MODELLING 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: 3 hospitals; 3 hospitals and 20 schools; and 5 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 when in combination with increasing the number of hospitals.

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 presents; 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 a further 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 18ºC; 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 above 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 and Dugdale 2002). It is for these reasons that computer simulations, in this study multi-agent systems (MAS), are a more viable method for exploring complex systems.

Studying complex systems through multi-agent systems has yielded useful results such as in: the 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 and Martens 2001); simulations of crowd behaviour aiming to understand its dynamic and consequent control (Gomez and 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 the 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 and Kachur 1999). In order for this to apply, the population must be completely aware of its symptoms and act consequently. Symptoms which can be easily mistaken 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, 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. We therefore attempt to 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 micro-environments: sea; hospitals; land; mountains; cities; roads; and schools. All of these micro-environments 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 Fig. 1.

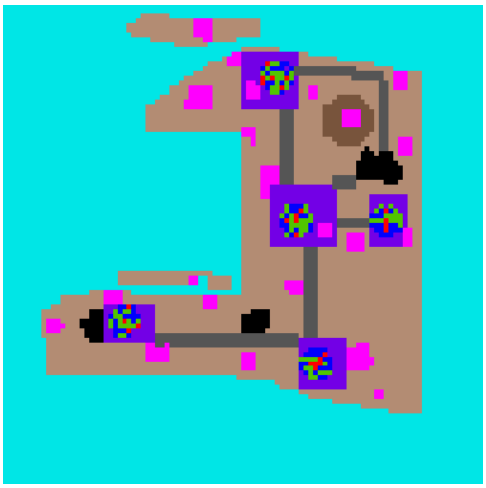

Figure 1 : StarLogo Simulation Interface

The Mosquito Population

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

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 micro-environments 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 degressively in: road; city; and mountain. No contamination occurs in a hospital or school. This stochastic order abides to the information given on such habitats (Baudon 2000), see Table 1.

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

The Human Population

The initial human population in our model is evenly distributed in the 5 cities in 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, see Fig. 2. These states are dependent on the interaction of agents with their surrounding environment.

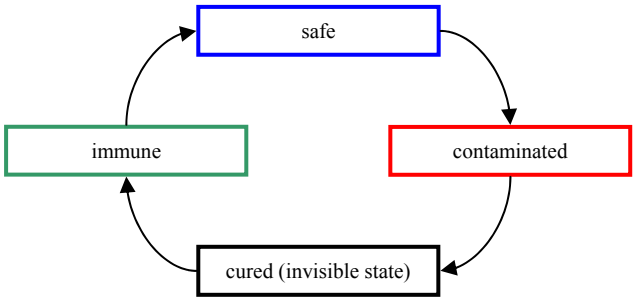

Figure 2: Agent State Cycle

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 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.

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 with the recognition of malaria symptoms and the gravity of not acting consequently. 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, where a contaminated agent with 1 education point 'waits' longer before heading towards 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 lies in 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 in a micro-environment and according to the probabilities.

Contaminated agents are to 'wait' an amount of time, depending on the education they have, as discussed above. 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 towards 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 1 year). Education's role is seen in the model when the contaminated agent, because of lack of malaria awareness, does not recognise symptoms in time and hence cannot reach a hospital. In our model death strikes when a period of 30 days has elapsed after symptoms appear, the average interval (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 6 times; and have at least an interval of 1 year after reproduction. (WHO 2001)

As well as 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 sex-less, 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, described attempts to encompass the present malaria situation in Haiti, in addition to information we have deemed relevant to the parasite problem. We ran simulations with 3 different scenarios: environment changes in our model. Henceforth, our 3 scenarios will be denominated in the following manner: Experiment A (3 hospitals); Experiment B (3 hospitals and 20 schools); and Experiment C (5 hospitals and 20 schools). Each experiment constitutes 10 simulations, whose duration is 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: not improving the present Haiti situation. Each curve in Fig. 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 can note minimal difference from Experiment A to 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.

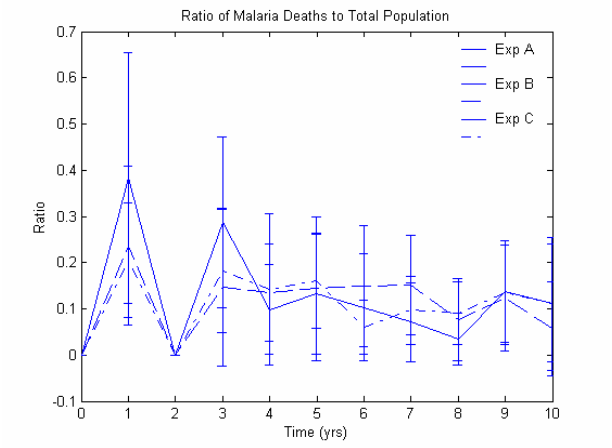

Figure 3 : Ratio of Malaria Deaths to Total Population

We found that despite a net improvement in average education as the simulation progressed (see Table 2), the malaria awareness acquired was not sufficient in decreasing malaria deaths, see Fig. 3. We attribute this to the great distances between some contaminated agents (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.

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).

Five Hospitals, 20 Schools (Experiment C)

This experiment was composed of modifying further our modelled environment, by adding 2 hospitals. By doing so, distances between certain contaminated agents and a hospital are reduced, thereby increasing the possibility of them obtaining medical attention.

The ratio of malaria deaths to total population in Fig. 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 hospital with respect to the entire contaminated population, see Fig. 4. It exposes the proportion, for the three experiments, of contaminated agents receiving medical attention. Calculating individual experiment AUCs result 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 C. The implication of this is explained in the Discussion section.

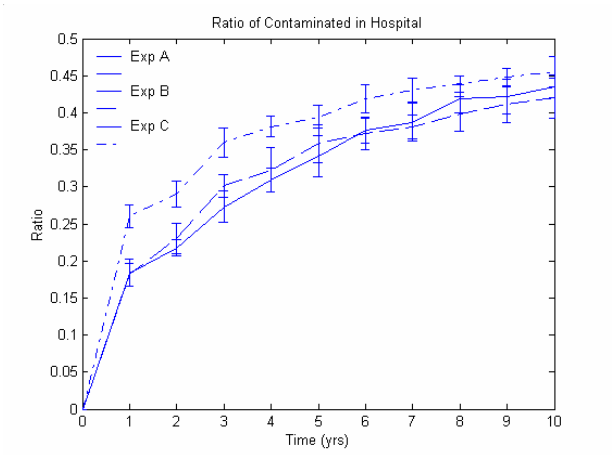

Figure 4 : Ratio of Contaminated Agents in Hospital to Entire Contaminated Population

Observing population dynamics was achieved by plotting them individually, see Figs. 5-7. Here the number of safe, contaminated and immune agents is recorded so as to examine whether differences exist between such states throughout the three experiments. When analysing results for Experiments A and B in comparison 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 influencing it not varying across experiments.

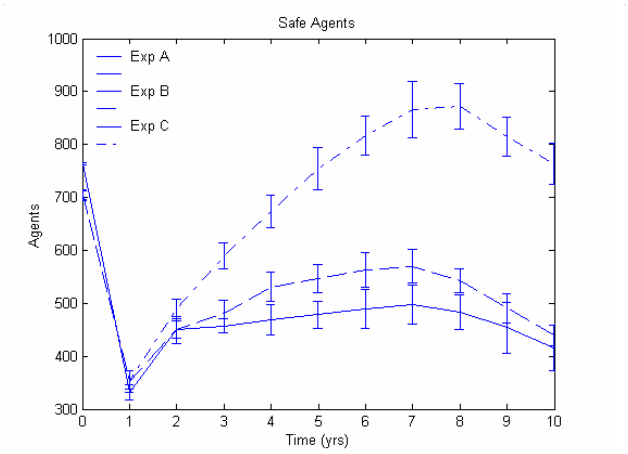

Figure 5 : Safe Agent Population

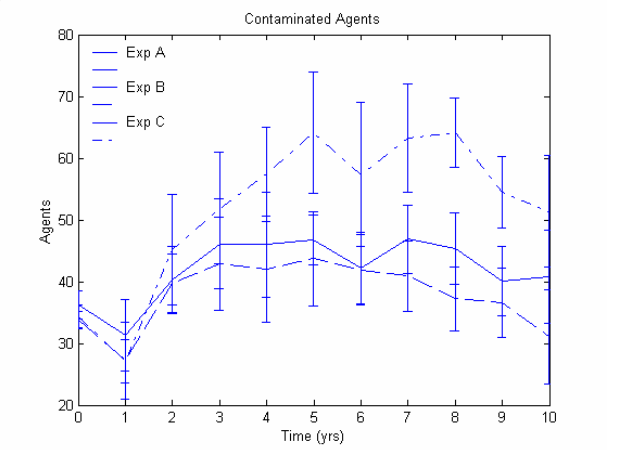

Figure 6 : Contaminated Agent Population

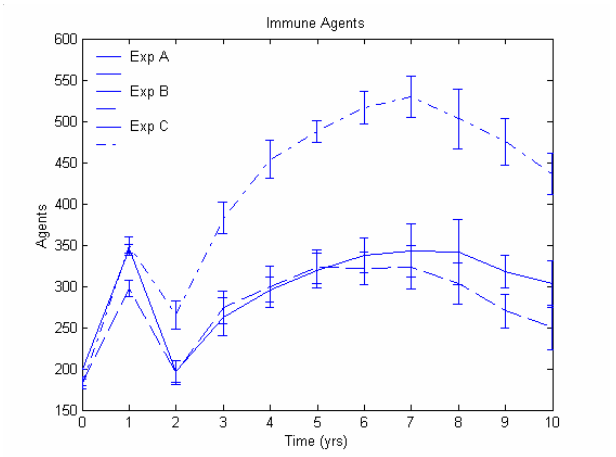

Figure 7 : Immune Agent Population

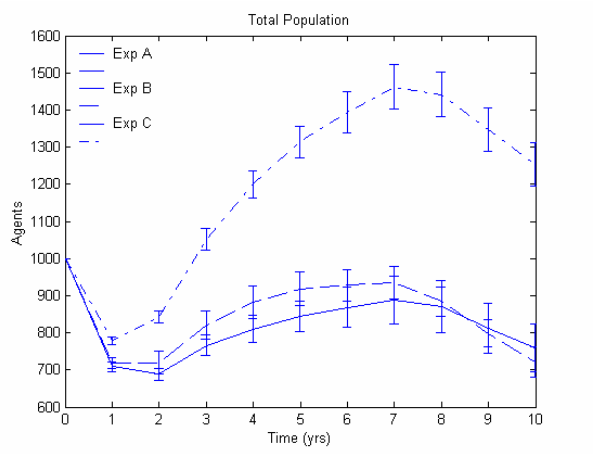

Figure 8 : Total Agent Population

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

Temporal population variations when observing the entire agent population, see Fig. 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 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' occurring, there was an increase in final education. This can be explained through natural selection. Those agents with a lower education level had not 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 to 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 hospital with respect to the entire contaminated population, see Fig. 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 Figs. 5-7. The contaminated population is very similar in all three experiments, which is to be expected as the contamination algorithm was not modified. However, the same cannot be said for the number of safe and immune agents (Figs. 7 and 5), as well as the entire population (Fig. 8). There is a significant increase in Experiment C in comparison to both A and B. The state cycle (see Fig. 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 1 year after birth). This implies that those immune agents must have visited a hospital, been cured and subsequently become immune. Intuitively, we can therefore 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 described above that there is an improvement not only when introducing schools but also increasing the number of hospitals in our model.

FUTURE WORK

Our aim was to encapsulate epidemiological, environmental and socio-economic factors in our model.

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

With respect to education, a future step could be modelling the loss of education points. This could be used to capture the idea that for example after 20 years, a person can forget what it has been taught or that the treatment will have progressed, 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 could then be to simulate the effect of improving road infrastructure and transport.

Our current model lacks realism in spatial constraints. For example with in real life hospitals there is a maximum patient capacity for every 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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