

Modeling the Impact of Climate Change on Malaria in Nigeria

Liam Morris, Dylan Burke, Benjamin Hannam, Matthew Hayes, Prof. Dorothy Wallace
Department of Mathematics, Dartmouth College

INTRODUCTION

Our experiment is based on the work put forth by S. Olaniyi and O.S. Obabiyi in their 2013 paper, “*Mathematical Model for Malaria Transmission Dynamics in Human and Mosquito Populations with Nonlinear Forces of Infection.*” Their paper first develops a model for the population dynamics of humans and mosquitos, then varies the proportion of antibodies produced by humans and mosquitos to combat malaria, and ultimately analyzes this effect on the overall levels of susceptible, exposed, infected, and recovered humans. We aim to further these studies by introducing and observing the role of climate on mosquito population growth rates.

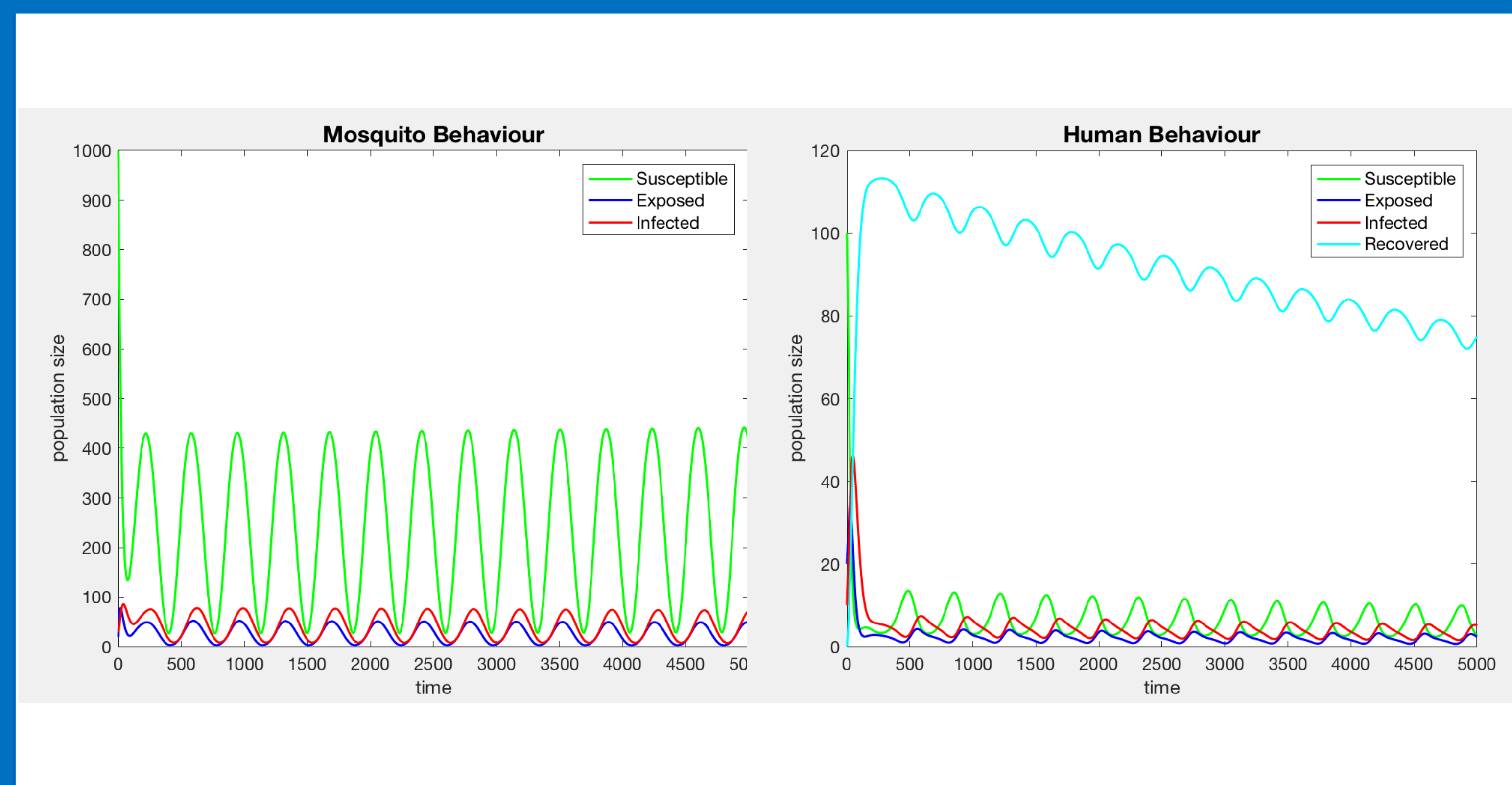
METHOD

The methods we used to generate and develop our model for the transmission of malaria in humans and mosquitos relied heavily on MATLAB. First we built Olaniyi and Obabiyi’s model in MATLAB, by creating a system of ordinary differential equations with parameters to produce the same graphs and behavior that we observed in their paper. Once we had our base model, we began to look into modeling standing-water and humidity levels in Nigeria. This data was unavailable, so we looked to two proxies that are highly correlated with the behavior of these climate variables: temperature and rainfall. We used MATLAB to fit a Fourier Series to rainfall/temperature data from the World Bank; we replaced the fixed parameters for mosquito recruitment and death rate with these sinusoidal functions.

To ensure the model exhibited realistic long-term behavior, we tweaked some of the parameters (as discussed in Model Development) and generated time-series graphs displaying the behavior of all populations over 5,000 days. Once we were satisfied with our long-term behavior, which was discussed in Model Analysis, we then generated time-series graphs over 700 days displaying the behavior of infected mosquitos and infected humans, our populations of interest, to examine their short term behavior.

Additional graphs plotted were that of infected mosquito population against our proxies for standing water and humidity in multiple scenarios, as well as EIR vs. percent infected.

DIAGRAM OR EXAMPLE OF STIMULI



RESULTS

We found that the populations with the greatest influence on the spread of malaria were infected humans and infected mosquitos. Notably, changes in mosquito population did not enact drastic changes to the infected human population. One theory that would support this behavior is that with the higher spike in infected human population initially for a severe climate change scenario that would suggest that early on there would be a greater recovered human population, resulting in fewer people to infect later on, so the baseline and lower climate change situations could have a higher infected population near the end of year two.

In the dry season, with low levels of standing water, humidity and mosquito population both decrease across the period. At the beginning of the dry season, when mosquito populations are at their peak, under severe climate change there are around 72 mosquitos versus 65 under baseline climate change, for a difference of 7. At the end, when mosquito populations are lowest, the population of mosquitos is 27 for severe climate change and 25 for baseline climate change, a difference of only 2. Thus, we see again that at higher levels of humidity, mosquitos are more sensitive to the effects of climate change.

From the beginning of the high humidity season to the end, the levels of mosquitos under severe climate change increases from roughly 57 to 76, and under baseline climate change the population increases from 47 to 67. Therefore, although the population increases with standing water, the gap between the two climate change levels does not change significantly. By contrast, from the beginning of the low humidity season to the end, under severe climate change the population of mosquitos decreases from 87 to 40, versus roughly 72 to 31. This suggests there is a convergence across the climate change levels during the low humidity period, unlike across the high humidity period.

CONCLUSIONS

Our model sought to modify an existing system of differential equations to account for the potential of climate change to impact mosquito population dynamics, and as a result, the transmission of malaria. To do so, we change the mosquito recruitment and death rate by introducing sinusoidal terms for rainfall and temperature, which we treat as proxies for standing- water and humidity, respectively.

We did get expected results on the population of infected mosquitos. Going from baseline to moderate climate change saw a substantial increase in population size at the peak, which was further accentuated by severe climate change. All graphs reflect this fact; level of time, humidity, or standing-water, mosquito populations were higher under the presence of climate change.

Further, while populations were sensitive to both levels of standing water and humidity across seasons, we noticed that approaching the lower-bound to humidity minimized differences across climate-change levels, supporting the theory that a certain level of humidity is required for mosquitos to survive (because, by extension, at low levels of humidity, it doesn’t matter how much climate change has increased standing-water, as mosquitos will struggle to survive regardless).

FUTURE DIRECTIONS...

Our most senior concern in future iterations of this experiment would be increased accuracy in our projections for human behavior. More specifically, we struggled with the last effect, or lack thereof, that changes in mosquito behavior as a result of climate change had on the infected human population. It’s possible humans don’t change because we changed the parameters to make mosquitos die off. Our results show that even if there were a large increase in the number of infected mosquitos, the number of infected humans would change very little, if at all. This was a surprising outcome of our model as one would expect that if there are more infected mosquitos then there would be more infected bites which would lead to a higher rate of infection in humans. One theory to explain this is that by using a scalar term to implement climate change, we were only implementing a “fixed” climate-change; as a result, we increase both peak and minimum growth rate, but the growth rate itself does not change over time.

ACKNOWLEDGEMENTS

Olaniyi, S., and O.S. Obabiyi. “Mathematical Model For Malaria Transmission Dynamics In Human And Mosquito Populations With Nonlinear Forces Of Infection.” *International Journal of Pure and Applied Mathematics*, vol. 88, no. 1, 2013, doi:10.12732/ijpam.v88i1.10.

R. Ross. *The prevention of malaria*. John Murray, London (1911).
“Climate 101: Why Does Climate Change Increase Rainfall?” *Climate Reality*. www.climate realityproject.org/blog/climate-101-why-does-climate-change-increase-rainfall.

Ukubulwe, A.C., et al. “Molecular Bases of Reproductive and Vectorial Fitness of Culex Pipiens Pipiens (Diptera: Culicidae) Mosquito Populations, for the Transmission of Filariasis in North Central Nigeria.” *Journal of Medical Sciences(Faisalabad)*, vol. 13, no. 3, 2013, pp. 201–207., doi:10.3923/jms.2013.201.207.

Scientific Consensus: “Earth’s Climate Is Warming.” NASA. NASA, 8 Feb. 2018. climate.nasa.gov/scientific-consensus/