



Modeling Malaria with Multi-Agent Systems

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ABSTRACT

Malaria is a vector-borne disease that greatly affects social and economic development. We adopt the complex system paradigm in our analysis of the problem. Our aim is to assess the impact of education on malaria healthcare. Multi-agent systems are employed to model the spread of malaria in Haiti, where we introduce malaria education as a possible way of regulating deaths due to the parasite. We launch three experiments, each with environment modifications: three hospitals; three hospitals and 20 schools; and five hospitals and 20 schools. The results of running 10 simulations for each experiment show that there is a reduction in malaria deaths not only when including schools, but in combination with increasing the number of hospitals.

Keywords: decentralised system; education; healthcare; malaria; multi-agent systems

INTRODUCTION

Our goal is to assess the effect of education on healthcare. We first introduce the global malaria problem, followed by the paradigm adopted for its analysis. This is followed by an insight into the current malaria situation in Haiti, the country we have chosen for our study.

The rest of the paper is organised as follows: the State-of-the-Art section introduces current efforts in the field; the following section discusses the model; then

the three experiments and their results are presented; the Discussion part gives some conclusions and a brief analysis; finally, Future Work discusses ideas for future work.

Malaria

Malaria is a vector-borne disease that greatly affects social and economic development in the world. In 1990, it was estimated that approximately 2.2 billion people were at risk of contracting the parasite, and

an additional 270 million were already infected. Endemic areas are characterised by “ideal” mosquito (anopheles being the parasite vector) habitats, which are largely where water is present, the temperature is at least 18°C, and there is little pollution (Baudon, 2000). Many third-world rural areas meet these conditions. Efforts to eradicate this deadly disease have included using DDT to minimise the vector population and administering antimalarial drugs to susceptible people as a prevention. However, both methods have proved only temporarily effective. The former was first adopted in the mid-1950s with a subsequent significant global decrease in mosquito population. This was soon to become a failure when a resurgence of malaria was detected as a result of anopheles developing a resistance to the insecticide (Krogstad, 1996; WHO, 1996). The latter prophylaxis was the use of chloroquine as an antimalarial drug. Resistance of *Plasmodium falciparum* (the more prevalent and deadly of the four existing parasite species) to chloroquine emerged due to the massive usage of the drug (Payne, 1987). As a consequence, a novel way of combating this plague would have to be devised.

Complex Systems

Pavard (2002) describes a complex socio-technical system to be one for which it is difficult, if not impossible, to restrict its description to a limited number of parameters or characterising variables without losing its essential global functional properties. Indeed, from this definition, four characteristics of such a system appear: non-determinism; limited functional decomposability; distributed nature of information and representation; and emergence and self-organisation.

Simulation as a Tool for Understanding Complex Systems

The properties discussed previously show that dealing with a complex system entails dealing with the impossibility to anticipate precisely its behaviour despite knowing completely the function of its constituents. This, combined with non-linear behaviour, means that it is quite problematic, if not impossible, to use a mathematical or statistical approach for its analysis (Bagni et al., 2002; Pavard & Dugdale, 2002). It is for these reasons that computer simulations (in this paper, multi-agent systems, MAS) is a more viable method for exploring complex systems.

Studying complex systems through multi-agent systems has yielded useful results such as in the following: evolutionary population dynamics of settlement systems in the search of emerging spatial regularities (Aschan-Leygonie, 2000); demographic phenomena through its roots in individual choice behaviour and social interactions (Janssen & Martens, 2001); simulations of crowd behaviour aiming to understand its dynamic and consequent control (Gomez & Rowe, 2003; Hamagami et al., 2003).

Haiti

The level of poverty in Haiti is approximately 65% (PAHO, 2001), a socio-economic factor affecting access to public healthcare. Not only is an adequate health infrastructure not fully developed, but individual poverty also hinders access to healthcare. This is aggravated further by not having the financial resources to travel to a place of care, or not judging it necessary to seek medical care.

Malaria is considered a public health problem in Haiti (PAHO, 2001), especially in rural areas. Malaria education, or its lack thereof, plays an extremely important role in the healing process. It is primordial for effective and efficient treatment that malaria be diagnosed at an early stage (Baume & Kachur, 1999). In order for this to apply, the population must be completely aware of its symptoms and act consequently. Symptoms that can be mistaken easily for another disease include high fever, vomiting, convulsions, and anaemia. Not only must the population attribute specific symptoms to malaria, but they must also seek the correct medical attention. The first problem to tackle is educating the population, which could be done through national schooling. However, school attendance by children from lower income families is limited by the cost of school fees and curtailed by child labour.

STATE OF THE ART

The motivations that drive us to develop our model are various. Recent research has demonstrated approaches to the global problem, using MAS, from two angles. Janssen and Martens (1997) focus on the adaptiveness of mosquitoes to insecticides and malaria parasites to antimalarial drugs. This work aims to find a solution to controlling the spread of the disease by understanding the mechanism that renders this prophylaxis useless. Similarly, the same result is sought by Carnahan et al. (1997), but by studying the problem at a different level — the dispersal of anopheles. Here, there is a focus on understanding the behaviour of malaria-transmitting mosquitoes and their geographical displacement, with the aim to consequently monitor their movements and thus reduce the

number of malaria cases. Presently, there is little information available showing the impact of education on healthcare in general, and even less in tackling the problem of malaria. Therefore, we will approach the problem from this standpoint using MAS (StarLogo, <http://www.media.mit.edu/starlogo/>), more specifically applied to Haiti.

THE MODEL

Our model aims to encompass the malaria problem in Haiti. We have programmed the environment to represent the geographical terrain and the agents to represent the human population.

The Environment

The environment we create for our agents to inhabit is made up of a model map of Haiti, with geographical terrain granularity sufficient to represent that which affects the dynamics of what we intend to model. This granularity is such that the simulation space is divided into microenvironments — sea, hospitals, land, mountains, cities, roads, and schools. All of these microenvironments have a direct impact on our agents and, hence, the simulations we run, as will be described further in the Human Population section. A snapshot of the simulation graphical user interface can be seen in Figure 1.

The Mosquito Population

Our model represents only the parasite carriers of the entire anophel population, unlike in Janssen and Martens (1997). We do not model seasonal mosquito population variations. All of our modeled mosquitoes pose a malaria threat to the human (agent) population concerned.

Figure 1. StarLogo simulation interface



We have decided not to model mosquitoes as an agent whose behaviour is affected by its interaction with both the environment and other agents. Their presence in the model is stochastic, embedded in the environment we create. The probability of an agent contracting malaria varies according to conditions the seven microenvironments present; the probability of an agent contracting malaria differs. We can observe, for example, that land (rural areas) is the ideal breeding ground for mosquitoes. This is contrary to mountains where, despite the adequate water level and lack of pollution, elevation lowers ambient temperature, making it an unsuitable mosquito habitat. We consequently say that the highest probability of malaria infection is in land, and digressively in: road, city, and mountain. No contamination occurs in a hospital or school. This stochastic order abides by the information given on such habitats (Baudon, 2000) (Table 1).

The Human Population

The initial human population in our model is evenly distributed in the five cities

Table 1. Mosquito contamination probabilities

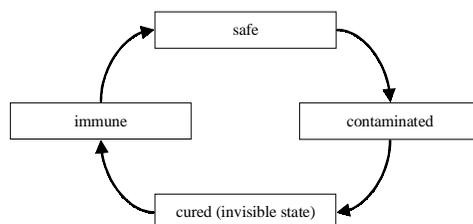
Micro-environment	Contamination Probabilities
Land	2%
Road	1%
City	0.66%
Mountain	0.5%

Micro-environments not included are those with 0% probabilities

on our map, with 200 agents in each. Our agents have been assigned one of the following three states: safe, when they are susceptible to contracting malaria; contaminated; and immune. Each agent can go through the malaria cycle of being safe, becoming contaminated, and consequently either dying of lack of treatment or becoming cured as a consequence of a hospital visit (Figure 2). These states are dependent on the interaction of agents with their surrounding environment.

We have endowed some of our agents with the ability to be mobile and, if so, a fraction with a car. This translates into those who are mobile exiting their city of origin with greater ease than those not mobile. Similarly, car owners can move throughout the country at a greater speed, especially on roads, than those without a vehicle.

Figure 2. Agent state cycle



Natural inoculation occurs through continuous repetitive contamination, where a person cured from malaria is immune to the parasite for an average of one year (Baudon, 2000). As there must be malaria-person contact, and a greater number of anopheles are found in rural areas, the initial immune and contaminated populations are all mobile.

Baume and Kachur (1999) stress the importance of educating the population on the recognition of malaria symptoms and the gravity of consequently not acting. We have introduced this facet of the problem by creating an education scale, where agents have education points ranging from 1 to 20. Points represent the time agents take to attribute existing symptoms to malaria (e.g., a contaminated agent with one education point waits longer before heading toward a hospital than its counterpart with 20 points, who as soon as it is contaminated seeks medical attention). The maximum waiting period is 29 days, because 30 days after contamination, an agent outside a hospital dies. Points are cumulative only. Schools are distributed throughout our Haiti map, both in rural and urban areas. The utility of a school is that agents moving randomly arrive at a school and leave with more malaria awareness. They enter the school, if they do not have 20 points and are not contaminated. They remain for a period of three days, after which they gain an education point.

The model emulates the contamination process stochastically through its environment. Only those agents whose state is safe can be contaminated when they are in a microenvironment and according to the probabilities.

Contaminated agents are to wait an amount of time, depending on the education they have, as previously discussed. If

a contaminated agent has a maximum education of 20, the shortest distance between itself and the existing hospitals will be calculated. Subsequently, the agent will start heading toward medical attention. As a contaminated agent, the speed at which it proceeds is diminished by 50% due to weakness caused by the parasite. Those contaminated who have reached a hospital in time, will remain there for a period of 20 days, the average malaria recovery time (Malaria Foundation International 2000), and subsequently, the agent's state changes to immune (during one year). Education's role is seen in the model when the contaminated agent, because of lack of malaria awareness, does not recognize symptoms in time and, hence, cannot reach a hospital. In our model, death strikes when a period of 30 days (the average interval) has elapsed after symptoms appear (Malaria Foundation International, 2000).

The sex of an agent is not explicit. This factor only affects our model when breeding occurs. We have embodied it by using a random number generator allowing an agent to reproduce 50% of the time, as the male to female ratio is approximately 1:1 in Haiti. The above condition, in combination with the following, must be satisfied before an agent can reproduce: minimum age of 14 years; maximum age of 49 years; not have reproduced more than six times; and have at least an interval of one year after reproduction (WHO, 2001).

In addition to death caused by malaria, we have included natural deaths. The average life span for men and women in Haiti is 50.6 and 55.1 years, respectively (WHO, 2001). In order to accommodate these data, bearing in mind that our agent population is sexless, we have set a maximum age of 55 years. If an agent survives malaria, it dies when attaining that age.

EXPERIMENTS AND RESULTS

Our model attempts to encompass the present malaria situation in Haiti and includes additional information we have deemed relevant to the parasite problem. We ran simulations with three different scenarios of environment changes in our model. Henceforth, our three scenarios will be denominated in the following manner: Experiment A (three hospitals); Experiment B (three hospitals and 20 schools); and Experiment C (five hospitals and 20 schools). Each experiment constitutes 10 simulations with a duration of 10 years.

Three Hospitals, No Schools (Experiment A)

This experiment is our benchmark. We have obtained results from running simulations of our original model.

Three Hospitals, 20 Schools (Experiment B)

Our aim is to observe the effect of adding schools to the model environment. We therefore ran a further 10 simulations with 20 schools, distributed randomly in the environment. These represent malaria education initiatives that could be adopted in order to reduce deaths.

Our hypothesis of education having a significant positive effect on controlling malaria deaths, yielded mediocre results: it did not improve the present Haiti situation. Each curve in Figure 3 is an average taken from the 10 simulations in each experiment, with corresponding standard deviations. The goal is to minimise this curve. Graphically, we noted minimal differences between Experiment A and Experiment B.

However, taking the area under each curve (AUC) pointed to a slight improvement with Experiment B: $AUC(A)=1.30$; $AUC(B)=1.19$.

We found that despite a net improvement in average education as the simulation progressed (Table 2), the malaria awareness acquired was not sufficient in decreasing malaria deaths (Figure 3). We attribute this to the great distances between some contaminated agents, who were aware of their malaria state, and the closest hospital to them. Regardless of having maximum education, the symptom appearance interval elapsed before the agent could reach medical assistance. These preliminary results drove us to experiment with increasing the number of hospitals to five, one for each city.

Five Hospitals, 20 Schools (Experiment C)

This experiment was composed of modifying further our modeled environment by adding two hospitals. By doing so, distances between certain contaminated agents and a hospital are reduced, thereby

Figure 3. Ratio of malaria deaths to total population

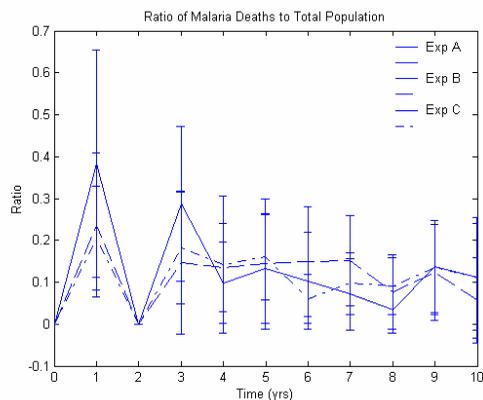


Table 2. Average education

Average Education (σ)	Initial	Final
Experiment A	9.43 (0.19)	13.84 (0.26)
Experiment B	9.55 (0.23)	19.23 (0.21)
Experiment C	9.53 (0.20)	19.27 (0.10)

We present the average education of initial and final simulation populations for each experiment. Standard deviations refer to the spread of the 10 experiments (within each experiment group).

increasing the possibility of them obtaining medical attention.

The ratio of malaria deaths to total population (see Figure 3) decreases in Experiment C, where $AUC(C)=1.13$, a lower value, as expected, than $AUC(A)$ and $AUC(B)$.

In order to help us have a deeper insight into the impact of education, we plot the ratio of contaminated agents in a hospital with respect to the entire contaminated population (Figure 4). For the three experiments, it exposes the proportion of contaminated agents receiving medical attention. Calculating individual experiment AUCs results in: $AUC(A)=3.15$; $AUC(B)=3.17$; $AUC(C)=3.65$. There is a noticeable increase from Experiment A to B, and finally to C. The implication of this is explained in the Discussion section.

Observing population dynamics was achieved by plotting them individually (Figures 5, 6, and 7). Here, the number of safe, contaminated, and immune agents is recorded in order to examine whether differences exist between such states throughout the three experiments. When analysing results for Experiments A and B and comparing them to Experiment C, the immune and safe populations display a considerable increase for the latter. This, however, cannot be said for the contaminated population where we observe minimal variations between experiments due to the factors

Figure 4. Ratio of contaminated agents in hospital to entire contaminated population

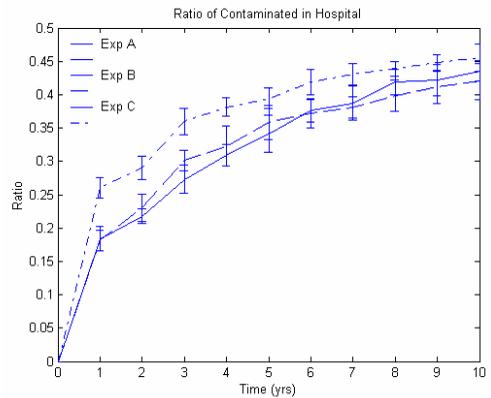


Figure 5. Safe agent population

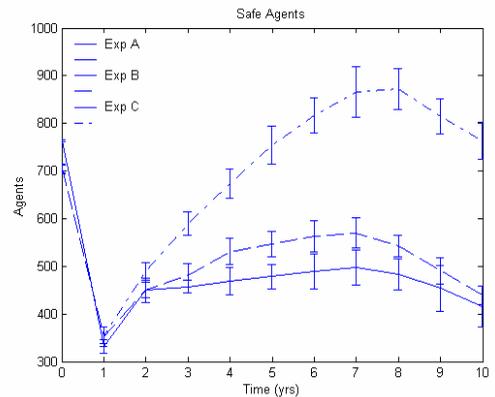
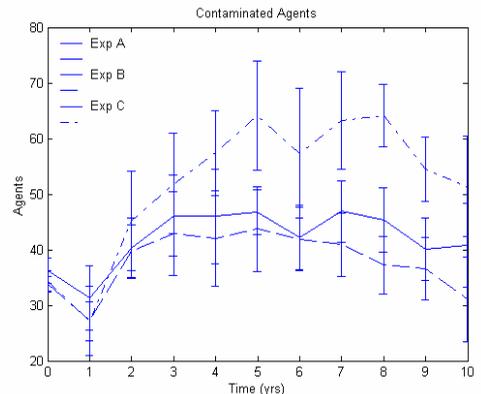


Figure 6. Contaminated agent population



influencing it not varying across experiments.

Temporal population variations, when observing the entire agent population (Figure 8), show a clear increase in experiment C with respect to experiments A and B.

DISCUSSION

Our results demonstrate the impact of education on malaria deaths. We have

Figure 7. Immune agent population

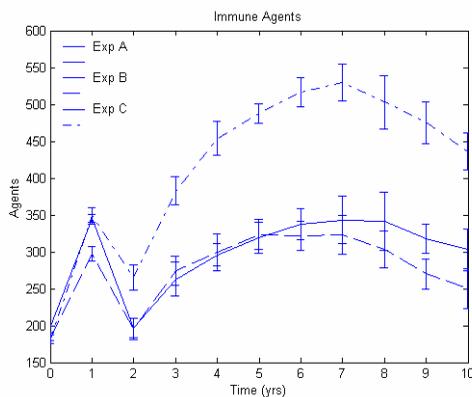
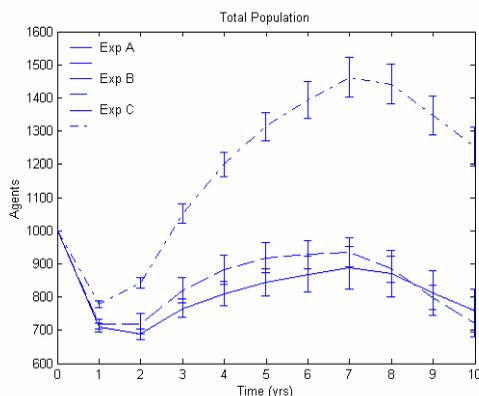


Figure 8. Total agent population



Individual and total population variations. The figures represent averages of 10 simulation runs within each experiment, and their corresponding standard deviations.

seen in Table 2 the changes in average education throughout the entire agent population for all three experiments. In Experiment A, despite the absence of schools (hence, no learning occurred), there was an increase in final education. This can be explained through natural selection. Those agents with a lower education level did not have enough time to obtain medical assistance and consequently died. However, in the case of Experiments B and C, there is a significantly higher final average education, not only because of natural selection, but also due to the addition of schools.

The effect of education was viewed from many facets of our model. One of these is the ratio of malaria deaths to the entire population. The improvement displayed by Experiment B, in comparison to Experiment A, was not as pronounced, as expected. Taking the area under the curve reflected a crisper improvement, similarly with Experiment C.

Moreover, our new hypothesis (the positive impact of adding schools and hospitals), is somewhat confirmed by observing the dynamic ratio of contaminated agents in a hospital with respect to the entire contaminated population (see Figure 4). We expected to witness an increase in this ratio as the simulation progressed, whereby a greater number of contaminated agents are in a hospital obtaining medical attention. There is a clear improvement in Experiment C, where its temporal variations surpass those of experiments A and B. This visual observation is confirmed when calculating AUCs for each experiment.

To corroborate the above results, we can observe individual population variations in Figures 5, 6, and 7. The contaminated population is very similar in all three experiments, which is to be expected since the contamination algorithm was not modi-

fied. However, the same cannot be said for the number of safe and immune agents (Figures 5 and 7), as well as the entire population (Figure 8). There is a significant increase in Experiment C in comparison to both A and B. The state cycle (Figure 2) is such that an immune agent must be previously a contaminated agent, unless it is a child of an immune agent (children of immune agents are also immune up to one year after birth). This implies that those immune agents must have visited a hospital, been cured, and subsequently become immune. Intuitively, we therefore can say that the increase in the immune population in Experiment C is due to a greater number of contaminated agents having sufficient education and being close enough to a hospital in order to rid themselves of the parasite.

In conclusion, we notice from the several experiment results that there is an improvement, not only when introducing schools, but also when increasing the number of hospitals in our model.

FUTURE WORK

Our aim was to encapsulate epidemiological, environmental, and socioeconomic factors in our model. However, we would like to attempt to include greater realism in our current efforts. This would include rural population and climatic seasons. The latter emulates the fluctuations in mosquito population and, hence, in probabilities of malaria contamination. Our intention also is to run simulations for a longer period.

With respect to education, a future step could be modeling the loss of education points. This could be used to capture the idea that after 20 years, for example, a person can forget what he or she has been taught, or the treatment will have pro-

gressed, and, therefore, information acquired previously has become obsolete.

As we have demonstrated, education was not sufficient in our model. We had to include more hospitals. This reflects the vast distances that some agents had to travel. A future step then could be to simulate the effect of improving road infrastructure and transport.

Our current model lacks realism in spatial constraints. For example, in actual hospitals, there is a maximum patient capacity for each hospital. This could be achieved by applying a cellular automata layer as described by Hamagami et al. (2003).

Finally, we can say that our model could be extended to produce a generic model adaptable to different countries or geographical areas, with changes in certain parameters. Only parameter changes are needed, as the mechanisms of the malaria problem (described in the Model section) are universal. This could be the basis of an adaptable, flexible model.

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