Modelling the Prevalence of Infectious Diseases with Mosquito Vectors when Affected by Climate Change

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Introduction

Vector-borne diseases have shown to be extremely sensitive to climate conditions. The transmission cycles of diseases that require a vector or non-human host are more susceptible to external environmental conditions than diseases that have cycles that include only the pathogen and the human [1, 2]. Previous studies conducted in areas of extreme climatic events have concluded that mosquito breeding and survival increases with heavy rainfall and temperature. For example, one study that investigated malaria epidemics in a river-irrigated region of India found that the risk for malaria increased five-fold in the year following an El Nino cycle [1].

The geographical distribution and/or seasonal patterns of disease carrying vectors such as mosquitoes may differ with changes in global temperature [1]. Elevated temperature and flooding can therefore affect the frequency and severity of epidemics of infectious diseases in the future [3]. It is essential to recognize that the increase of epidemics of an infectious disease can lead to it becoming endemic in that area, as has happened with West Nile Virus [4]. With the possible detrimental effect climate change could have on health, the healthcare system must make current and future preparations to face the challenge [5].

Models simulating outbreaks of mosquito-borne illnesses need to consider climate factors, such as temperature and precipitation, to predict the incidence and/or prevalence of an infectious illness. In regards to various mosquito species, previous literature has found that there is a range of temperatures, typically estimated to be between 68 °F to 93 °F, in which the mosquito populations thrive [6, 7, 8]. Under these ideal conditions, many mosquitoes are able to mature to an age in which they are potentially infectious and can reproduce. When the temperature falls outside of this range, below 68 °F or above 93 °F, mosquito populations often shrink in size, due to increased difficulty in reaching reproductive maturity, an increase in natural deaths, and thus a decrease in the susceptible vector population [6, 9].

Objective

The project aims to create a model of the relationships between the hosts, the vector-borne infectious disease pathogen, and the vectors in the context of climate change.

Methods

The Model

To simulate the impacts of climate change on mosquito vector populations, we adapted R code from an existing Dynamical Systems Approach to Infectious Disease Epidemiology (DSAIDE) R Studio shiny application, written and maintained by Dr. Andreas Handel from the University of Georgia's College of Public Health. The application we adapted code from was the "Vector Transmission" shiny app, as it contained existing parameters that could be used to simulate the effect of climate change on vector populations. The new app is named "Climate Change."

All of the parameters in the original Vector Transmission app were included in the new Climate Change app. These original parameters have been asterisked in **Table 1**. Two new parameters, average temperature (tp) and optimal temperature (topt), were added in the new app. The purpose of the chosen parameters is to simulate reality with regards to climate change. The full list of parameters and their definitions are outlined in **Table 1**.

Table 1. Parameters and parameter definitions for the climate change model.

Parameter	Parameter Definition
Sh0*	Initial number of susceptible hosts
Ih0*	Initial number of infected hosts
Sv0*	Initial number of susceptible vectors
tmax*	Maximum simulation time, units of months
b1*	Rate of transmission from infected vector to susceptible host
b2*	Rate of transmission from infected host to susceptible vector
m*	Rate of births of vectors
n*	Rate of natural death of vectors
g*	Rate at which infected hosts recover/die
w*	Rate at which host immunity wanes
tp	Average temperature being simulated in °Fahrenheit
topt	Optimal temperature in °Fahrenheit

* Adapted from the equations of the Vector Transmission DSAIDE app by Andreas Handel

For simplicity in our Climate Change model, we focused solely on the effect that temperature had on vector populations and on potential outbreaks, and we chose to exclude factors such as precipitation and humidity. The effect of temperature was integrated into the existing differential equations used in the SIR formulas of the current Vector Transmission app. We assumed linear seasonality, rather than modeling each season, to keep the model general. This allows the app to be usable for a variety of geographic locations with differing season and climate conditions.

Since we assumed linear seasonality, we chose to allow the user to set an average temperature, which is the value that is the mean of the start and end temperature of the chosen time-period being simulated. The user can set the average temperature to any value between 50 °F and 110 °F; these values are 30 degrees higher and lower than the value of the median of the optimal temperature range of 68 °F to 93 °F which is 80 °F. To ensure that a realistic temperature is chosen for the optimal temperature, the highest and lowest values that the user can choose for this parameter are the values within this aforementioned optimal range. Since our chosen range of values for the average temperature are larger than those for the optimal temperature range, the user can observe the disease dynamics and changes in a vector population when the average temperature is set to a value outside of the optimal temperature range.

All of the differential equations in our model, excluding the equation that accounts for susceptible vectors (dSv), are the same as those used in the Vector Transmission app because the relationships we wanted to model were the same as those in that app. We added a term to the dSv formula which accounts for susceptible vectors. When the difference between the average temperature and the optimal temperature increases, the susceptible vector population decreases by some amount, due to the fact that for temperatures outside optimal ranges, mosquito populations often shrink in size [6]. To model this gradient that the difference between the average and optimal temperatures introduces to the vectors' natural death rate, n, and the number of susceptible vectors, Sv, we created the term $(\boldsymbol{1+a(tp-topt)^2})$), and multiplied it to those variables.

The term $(\boldsymbol{1+a(tp-topt)^2})$) finds the difference between the optimal and average temperature and squares it to magnify the difference and remove negatives. The resulting term is then multiplied by some value 'a.' The value 'a' is a constant and allows us to set the magnitude of the impact of the difference between average temperature and optimal temperature on the rate of natural vector death and susceptible vector population. In our model, we manually set 'a' to 0.7; however, in the future, this can be changed to reflect changes in climate, geographic location, or literature. We set 'a' to 0.7 after experimenting with the model and finding that 0.7 caused the gradual decrease in mosquito population observed in nature above and below the 68 °F to 93 °F range. We added 1 to the resulting term so that if the average and optimal temperature are turned off or are equal, the natural deaths and susceptible vectors are multiplied by 1, instead of 0, and will therefore remain turned on rather than becoming turned off. The differential equations resulting from incorporating the new parameters are shown below.

$\boldsymbol{dSh = -Sh * b1 * Iv + w * Rh}$ **(susceptible hosts)**
$\boldsymbol{dIh = Sh * b1 * Iv - g * lh}$ **(infected, symptomatic hosts)**
$\boldsymbol{dRh = g * Ih - w * Rh}$ **(recovered, immune hosts)**
$\boldsymbol{dSv = m * p - n * (1 + a(tp - topt)^2) * Sv - b2 * Ih * Sv}$
(susceptible vectors)
$\boldsymbol{dIv = b2 * Ih * Sv - n * Iv}$ **(infected vectors)**

<u>*Tasks*</u>
To test our created model for the Climate Change App, we designed six tasks to demonstrate important disease dynamics, as related to climate change, vector population, and outbreaks. For each task, the variables outlined above (**Table 1)** were set to specific values in order to demonstrate a desired natural phenomenon.

For task one, we wanted to show the absence of an outbreak due to no transmission between hosts and vectors. To achieve this, the transmission rates between host and vector and vector and host were both set to 0. Vector births and vector death rate were set to 50 and 0.05, respectively. Waning immunity was turned off. The average and optimal temperature variables were also turned off in order to keep the focus on the effect of no transmission.

The second task was created to model an outbreak occurring in an environment with an "optimal temperature." As discussed in the introduction, mosquito vector populations thrive under ideal temperatures, which are usually between 68 °F and 93 °F. These ideal conditions are often associated with in an increase in the number of mosquito births and a steady population death rate. To simulate this phenomenon, the average and optimal temperature were set to the same value of 80 °F, as this is the median value in the range of optimal temperatures. The rate of transmission from infected vector to susceptible host was set to b1=0.0015, while the rate of transmission from infected host to susceptible vector was set to b2=0.005. All other variables were kept the same as in task one.

Task three demonstrates how extreme temperatures could impact vector populations. Mosquito vectors don't reproduce as often in environments of very low or very high temperatures. This, in turn, results in a smaller mosquito vector population, creating a lower chance for a potential outbreak. To demonstrate this, the optimal temperature was set at 80 °F, while the actual temperature was set 30 °F below and above the optimal temperature. Two simulations were run, one with the actual temperature set to 50 °F and one with the actual temperature set at 110 °F. All other variables were kept the same as in task two.

The fourth task focused on vector births and the impact this variable has on potential outbreaks. We chose to focus on vector births to model what would occur if a factor related to climate change besides temperature caused a change in vector births that counteracted or magnified the effects of temperature on the vector population. The actual temperature was set back to 80 °F. The optimal temperature also remained at 80 °F. Vector births was set to 5, while the vector death rate was kept at 0.05. The vector births were then set to 500 with the death rate kept at 0.05. All of the other parameters were kept the same as in task two.

The fifth task focused on waning immunity. Waning immunity accommodates for the replenishment of hosts, allowing the user to observe a steady endemic state with a constant, non-zero number of infected hosts and vectors. The user is instructed to initially set the rate of waning immunity to 0.5. The users are then instructed to experiment with different waning immunity values to observe dynamics in a situation in which susceptible hosts are replenished. All of the other parameters were kept the same as in task two.

Task six was designed to let Climate Change App users explore the different variables and outcomes independently. They are instructed to manipulate any of the parameters and observe what happens for the simulated outbreak.

Results

The parameters chosen for all of the tasks produced each of the desired natural phenomena we wanted to model. In task one, no outbreak occurred, as we set both transmission from host to vector and transmission from vector to host to 0. Task two was meant to simulate the dynamics that would occur if transmission was turned on and if the average temperature was the same as the optimal temperature; this task successfully resulted in a relatively large outbreak. Task three modeled what would happen if the average temperature was an extreme temperature outside the optimal temperature range. The results from this task successfully showed a lack of a susceptible vector population and thus no outbreak. It is important to note that setting the actual temperature variable to 50 and to 110 for the two simulations yielded the same result; this was as expected since both extreme temperatures were equally far away from the optimal temperature but in different directions yielding the same effect on the susceptible vector population. Task four which modeled altered vector births, successfully showed a small outbreak when there were a tenth of the initial amount of vector births and a large outbreak when there were ten times the initial amount of vector births. The purpose of task five was to model what would occur if waning immunity was introduced to the model, and as desired, the resulting outbreak was larger than it was without the replenishment of susceptible hosts. The specific parameters used for each task and the results for those respective parameters can be found in **Table 2.** The graphs/visualizations of the simulated outbreaks in each of the tasks can be found in **Table 3.**

Table 2. Results of model corresponding to different parameters.

Task 1: No Outbreak Parameter Values: Sh0=1000; Sv0=1000; Ih0=1; Iv0 =1; tmax=60; w=0; b1=0.0; b2=0.0; g=2; m=50; n=0.05; tp=0; topt=0		
	Minimum and Maximum during simulation	***Number and Fraction at end of simulation***
Susceptible Hosts (Sh)	1000 and 1000	1000 and 1
Infected Hosts (Ih)	0 and 1	0 and 0
Recovered Hosts (Rh)	0 and 1	1 and 0
Susceptible Vectors (Sv)	1000 and 1000	1000 and 1
Infected Vectors (Iv)	0.05 and 1	0.05 and 0
Task 2: Outbreak with average temperature at optimal temperature Parameter Values: Sh0=1000; Sv0=1000; Ih0=1; Iv0=1; tmax=60; w=0; b1=0.0015; b2=0.005; g=2; m=50; n=0.05; tp=80; topt=80		
	Minimum and Maximum during simulation	***Number and Fraction at end of simulation***
Susceptible Hosts (Sh)	0 and 1000	0 and 0
Infected Hosts (Ih)	0 and 182.9	0 and 0
Recovered Hosts (Rh)	0 and 1001	1001 and 1
Susceptible Vectors (Sv)	159.97 and 1000	941.04 and 0.94
Infected Vectors (Iv)	1 and 840.78	59.01 and 0.06

Task 3: No outbreak with average temperature below optimal range and above optimal range
Parameter Values: Sh0=1000; Sv0 = 1000; Ih0=1; Iv0=1; tmax=60; w=0; b1=0.0015; b2=0.005; g=2; m=50; n=0.05; tp=50 or 110; topt=80

	Minimum and Maximum during simulation	***Number and Fraction at end of simulation***
Susceptible Hosts (Sh)	964.05 and 1000	964.05 and 0.96
Infected Hosts (Ih)	0.06 and 1	0.06 and 0
Recovered Hosts (Rh)	0 and 36.89	36.89 and 0.04
Susceptible Vectors (Sv)	1.58 and 1000	1.58 and 0.95
Infected Vectors (Iv)	0.08 and 1.15	0.08 and 0.05

Task 4: Altering vector births
Parameter Values: Sh0=1000; Sv0 = 1000; Ih0=1; Iv0=1; tmax=60; w=0; b1=0.0015; b2=0.005; g=2; m=5; n=0.05; tp=80; topt=80

	Minimum and Maximum during simulation	***Number and Fraction at end of simulation***
Susceptible Hosts (Sh)	0 and 1000	0 and 0
Infected Hosts (Ih)	0 and 165.69	0 and 0
Recovered Hosts (Rh)	0 and 1001	1001 and 1
Susceptible Vectors (Sv)	71.42 and 1000	97.67 and 0.67
Infected Vectors (Iv)	1 and 676.72	47.19 and 0.33

Parameter Values: Sh0=1000; Sv0 = 1000; Ih0=1; Iv0=1; tmax=60; w=0; b1=0.0015; b2=0.005; g=2; m=500; n=0.05; tp=80; topt=80

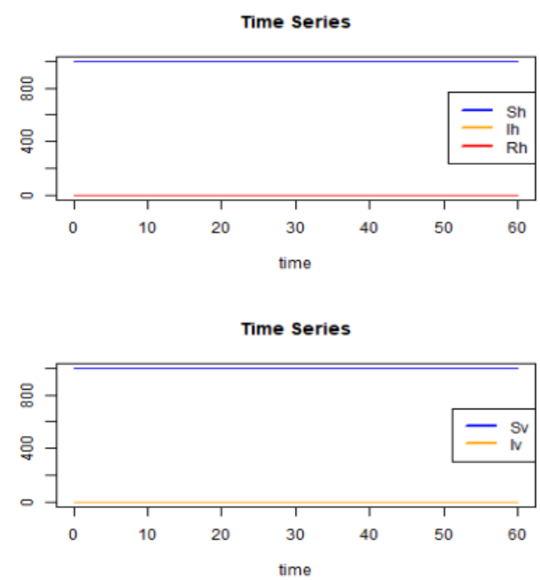
	Minimum and Maximum during simulation	***Number and Fraction at end of simulation***
Susceptible Hosts (Sh)	0 and 1000	0 and 0
Infected Hosts (Ih)	0 and 283.84	0 and 0
Recovered Hosts (Rh)	0 and 1001	1001 and 1
Susceptible Vectors (Sv)	609.31 and 9409.77	9409.77 and 0.99
Infected Vectors (Iv)	1 and 2151.62	142.2 and 0.01

Task 5: Waning Immunity
Parameter Values: Sh0=1000; Sv0 = 1000; Ih0=1; Iv0=1; tmax=60; w=0.5; b1=0.0015; b2=0.005; g=2; m=50; n=0.05; tp=80; topt=80

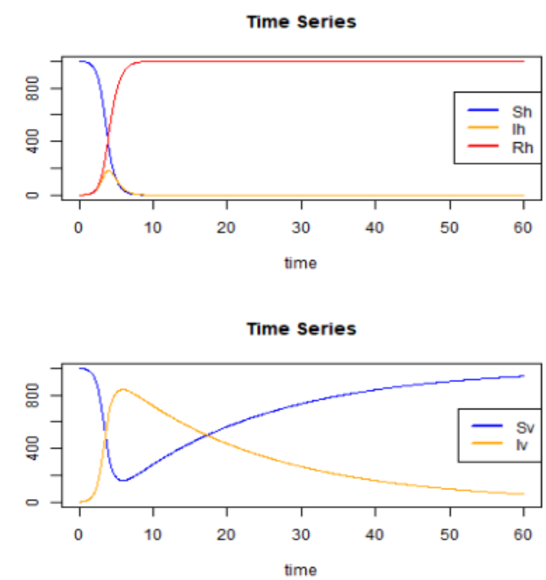
	Minimum and Maximum during simulation	***Number and Fraction at end of simulation***
Susceptible Hosts (Sh)	221.18 and 1000	221.25 and 0.22
Infected Hosts (Ih)	0.98 and 215.77	155.95 and 0.16
Recovered Hosts (Rh)	0 and 623.86	623.8 and 0.62
Susceptible Vectors (Sv)	60.26 and 1000	60.26 and 0.06
Infected Vectors (Iv)	1 and 940.22	939.79 and 0.94
Task 6: Keep Exploring Parameter Values: Chosen by User		
	Minimum and Maximum during simulation	***Number and Fraction at end of simulation***
Susceptible Hosts (Sh), Infected Hosts (Ih), Recovered Hosts (Rh), Susceptible Vectors (Sv), Infected Vectors (Iv)	--	--

Table 3. App-simulated graph outputs corresponding to each task.

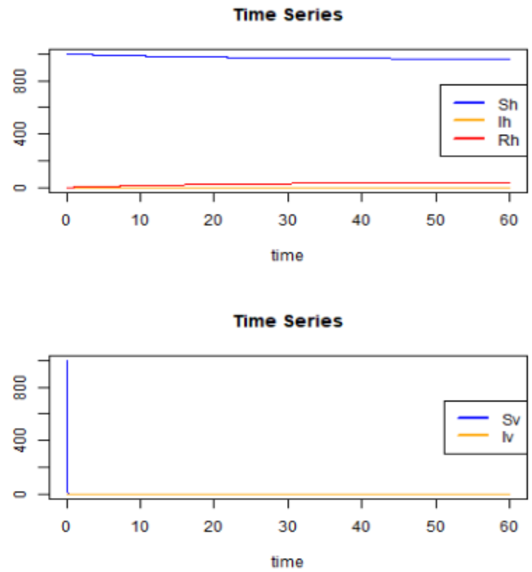
Task 1



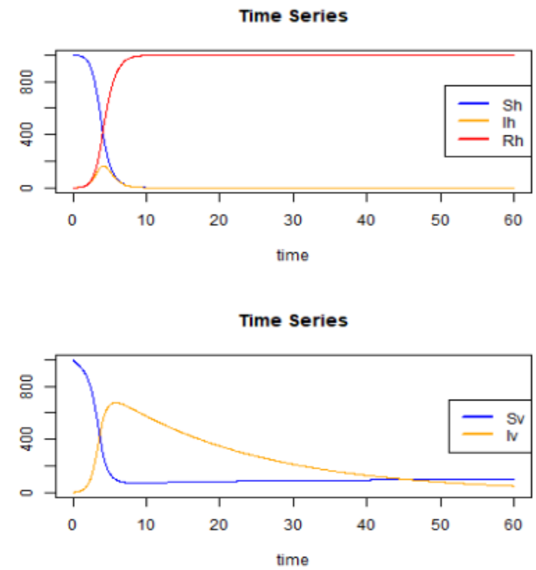
Task 2



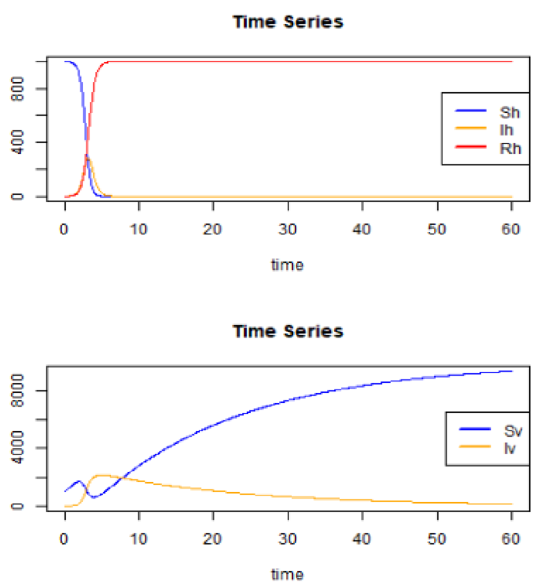
Task 3



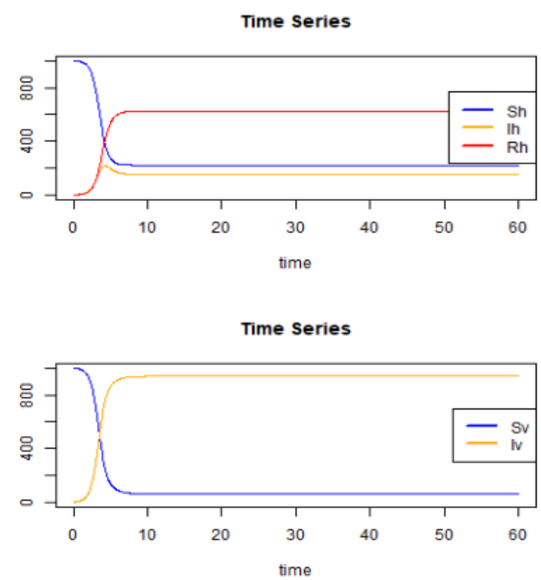
Task 4a



Task 4b



Task 5



Discussion & Conclusion

The results of our model for all six tasks reflect those found by other models discussed in the previous and current literature. Susceptible mosquito populations typically increase when the temperature is within an "optimal" range [6]. Specifically, mosquito populations decrease with extremely high or extremely low temperatures, a concept that has been supported with previous vector modelling literature [10, 11]. Our model also illustrates the effect temperature has on transmission rates from vectors to hosts and hosts to vectors. Previous mosquito literature and models have reflected this idea; in a study performed by

Moller-Jacob et. al, the researchers found that the transmission rates of malaria from vector to host were greatly impacted by temperature events [12].

A limitation of our model is that it doesn't allow temperature to change over time. In reality, temperature often changes since different seasons bring different temperature. Our model assumed linear seasonality which is not as realistic as allowing for seasons that don't change in a linear manner. Another limitation of our model is the lack of climate and weather factors besides temperature. Many of these other factors could also affect the rate of transmission from infected vector to susceptible host (b1 in our model) and the rate of transmission from infected host to susceptible vector (b2 in our model). For example, precipitation would have been a valuable variable to include in the model, as literature has shown that precipitation impacts vector breeding areas. Similar to temperature, previous vector transmission research has found there to be an ideal amount of rainfall per month for successful mosquito breeding; this amount is high enough to create stagnant water breeding sites, or "puddles," but not high enough to wash out existing breeding sites. [6, 8, 10]. A third limitation of this model is that some uncertainty exists regarding the gradient we used to determine the magnitude that the vector population changes as the magnitude of the difference between the average temperature and optimal temperature changes. While we extensively researched previous models for climate and vectors, more research needs to be done to accurately quantify the exact gradient value.

Future expansion of this model should include precipitation and other weather and climate factors to better simulate reality. Another feature that can be added in future expansions of this model is the ability for the temperature to change over time so that different seasons can be modeled.

Our model can be used in prevention and preparation efforts for potential future vector-borne disease outbreaks. Manipulating the values of the parameters could help identify the potential risk of a vector-borne disease becoming a pandemic or epidemic given certain climate conditions. For example, an application of our model stems from the fact that there has been an increase in the amount of hurricanes in recent years. With a future expansion of our model to include precipitation, it can be used to predict the magnitude of vector-borne disease outbreaks given increased amounts of rainfall. Predicting the magnitude of an outbreak before it occurs would help with preparation efforts, including predicting the amount of resources needed to handle certain natural events. The usage of models such as ours prove to be invaluable tools for prevention of disease outbreaks.

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Deliverables

We created a new app for DSAIDE called Climate Change that models the effects of climate change on infectious diseases with a mosquito vector and shows the prevalence of the disease over a specific amount of time, both in text and graph format. The app allows a user to enter in a range of numbers for each of the factors included in the model (ex. average temperature, optimal temperature, etc.), hit "run simulation," and receive text of the SIR numeric outcome related to the outbreak of the disease, as well as a graph that shows the outbreak over time. Each of the tabs of the app as well as the app itself is shown below.

Overview Tab

Instructions

Overview | The Model | What to do | Further Information

Overview

This app allows you to explore a simple model for vector-borne transmission in the context of climate change. Read about the model in the "Model" tab. Then do the tasks described in the "What to do" tab.

The Model Tab

Instructions

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The Model

Model Overview

This is a simple 2 species (hosts and vectors) model, using the basic SIR framework as follows.

The model has the following compartments:

- **Sh** - uninfected and susceptible host
- **Ih** - infected/infectious hosts
- **Rh** - recovered/removed hosts
- **Sv** - susceptible vectors
- **Iv** - infected/infectious vectors

We assume that once a vector is infected, it stays infected until it dies. Therefore, recovered vectors are not included in the model.

The processes being modeled are:

- Susceptible host can become infected by contact with infected vectors at rate b_1
- Susceptible vectors can become infected by contact with infected hosts at rate b_2
- Infected hosts recover after some time (specified by the rate g).
- New susceptible vectors are born at a rate m. Susceptible and infected vectors die at rate n. The inverse of this rate is the average lifespan.
- Recovered hosts lose their immunity at rate w.
- The average temperature, assuming linear seasonality is *tp*.
- The optimal temperature for the vector population is *topt*.

We envision hosts to be humans and vectors to be e.g. mosquitos. We further assume the time scale for the model is short enough that we can ignore births and deaths for human hosts but not vectors. This is likely a decent approximation as long as our simulation time is not more than few years.

- Susceptible host can become infected by contact with infected vectors at rate b_1
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- Infected hosts recover after some time (specified by the rate *g*).
- New susceptible vectors are born at a rate *m*. Susceptible and infected vectors die at rate *n*. The inverse of this rate is the average lifespan.
- Recovered hosts lose their immunity at rate *w*.
- The average temperature, assuming linear seasonality is *tp*.
- The optimal temperature for the vector population is *topt*.

We envision hosts to be humans and vectors to be e.g. mosquitos. We further assume the time scale for the model is short enough that we can ignore births and deaths for human hosts but not vectors. This is likely a decent approximation as long as our simulation time is not more than few years.

Model Implementation

The flow diagram and the set of ordinary differential equations (ODE) which are used to implement this model are as follows:

Image of flow diagram for the climate change transmission model will come soon!

$$\dot{S}_h = -b_1 S_h I_v + w R_h$$

$$\dot{I}_h = b_1 S_h I_v - g I_h$$

$$\dot{R}_h = g I_h - w R_h$$

$$\dot{S}_v = m - b_2 S_v I_h - n(1 + 0.7(topt - tp)^2) S_v$$

$$\dot{I}_v = b_2 S_v I_h - n I_v$$

__What To Do Tab__

Instructions

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What to do

The tasks below are described in a way that assumes everything is in units of MONTHS (rate parameters, therefore, have units of inverse months). If any quantity is not given in those units, you need to convert it first (e.g. if it says a week, you need to convert it to 12 months).

Task 1:

- Set the model parameters such that it corresponds to the following settings:
  - 1000 initially susceptible for both hosts and vectors, 1 initially infected host, 1 infected vector, simulation duration approximately 5 years.
  - Set host -> vector transmission rate, b_2=0. Keep b_1 = 0.
  - Assume that the duration of the infectious period in hosts is half a month (about 2 weeks) long.
  - Set the vector births to 50 and and death rate to 0.05.
  - Turn off waning immunity for now.
  - Set the average temperature and optimal temperature to 0 to turn temperature off.
- Run the simulation, observe what you get.
- You should not see any outbreak happening. Make sure you know why.

Task 2:

- Set b_1 = 0.0015 and b_2 = 0.005.
- Set the new vector births to 50 and vector deaths to 0.05.
- Set the average temperature to 80. Set optimal temperature to 80.
- Rerun. You should see an outbreak.
- Record the numbers/fractions of susceptible/infected/recovered hosts and vectors.

Task 3:

- Set the average temperature to 50 degrees. Keep optimal temperature at 80 degrees. Keep all other variables the same as in task #2.
- What do you expect to see? Run the simulation to check your expectation.
- Record the numbers/fractions of susceptible/infected/recovered hosts and vectors.
- Now, set the average temperature to 110 degrees. Keep the optimal tempearture at 80 degrees.
- What do you expect to see? Run the simulation to check your expectation.
- Record the numbers/fractions of susceptible/infected/recovered host and vectors.
- Play around with different average and optimal temperatures. Anything surprising happening? Do you understand why you see what you see?

Task 4:

- Now set everything back as in task #2. Set the average temperature and the optimal temperature to 80 degrees.
- What do you expect to see? Run the simulation to check your expectation.
- Record the numbers/fractions of susceptible/infected/recovered hosts and vectors.
- Set the number of vector births to 5. What do you expect to see?
- Now set the number of vector births to 500. What do you expect to see? How does increasing vector births impact the outbreak within hosts and vectors?
- Continue to experiment with different values for vector births and death rates. How is the vector population affected during the outbreak?

Task 5:

- Set everything back as in task #2. Assume host immunity wanes after an average of 2 months.
- What do you expect to see? Run simulations to check your expectations.
- You should get a steady endemic state with a constant, non-zero number of infected hosts and vectors. Record the number of infected vectors at a steady, endemic state.
- Experiment with different values for waning immunity. How does the number of infected hosts and vectors change?

Task 6:

- Keep exploring.
- Try to figure out how the different parameters influence the dynamics, specifically the (lack of) sustained cycles.

<u>Further Information Tab</u>

Instructions

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Further Information

- For this app, the underlying function running the simulation is called `simulate_climatechange.R`. You can call this function directly, without going through the shiny app. Check the help file for the function for more information. If you go that route, you need to use the results returned from this function and produce useful output (such as a plot) yourself.
- You could also modify this R function for your own purposes.
- To learn more about the underlying simulations and how to access and use the code, see the package vignette, which you can open by typing `vignette('DSAIDE')` in the R console.
- Some more information on vector-borne diseases and modeling can be found in (Kilpatrick and Randolph 2012, Luz, Struchiner, and Galvani (2010)).

References

Kilpatrick, A Marm, and Sarah E Randolph. 2012. "Drivers, Dynamics, and Control of Emerging Vector-Borne Zoonotic Diseases." *Lancet (London, England)* 380 (9857): 1946–55. doi:10.1016/S0140-6736(12)61151-9.

Luz, Paula M, Claudio J Struchiner, and Alison P Galvani. 2010. "Modeling Transmission Dynamics and Control of Vector-Borne Neglected Tropical Diseases." *PLoS Neglected Tropical Diseases* 4 (10): e761. doi:10.1371/journal.pntd.0000761.

App Interface

DSAIDE - Dynamical Systems Approach to Infectious Disease Epidemiology

A collection of Shiny/R Apps to explore and simulate the population dynamics of infectious diseases.
Written and maintained by Andreas Handel, with contributions from Spencer Hall, Brian McKay, John Rossow, Sina Solaimanpour, Eliza Ali, and Lindsey Roles.

Climate Change App

Run Simulation

Exit App

Simulation Settings

initial number of susceptible hosts (Sh0)	initial number of susceptible vectors (Sv0)	initial number of infected hosts (Ih0)
1000	1000	0

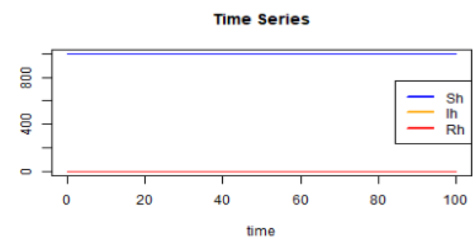
initial number of infected vectors (Iv0)	Maximum simulation time (tmax)	Rate of waning immunity (w)
0	100	0

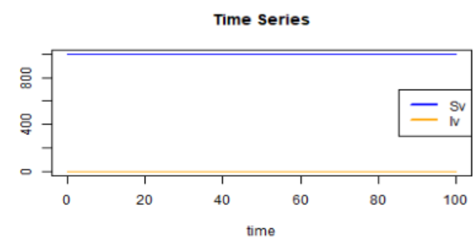
vector to host transmission rate (b1)	host to vector transmission rate (b2)	Rate of recovery of infected hosts (g)
0	0	1

Rate of new vector births (m)	Vector death rate (n)
0	0

avg temperature (tp)	optimal temperature (topt)
0	0

Simulation Results





Minimum and Maximum of Sh during simulation: 1000 and 1000
Number and Fraction of Sh at end of simulation: 1000 and 1
Minimum and Maximum of Ih during simulation: 0 and 0
Number and Fraction of Ih at end of simulation: 0 and 0
Minimum and Maximum of Rh during simulation: 0 and 0
Number and Fraction of Rh at end of simulation: 0 and 0

Minimum and Maximum of Sv during simulation: 1000 and 1000
Number and Fraction of Sv at end of simulation: 1000 and 1
Minimum and Maximum of Iv during simulation: 0 and 0
Number and Fraction of Iv at end of simulation: 0 and 0

For stochastic simulation scenarios, values shown are the mean over all simulations.