Effect Analysis of Climate Change on the Reproduction of Mosquitoes and Infection Rate Sensitivity for SI/SIR Epidemical Model in the Case of Malaria Disease

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Abstract-The purpose of this study is to improve the current methodology SI/SIR by introducing the sensitivity of infection rate to climate change variables such as temperature and humidity to reproduce infection by anophelines gambaie. The improvement provides a satisfactory model, where the number of mosquitoes is controlled by the time and seasons, which change the malaria reaction. Rwanda weather facilitates the lodgment of these vectors where the variation of temperature is ranged between 10 and 29°C and humidity is in the range of 30% - 97%. With climate change, distress the change into the number of mosquitoes is complex to change, this makes the reaction of the infection rate to respond proportionally to the change of mosquito and it is effective for the population at risk of malaria to respond to this change, especially in some season where the infection rate can be more than 0.2. Furthermore, analysis and comparison are made, where the infection rate as a time-dependent variable, demonstrate a significant result where the explanation of the result has the meaning of the climate change variables. The result provided by the new model proves the importance of the focus mostly on infection rate sensitivity.

Index Terms—climate change, variables, seasonal, humidity, temperature, approach, mosquito, anopheline gambaie, malaria disease, population, human, SI/SIR model, infection rate, sensitivity

I. INTRODUCTION AND BACKGROUND

The world has been and is still facing the presence of Malaria disease, which is among the high placed problem of the world. This disease has been discovered in 1880 [1], its studies have been conducted and there have been many new discoveries about the disease. The disease was defined to be a mosquito-borne epidemiologic disease that is transmitted from human to human by the bites of infected female mosquitoes, and this varies depending on the season. Like most of the sub-Sahara countries in Africa, Rwanda is distress with the disease, which presents different risks, including death.

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Rwanda has seasons that allows mosquitoes' to be active and this makes the presence of malaria disease highly infectious in this region since it has been discovered. Numerous strategies to eradicate the incidence were applied but the disease still exists and the result is not enough.

Previous works [2]-[8] review the climate change variables involvement into, mosquitoes' life cycle and how mosquitoes' presence makes a big change to the disease spreading into Human [3] and [9]. The infection rate of the disease depends on time, temperature and related to humidity because they take an effect on the life cycle of the anophelines reproduction, and increase the number of bites [10], [11]. SI/SIR model has been used to study the influence of climate change on the effect of Malaria disease.

The study [4] focused on the mosquitoes' birth and statistical determination of rates of mosquitoes' type. In this work, focusing on the life cycle of the mosquito, some data analyses were applied to improve the beta sensitivity and apply in the SI/SIR model, for the improvement of the model.

Beta sensitivity epitomizes the reaction for the infection rate by the time goes by with the dependency of different factors; in this case, temperature and humidity are the main variables

Susceptible-Infected-Recovery (SIR) is a methodology to predict the spreading disease based on the data in a previous year. This model has been studied and modified by many researchers [9], [12]-[15] depending on their goals; especially Malaria disease study. To solve differential equations in this model, we set the initials variables for certain variable before the use of the function, and those following result will depend on the output of currently vectors result, this is how this model work. As for malaria disease, infection rate should vary depending on the change of the climate condition and change of mosquito number. Applying the model to malaria disease, it does not support these changes, since it treats the infection rate as just a constant. The reason why for this study, is to analyze the influence of climate change on a reproduction of anophelines gambaie, explores the sensitivity of infection late for malaria disease in Rwanda.

II. METHODOLOGY

A. Context

This research focuses on climate effects on the sensitivity of a reproduction rate, a death rate, and an infection rate, focusing on a life cycle of mosquitoes based on the change of temperature and related to humidity.

B. Setting

Rwanda meteorology data for 2017 are applied to study the change in mosquitoes Reproduction base on the climate change variables where the temperature vary with the minimum equal to 10 and the maximum at 29 and related to humidity vary within the range of 30% - 97%.

C. Stakeholders

• Mosquito identification

The used data were generated based on the climate variables. The mosquitoes' birth rate took two values; it was 50 for the case either temperature or humidity was lower and, otherwise, it was 200. A study [4] have been conducted about the mosquitoes' birth in some locations, one of which was in Rwanda, and it identified two mosquito types, 73.8% of which were culicine and 26.2% were anophelines. All anophelines were categorized into three, gambiae with 94.3%, Funestus with 0.4% and other anophelines with 5.3%. The most important one was the anopheline gambiae [4], the female mosquitoes responsible to distribute malaria disease among the population.

Human population

In this study, the human was the second group that faces the risks of this disease like death. Web sites such World population review have been used to collect information about population changes in Rwanda, including the growth such as the number of born people (around 1,000), dead people (around 200) and the total number of people (12,636,816) reported day by day.

III. MODEL

A. A brief review of SI/SIR model

An SIR model divides a population into three categories; Susceptible (S) that represents the population on the risk to get infected by the disease, Infected (I) that represents the infected population and Recovered (R) stands for the population recovered for the disease over the time. The model was built for spreading diseases such as Malaria, Dengue, and Ebola in order to forecast the result in the following year based on data of the current year [3], [9], [12]-[20]

The employment of the model works for Malaria as other spreading diseases. Depending on target diseases, such as malaria, the model has been extended to support new variables to describe a spreading system of the disease. Since some mosquitoes are known to be the cause of Malaria spreading into the human population, new variables to describe them as an SI model that has no recovery for the mosquito with Malaria disease(Fig. 1).



Figure 1. SI/SIR model with a demonstration on how the βm and βh associate the interaction between mosquito and human.

A combination of the original SIR model and the SI model has been used to analyze diseases spread [6] by an interaction between two species such as human and mosquitoes for Malaria. The following are the model's equations (a prime mark denotes a derivative):

 $\begin{array}{l} S'_{m} = \nu_{M} - (r * \beta'_{m} * S_{m} * I_{h}) - \delta_{m} * S_{m} \\ I'_{m} = (r * \beta'_{m} * S_{m} * I_{h}) - \delta_{m} * S_{m} \\ S'_{h} = \nu_{h} - (r * \beta'_{h} * S_{h} * I_{m}) - \delta_{h} * S_{h} \\ I'_{h} = (r * \beta'_{h} * S_{h} * I_{m}) - \delta_{h} * S_{h} - \gamma_{h} * I_{h} \\ R'_{h} = \gamma_{h} * I_{h} \end{array}$

 TABLE I.
 Definition of the Parameter for the Differential Equations

Symbole	Definitions
V _m	The newborn rate for the mosquito
ν _h	The newborn rate for the human
γ_{h}	Human recovery rate
$\delta_{\mathbf{m}}$	The death rate for mosquito
$\delta_{\mathbf{h}}$	The death rate for human
β' _h	The probability of mosquito to infect human
β' <u>m</u>	The probability for a human to infect the mosquito
r	Bitting rate of mosquito
Sm	Mosquito-size on the risk to get infected by the disease
S _h	The human population on the risk to get infected by the disease
Im	Mosquito-size infected by the disease
I _h	Human population size infected by the disease
R _h	Human population size recovered from the disease

IV. MODIFICATION OF THE MODEL

We used the SI/SIR model with additional variables, which are required to reflect climate effects. They included some ratio, such as an infection ratio ($\beta_m = r \cdot \beta'_m \cdot I_h$ and $\beta_h = r \cdot \beta'_h \cdot I_m$), the probability of infection for the susceptible population, and a recovering ratio γ_h . In fact, through the introduction of these two is not novel, they have been considered as constants as the rates of newborn (v), death rate (δ). In our correction, we change β_H , β_M and ν_m depending on climates.

To start using equations of the SI/SIR model, initial values must be set for all of the variables. Total number of mosquitoes used in the model equal to 340684 [4], with the Human size of 600000 estimated randomly, S_h is equal to human size (600000), in this case, everyone is considered to be on the risk to get infected, S_m is equal to 340684, the size of mosquito. As an initial value, we set Ih=1 and Im=1. The test of the SI/SIR mode was conducted into two different ways. The first test was to analyse the change of SI/SIR with constant variables, such as newborn rate for both human ($v_h=0.024$) and mosquito (v_m =0.027871) and for infection rate for Human $(\beta_h=0.000005)$ and Mosquito $(\beta_m=0.000008)$, recovery rate for Human (γ_h =0.0033), death rate for both human $(\delta_h = 0.0067)$ and mosquito $(\delta_h = 0.027871)$. With these initial variables, the output generated.

Mosquito is known to be the cause of malaria disease into the population through a bite. This transmission on malaria from the human to another human cannot happen if there is no mosquito. Since the change in the number of mosquitoes should have something to do with the change of climate [6], [7], [8], [15] and [21] there should be some variables that control the number of mosquitoes. The candidates are temperature and humidity especially in the areas where there do not face winter season

The generation of mosquito number was based on two conditions, related to the mean temperature, 20.2°C, and the mean humidity, 65.115% in Rwanda. With the range of mosquitoes, the number is between 50 to 200 mosquitoes, the 50 mosquito's birth will be generated when the temperature is lower or equal to the mean temperature with the humidity, which is lower or equal to the mean. In the case of 200 mosquitoes is when the temperature and humidity are higher than there mean values.

We also need to take account of their life cycle: mosquitoes are considered to live for only three weeks and die on the twenty-first day [8]. This theory is used to evaluate the daily number of mosquitoes. We used the meteorology data for 2017 obtained from the institution in charge of meteorology in Rwanda.

Counting the lifecycle of mosquito, they have to feed with the human or other animal's blood to survive and reproduce. Once a mosquito bites, it has to stay resting for three days before the next bite. This is the process until the twenty-first days. Having the number of mosquitoes generated, this facilitates to get the number of the daily bites based on the population number and the mosquitoes 'number. In our formulation, the bite is representing by r, which is a ratio of the number of available mosquitoes to the total number of the available population. The bite probabilities, or infection ratios β_i (t) are given as the product of the bite rate r and initial probability for i to be infected (β '):

$\beta_i(t) = r \cdot \beta'_i$ (i= h, m)

where i represent the human and mosquito. In order to estimate β_i (t), we firstly estimated the number of available mosquitoes based on the rule of mosquitoes'

new birth. After that, we applied it to the SI/SIR model with changing v_M , which also follows the rule of the new birth.

This analysis focused on the infectious mosquito type of anophelines gambaie, where 26.2% and anophelines mosquitoes where gambaie has 94.3% and this have been put into consideration during the analysis [4]. This change does not only affect infection rate only but also the newborn of the mosquitoes and the death rate.

V. RESULT





Figure 2. Infection rates ($\beta_m(t)$) for mosquito and Beta_H for human ($\beta_h(t)$) year 2017.



Figure 3. Variation of climate change variables (Temperature and Humidity) daily data for the year 2017.

Fig. 2 shows the resultant daily changes of the infection rates of anophelines gambaie caused by temperature and humidity. It shows β h takes high value more than 0.2 from May to June ending (Fig. 3 shows the actual humidity and temperature used in the calculation). Fig. 4 and Fig. 5 show the time series variation of S and I for human with constant β (Fig. 4) and with time varying β (Fig. 5). These show that when the humidity decrease, the number of patients IH decreases and when the humidity increases the number of patients increases. This suggests how malaria incidences may change by the time in a year depending on the temperature and humidity, and

this shows how risk the disease will be depending on the season changing.

The high sensitivity is caused by the new birth of mosquitos, which makes the biting rate to increase. Moreover, the infection rates are β_m and β_h in Fig. 2 suggests they are sensitive to the humidity. This makes a change of the disease in the human population to increase in Fig. 5, especially during the period when the humidity is high and the infection rate is more than 0.2, specifically from May to June end.



Figure 4. The result obtained from the SI model from Human by applying constant infection rate (β_h) .



Figure 5. The result obtained from the SI model from Human by applying time depended on infection rate $(\beta_h (t))$.

VI. DISCUSSION OF THE RESULT

In this section, we discuss the result of the analysis for the proposed mathematical model SI/SIR focusing on the infection rate (β_i (t)) improvement.

This climate change variable analysis proved an effect on the mosquito reproduction, especially during the rainy season [6], [7] and [8]. In the season, the increasing number of mosquitoes was much more than human, which increased the biting rate in the study. In addition, we assumed the product of the biting rate and the infection probability β ' gave infection rate, which represents the probability of infection to the human. The initial value of the infection rate of a year should be given by the last rate in the last year. The mosquito number increase makes a big effect on the infection rate to increase.

Following the paper [4], we assumed the breakdown of the number of mosquitos was 26.2% for the anopheline and 94.3% of the 26.2% for anopheline gambaie, which was focused on in this study. We used it in order to focus on the risk of anopheline gambaie mosquitoes on human, as they are the main cause of the spreading of Malaria disease. The results of our analysis showed a link between the climate change especially humidity and the change of infection rate as is shown in Fig. 2. This makes an effect on the SI/SIR model, and results in the result shown in Fig. 3 and Fig. 5.

Our version SI/SIR model is focusing on the improvement of the infection rate through the influence of climate change on the growth of mosquitos. Typically, the infection rate has been treated as a constant. Its result has been unsatisfactory because it does not reflect sensitivity to the variation of the climate as shown in Fig. 4. In our theory, the new infection rate $\beta_i(t)$ is applied to the number of human on risk S_h combined with the infected mosquito size I_m . Fig. 5 shows a graph of S_h responsive to the new time-dependent $\beta_i(t)$. It shows that, when the mosquito number is high, infection probability of the S_h can be also high. This leads that the larger $\beta_i(t)$ is, the more the humans on risk get infected.

Mosquito reproduction affects human by spreading the disease. A new birth of mosquito determines daily bite rate of the mosquito to human. Fig. 5 shows the result obtained by the new infection rate based on time-dependent value of anophelines gambaie mosquitos' bites. This suggests the inflation of mosquito reproduction in the period where the humidity is more 80%. This is because we dealt with the birth rate is not constant in SI model for mosquitoes. Since the bite rate r is proportional to the number of mosquitoes and the number of mosquito increases exponentially under the conditions, the impact of the high birth rate during hot and high humidity season can accelerate the increase of mosquitoes and enhance the spread of infection.

VII. CONCLUSION

The model SIR was built to simulate epidemiological diseases. In this study, some variables that have been dealt as constants are regarded as time-varying variables depending on factors related to weather. The analyses focused on the mosquitos' birth affected by temperature and humidity over the time. The bite ratios in the model were affected by this change. The simulation using the real climate data in Rwanda showed that the number of mosquitoes and the number of patients change exponentially mainly caused by humidity change.

Since our simulation suggests the humidity has large impact on the mosquito increase and malaria patient increase, we will improve our model to forecast malaria disease in Rwanda based on the humidity data.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

In this paper, INGABIRE Emma Marie has contributed to the generation of new infection rate based on the bite rate using the temperature and humidity. Her contribution has made the present epidemiological model more dynamic and realistic by using the dynamic variables instead of the constant variables with the current existing models, under the supervision and guidance of Masaomi KIMURA.

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