvia production decreased. We argue if may be possible that mosquitoes are producing nonviable eggs. Even though there are differences between the curves, they behave in similar way. The curves in the graphic presented by Fig. 8 are similar.

3.2.2. Post-trap period – general evaluation greenhouse experiment

We made two simulations on the post-trap period. An experiment was carried out considering a trap placed in the middle of the greenhouse, and we simulated considering what could happen if de trap was not used. We do not calibrate any parameter in this experiment, so it is an evaluation experiment.

The trap mimics a human host. The female mosquito is attracted and captured. After the trap had been placed into the greenhouse, the student entered the place as often as in the pre-trap period, but he was less often attacked by the mosquitoes due to the presence of the trap. The simulations were made considering that human agent was bitten up to 15 times everyday.

The results obtained from these experiments illustrate the mosquito-population dynamics in the simulated scenery, in response to feeding and the presence of a trap. Figs. 12 and 13 show how the experiments evolved.

The trap was placed into the greenhouse on the 112th day of experiment. The graphic presented in Fig. 13 shows that, after the 112th day of experiment, the mosquito population keeps growing and starts to decrease a few days later. This occurs in the real experiment, as well as in the computer simulations, except for the simulation without trap.

3.2.3. Stability of model

We cannot assure a theoretical stability (Goh, 1977; Lyapunov, 1992; May, 1974).

Chli et al. (2003) consider the multi-agent system as a discrete time Markov chain with a potentially unknown transitional probability distribution. Markov processes are memoryless. So, only the current state is required to describe its next state. They consider a system stable when its state has converged to an equilibrium distribution. *SimPopMosq* is a Markov process, and we made some sensitivity analysis experiments by adjusting up and down by ($\sim$10%) for each calibrated adopted parameter. Some of these experiments had an unstable or chaotic result.

Fig. 14 shows an experiment where we changed the initial number of gravid mosquito females into the greenhouse. Two situations were performed and results were compared with basic greenhouse experiment (50 females initially). The first considers 45 females initial ($-$10%) and the second considers 55 females ($+$10%).

We can see in Fig. 14 that the accumulative production of eggs is inversely proportional to the number of females initially introduced initially into the greenhouse. This happened because the food into the greenhouse was maintained constant, and, consequently, more mosquitoes competed for the food. The success of outbreak (born) of eggs depends on the quantity of blood ingested by the females.

3.3. Belo Horizonte block experiment 2004–2005

Fig. 15 presents a comparison between real data and simulation results. The Zoonozes Control Center tries to control the entire city, a city with more than a two-million inhabitants. So, the data about one special block was not detailed. We do not have information about where the Ovitrap was placed in the block. But, some preliminaries simulations showed that the placement can affect results obtained. We decided to compare real data (the number of eggs collected in the Ovitrap) with average of eggs per liter of all water-holding containers in the simulated scenario. We can say that the simulation was able to capture the moment when the mosquito population began to increase. The Pearson correlation coefficient between field and predicted data is 0.97.

3.3.1. Cases study – city block

We made a series of experiments to evaluate if a human odor trap (BG-Sentinel trap) could be able to control to mosquito population in a small area of a city block. The experiments were made with the objective to verify where to locate these traps, and how many traps were necessary for an efficient population control. The results got are presented in Figs. 16–18.

What can we imply from experiments? We found that the number of traps to extinguish the population has an optimum between 8 and 12 traps in the studied area (66 m $\times$ 66 m) – Fig. 16. But even if there are not enough traps to extinguish the results shown that they are able to slow the increase in population. This number is important if we want to think that the active control as an official tactics to control the mosquito population, because of the involved costs. We also noticed that the trap location affects the results. The simulation showed that is better to put the traps outside the house (Fig. 18), and if possible, closer of the possible mosquito nurseries (Fig. 17). Instead of put the trap at the head of the bed.

4. Comments and conclusions

With the developed model we can assess various situations that other models are unable to address. These situations may lead to useful practices for controlling the mosquito population. Future simulations may help to answer some of the following questions: Are insect repellents effective in protecting the human population, or in controlling the insect population? Do mosquito nets work? Does architecture (doors, windows, swimming pool) have an influence on the mosquito population?

Experiments were performed to assess how the placement and number of traps could affect an active control policy. However, several other issues can be researched. For example, how could a control policy based on the encouragement of people to use individual protection, such as repellents, help control the mosquito population? If people stay-at-home with the doors and windows closed, could this affect the mosquito population? What is better: setting traps, or using poison? Where, when and how to place the traps? What kind of trap to use? Is it best to use traps or poison for host seeking or gravid female mosquitoes? We could research whether or not it is better for people to remain indoors while mosquitoes are most active. The simulation could show how human behavior has an effect on the number of bites and the mosquito population. With the proposed model, various control policies proposed in the literature could be tested.

In view of the problems associated with estimating a mosquito population and the limitations of current models and tools, the present work introduces a computer simulation that provides new results concerning the experiments performed.

The simulator consists of a population simulation model for the *A. aegypti* mosquito called *SimPopMosq*. This simulator has been described in terms of concept and implementation. Results of simulations made with the simulator in question were analyzed and compared to real experimental data. The implementation characteristics of the model allow it to be improved. Each of the details, agents, objects, laws or rules can be modified and improved.

For the conceptual modeling of the population simulator, models of agents, objects and the environment were proposed. One contribution of this work is a structured definition of a decision-making model for the male and female *A. aegypti* mosquito. To date, no similar decision-making model for this particular mosquito can be found in literature. The proposed simulation model can give the user insights about how to control an insect population in an urban environment. The proposed model provides quantitative information although we cannot say yet that we have definitive results.

The scenery and the initial conditions simulated are similar to those of the real experiment conducted in the greenhouse. Many simulations were performed in order to calibrate and validate the *SimPopMosq* simulation model. The results obtained from the simulations were compared to those obtained from the greenhouse experiment. The correlation between these results proved satisfactory and reached a similarity level higher than 98% for some variables.

A case study to evaluate the post-trap period revealed that the BG-Sentinel trap is effective in controlling the mosquito population in a closed environment. The case study also indicated that making it more difficult for females to consume blood leads to egg production control and consequently to population control. These results indicate that the BG-Sentinel trap might also have an effect in the field to reduce a local population of *A. aegypti*. We found that if we have a sufficient number of traps it will be possible to control the mosquito population.

One of the difficulties found in the present work is related to the parameter adjustment. Many of the parameters comprised by the simulation model have not been found in literature. Due to this limitation, some of the parameters were estimated and others were determined by a series of oriented experiments through an optimization method called descendent coordinates. One of the disadvantages of the agent-based model compared to analytical models is the demand for intensive computer resources. Upon running, the simulation requires intensive computing as it is a natural candidate for using computer grid resources.

In biology there are a strong study interest in mosquito ecology and control. Biology has worked to understand the mosquito biology.

“Social and behavioral responses can help control vector-borne disease” (Campbell-Lendrum and Molyneux, 2005). The simulation model proposed can be used to study what could be the impact of these responses.

We can also use the same developed framework to study other vectors. The application of the proposed model is straightforward with other vectors. We need only to change the mosquito agent model to the new kind of agent. Another vector-borne disease problem that our city is suffering is Leishmaniasis. Leishmaniasis is caused by parasites of the genus Leishmania and it is transmitted by sandflies (subfamily Phlebotominae) (Berman, 2005). The death number from leishmaniasis in Minas Gerais state (Brazil) grew 72.7% between 2008 – when 35 people has died – and 2009 – when 35 people has died. In the city of Belo Horizonte, 10,227 dogs were sacrificed, 161 human beings were infected and 18 died from Leishmaniasis. These numbers can motivate researchers to investigate the use of computer simulation models on Leishmaniasis disease.

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References

Anholt, B.R., 1997. How should we test for the role of behaviour in population dynamics? Evolutionary Ecology 11, 633–640.
Athanasiadis, I.N., Milis, M., Mitkas, P.A., Michaelides, S.C., 2009. A multi-agent system for meteorological radar data management and decision support. Environmental Modelling & Software 24 (11), 1264–1273.
Barrett, C.L., Eubank, S.G., Smith, J.P., 2005. IF SMALLPOX STRIKES PORTLAND. EPISIMS unleashes virtual plagues in real cities to see how social networks spread disease. That knowledge might help stop epidemics. Scientific American 292 (3), 42–49.
Batty, M., Mackie, S., 1972. The calibration of gravity, entropy and related models of spatial interaction. Environment and Planning 4, 205–233.
Bellows Jr., T.S., Van Driesche, R.G., Elkinton, J.S., 1992. Life-table construction and analysis in the evaluation of natural enemies. Annual Review of Entomology 37, 587–614.
Berman, J., 2005. Recent developments in leishmaniasis: epidemiology, diagnosis, and treatment. Curr Infect Dis Resp 7, 33–38.
Bithell, M., Brasington, J., 2009. Coupling agent-based models of subsistence farming with individual-based forest models and dynamic models of water distribution. Environmental Modelling & Software 24 (2), 173–190.
Bomblies, A., Duchemin, J.-A., Eltahir, E.A.B., 2008. Hydrology of malaria: model development and application to a Sahelian village. Water Resources Research 44:26 (12).
Campbell-Lendrum, D., Molyneux, D., 2005. Ecosystems and vector-borne disease control. In: Epstein, P., Githeko, A., Rabinovich, J., Weinstein, P. (Eds.), Ecosystems and Human Well-being: Policy Responses, vol. 2. Island Press, Washington, DC, pp. 353–372.
Chli, M., De Wilde, P., Goossenaerts, J., Abramov, V., Szirbik, N., Correia, L., Mariano, P., Ribeiro, R., 2003. Stability of Multi-Agent Systems. In: Proceedings of the 2003 IEEE International Conference on Systems, Man, and Cybernetics, pp. 551–556.
Chung, C.A., 2003. Simulation Modeling Handbook: A Practical Approach. CRC Press.
Consoli, R.A.G.B., Oliveira, R.L., 1994. Principais Mosquitos de Importância Sanitária no Brasil. Editora Fiocruz, Rio de Janeiro.
Costero, A., Edman, J.D., Clark, G.G., Kittayapong, P., Scott, T.W., May 1999. Survival of starved *Aedes aegypti* (Diptera: Culicidae) in Puerto Rico and Thailand. Journal of Medical Entomology 36 (3), 272–276.
CPTEC-INPE, 2009. Centro de previsão de tempo e estudos climáticos. Available from: http://www.cptec.inpe.br/ (accessed 4 April 2010).
Derouich, M., Boutayeb, A., Twizell, E., 2003. A model of dengue fever. BioMedical Engineering OnLine.
Dye, C., 1984. Models for the population dynamics of the yellow fever mosquito, *Aedes aegypti*. Journal of Animal Ecology 53 (1), 247–268.
Eiras, A.E., 2000. Chapter 40: Culicidae. In: Neves, D.P., et al. (Eds.), Parasitologia Humana. Atheneu.
Ericson, C., 2004. Real-Time Collision Detection. Morgan Kaufmann.
Fahse, L., Wissel, C., Grimm, V., 1998. Reconciling classical and individual-based approaches in theoretical population ecology: a protocol for extracting population parameters from individual-based models. The American Naturalist 152 (6), 838–852.
Ferguson, N.M., Keeling, M.J., Edmunds, J.W., Gani, R., Grenfell, B.T., Anderson, R.M., Leach, S., 2003. Planning for smallpox outbreaks. Nature 425, 681–685.
Ferreira, C.P., Yang, H.M., 2003. Estudo dinâmico da população de mosquitos *Aedes aegypti*. CNMAC - Congresso Nacional de Matemática Aplicada e Computacional, pp. 187–196.
Focks, D.A., Haile, D.G., Daniels, E., Mount, G.A., 1993a. Dynamic life table for *Aedes aegypti* (Diptera: Culicidae): analysis of the literature and model development. Journal of Medical Entomology, 1003–1017.
Focks, D.A., Haile, D.G., Daniels, E., Mount, G.A., 1993b. Dynamic life table for *Aedes aegypti* (Diptera: Culicidae): simulation results and validation. Journal of Medical Entomology, 1018–1028.
Focks, D.A., Daniels, E., Haile, D.G., Keesling, J.E., 1995. A simulation model of the epidemiology of urban dengue fever: literature analysis, model development, preliminary validation, and samples of simulation results. American Journal of Tropical Medicine and Hygiene, 489–506.
Goh, B.S., 1977. Global stability in many-species systems. American Naturalist 111, 135–143.
Gomes, A.S., Sciavico, C.J.S., Eiras, A.E., 2006. Periodicidade de oviposição de fêmeas de Aedes aegypti (Linnaeus, 1762) (Diptera: Culicidae) em laboratório e campo. Journal of Brazilian Society of Tropical Medicine, 327–332.
Grand Challenges in Global Health, 2009. Available from: http://www.grandchallenges.org/ControlInsect/Pages/default.aspx (accessed 4 April 2010).
Grimm, V., 1999. Ten years of individual-based modelling in ecology: what have we learned, and what could we learn in the future. Ecological Modelling, 129–148.
Grimm, V., Railsback, S.F., 2005. Individual-based Modeling and Ecology, New Jersey.
Grimm, V., et al., 2006. A standard protocol for describing individual-based and agent-based models. Ecological Modelling, 115–126.
Houghton, J.T., Meira Filho, L.G., Griggs, D.J., Maskell, K., 1997. Stabilization of atmospheric greenhouse gases: physical, biological and socio-economic implications. IPCC Technical Paper III. IPCC, pp. 51.
Hagelbäck, J., Johansson, S.J., 2008. Using multi-agent potential fields in real-time strategy games. In: Proceedings of International Conference on Autonomous Agents and Multi-agent Systems (AAMAS).
Hawkins, B.A., Cornell, H.V., Hochberg, M.E., 1997. Predators, parasitoids, and pathogens as mortality agents in phytophagous insect populations. Ecology 78, 2145–2152.
Kröckel, U., Rose, A., Eiras, A.E., Geier, M., 2006. New tools for surveillance of adult yellow fever mosquitoes: comparison of trap catches with human landing rates in an urban environment. Journal of the American Mosquito Control Association 22, 229–238.
Leonel, M.A., Yoneyama, T., 2000. Optimal and sub-optimal control in Dengue epidemics. Optimal Control Applications and Methods.
Lowry, I.S., 1965. A short course in hodel design. Journal of the American Institute of Planners 31, 158–165.

Luenberger, D.G., 1989. Linear and Nonlinear Programming. Addison-Wesley Publishing Co.
Lyapunov, A.M., 1992. The General Problem of the Stability of Motion. Taylor & Francis, London. Reprint.
Maciel-de-Freitas, R., Eiras, A.E., Lourenço-de-Oliveira, R., 2008. Calculating the survival rate and estimated population density of gravid Aedes aegypti (Diptera: Culicidae) in Rio de Janeiro, Brazil. Memórias of Instituto Oswaldo Cruz 24, 1–8.
May, R., 1974. In: Stability and Complexity in Model Ecosystems, second ed. Princeton University Press, Princeton, NJ.
Millington, I., 2006. Artificial Intelligence for Games. Morgan Kaufmann.
Minar, N., Burkhart, R., Langton, C., Askenazi, M., 1996. The Swarm Simulation System, A Toolkit for Building Multi-Agent Simulations.
Mwangi, R.W., Rembold, H., 1988. Growth-inhibiting and larvicidal effects of Melia volkensii extracts on Aedes aegypti larvae. Entomol. Exp. Appl. 46, 103–108.
North, M.J., Collier, N.T., Vos, J.R., 2006. Experiences creating three implementations of the repast agent modeling toolkit. ACM Trans. Model. Comput. Simul. 16 (1), 1–25.
Parunak, H.V.D., Savit, R., Riolo, R.L., 1998. Agent-Based Modeling vs. Equation-Based Modeling: A Case Study and Users Guide. In: Multi-agent Systems and Agent-based Simulation (MABS'98), vol. 1534. Springer-Verlag.
Peck, S.L., 2004. Simulation as experiment: a philosophical reassessment for biological modeling. Trends in Ecology and Evolution.
Perez, L., Dragicevic, A., 2009. Modeling mountain pine beetle infestation with an agent-based approach at two spatial scales. Modelling & Software 25 (2), 223–236.
Peters, T.M., Barbosa, P., 1977. Influence of population density on size, fecundity, and developmental rate of insects in culture. Annual Review of Entomology 22, 431–450.
Peterson, J., 1998. Global Warming Would Foster Spread of Dengue Fever into Some Temperate Regions.
Rahmandad, H., Sterman, J., 2008. Heterogeneity and network structure in the dynamics of diffusion: comparing agent-based and differential equation models. Management Science 54 (5), 998–1014.
Rao, D.M., Chernyakhovsky, A., Rao, V., 2008. Modeling and analysis of global epidemiology of avian influenza. Environmental Modelling & Software 24 (1), 124–134.
Sandholm, T., 1999. Multi-agent Systems: A Modern Introduction to Distributed Artificial Intelligence. MIT Press.
Swarm Development Group: Swarm 2.2, 2004. Swarm Development Group. http://wiki.swarm.org (accessed 4 April 2010).
Templin, R.J., 2000. The spectrum of animal flight: insects to pterosaurs. Progress in Aerospace Sciences, 393–436.
Vlassis, N., 2003. A Concise Introduction to Multiagent Systems and Distributed AI. Informatics Institute, University of Amsterdam.
Williams, C.R., Johnson, P.H., Long, S.A., Rapley, L.P., Ritchie, S.A., 2008. Rapid estimation of aedes aegypti population size using simulation modeling, with a novel approach to calibration and field validation. Journal of Medical Entomology, 1173–1179.
Wooldridge, M., 2002. An Introduction to MultiAgent Systems. Wiley, Chichester.
Dengue and Dengue Haemorrhagic Fever, 2002. World Health Organization. http://www.who.int/mediacentre/factsheets/fs117/en/ (accessed 4 April 2010).
Yang, H.M., 2003. Epidemiologia da Transmissão da Dengue. CNMAC – Congresso Nacional de Matemática Aplicada e Computacional, pp. 387–396.
Yang, H.M., Ternes, S., Ferreira, C.P., 2002. Dinâmica populacional do vetor transmissor da dengue. CNMAC – Congresso Nacional de Matemática Aplicada e Computacional, p. 478.