# MOSQUITO LARVAL HABITAT MODEL: A COMPLETE CLIMATE-DRIVEN APPROACH

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## ABSTRACT

In biological modeling, accurate modeling of the life cycle of an organism needs to account for the complexity of the organism, as well as the interactions between the organism and its environment. Mosquitoes are an organism commonly modeled as a vector for disease transmission. A wide range of habitats, depending on species and location, make mosquitoes an interesting and challenging organism to model. In this paper, we focus on modeling the mosquito larval habitat, which directly determines the amount of adult mosquitoes available to transmit disease. We developed a model intended to represent all of the possible climate-driven larval habitats available throughout the world. We explore various water storage equations for use within our model, then use a particular combination of a subset of these equations in our approach. Our study results include qualitative and quantitative comparisons. They show that our new model is capable of modeling natural, real-world habitats.

**Keywords:** disease, EMOD, malaria, population, hydrology.

## 1 INTRODUCTION

Malaria is one of the most important diseases today. It causes almost half a million deaths per year, mostly in children under 5. Human-based malaria is only transmitted by females of the genus *Anopheles*, with a few exceptions. The species *Anopheles gambiae* is one of the most efficient vectors in the world. In Sub-Saharan Africa, specifically, *Anopheles arabiensis* and *Anopheles funestus* join *Anopheles gambiae* to make this location particularly prone to a high case count. All three of these species have differing behaviors, such as when and where they prefer to feed. When female mosquitoes need to lay eggs, they require a specific type of larval habitat. This type of habitat can vary depending on species, region, and the local human population's habits. Examples include puddles, discarded tires, swamps, lakes, barrels, and agriculture. More generally, these habitats can be separated into several categories, including permanent, semi-permanent, temporary, and human-related.

In this paper, we define, implement, and test a new climate-based mosquito larval habitat model. We have found through experience that although there are a number of malaria transmission models that produce mosquito larvae using climate data, there are none that generalize enough to be used for all of the different climates that mosquitoes survive in. It is a normal practice in agent-based modeling to create models for the sake of a specific simulation need without attempting to ever expand it to fit outside situations. However, with the increasing ease to share information and tools, this trend will soon become problematic. Our new habitat model is an attempt to create a generalized model that can be utilized for any climate-based

*SpringSim-ADS 2017, April 23-26, Virginia Beach, VA, USA*

mosquito larvae simulation need. We compare our habitat model to the models within a widely used malaria transmission model, EMOD. First, we build a prototype of the model using dummy inputs to ensure the model produces what we want. Then we implement our new model within EMOD itself to allow for a direct comparison using the same simulated inputs. We believe this shows both the capability of the habitat model, but also the ability to provide increased generalizability to existing tools that are gaining a large user base.

The organization of this paper is as follows: Section 2 contains the background information that informs the creation of this model and some of the previous work involving this form of modeling. Section 3 describes the current form of the EMOD model, including its larval habitats. Section 4 describes, in detail, our new climate-driven habitat model. Section 5 describes the methodology behind our experiment, including our setup and validation steps. Section 6 discusses the results we received. Finally, Section 7 explores some of the future work needed to proceed with this research.

## 2 BACKGROUND AND RELATED WORK

In this section, we first describe the basics of the mosquitoes we model and the habitats in which their larvae naturally survive. We then briefly explain the agent-based modeling we use. Finally, we discuss some of the other related studies and models that we looked at for this work.

### 2.1 Mosquitoes

The mosquitoes responsible for malaria are primarily from the species of the genus *Anopheles*. This genus contains almost 500 species, of which about 100 transmit human-based malaria. However, only about 40 of these species are common disease carriers. The most well-known and efficient of these vectors is *Anopheles gambiae* (Arifin, Zhou, Davis, Gentile, Madey, and Collins 2014).

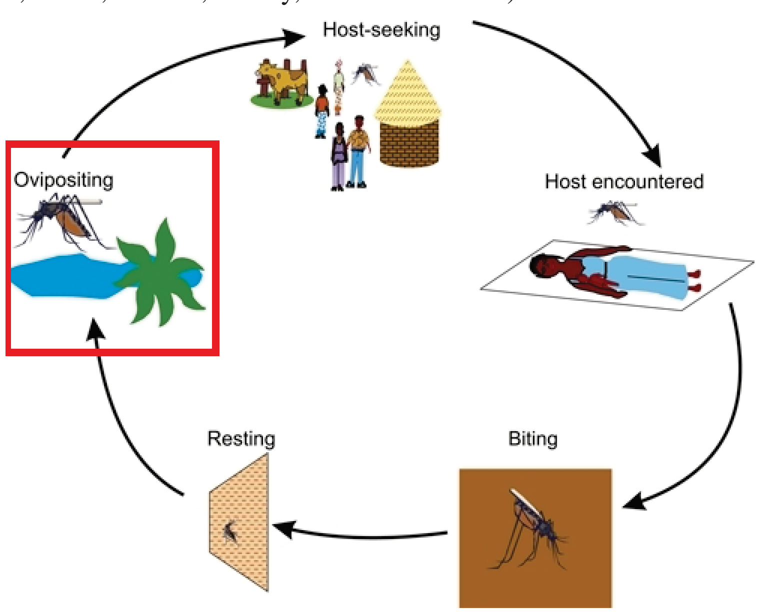



Figure 1: The gonotrophic cycle of the female mosquito (Chitnis, Schapira, Smith, and Steketee 2010).

The most important factor for disease transmission is the feeding cycle, or gonotrophic cycle, of the female mosquito. A simple diagram of this cycle is shown in Figure 1. After mating, the female must seek a blood meal from an animal host. Digesting the blood provides nutrients required for egg development. After successfully feeding, the female requires several days of rest to complete digestion and grow the eggs. Once the female has finished growing the eggs, she must lay them in a suitable aquatic habitat. Depending on weather conditions and human behavior, this may be difficult. Once egg laying is complete, the cycle starts over. This cycle can be completed several times during a female mosquito's lifetime.

### 2.2 Larval Habitats

As shown in Figure 1, egg laying, or ovipositioning, is an important step in the mosquito life cycle. Since each female lays hundreds of eggs every few days, the availability of the correct habitats is essential for mosquito larvae production. For disease transmission, since adult mosquito population size is the strongest driver, the amount of larvae in the environment becomes very important. The maximum amount of larvae a habitat can support is known as its capacity (Arifin, Zhou, Davis, Gentile, Madey, and Collins 2014).

Depending on the species, the gravid (pregnant) mosquito must find a specific habitat that is suitable for her larvae. Traditionally, these habitats are split into several categories. In some models, the main habitat types for mosquitoes are permanent, semi-permanent, temporary, and human-related (Eckhoff 2011). Permanent habitats are characterized by an ever-present carrying-capacity, no matter the weather, such as water reservoirs. Semi-permanent habitats are characterized by having a permanent carrying-capacity during certain certain seasons. These habitats include swamps, lakes, and rivers. Temporary habitats are characterized by only existing for a short time after each occurrence of rain, such as puddles and potholes. Human-related habitats are characterized by water containers that only exist due to human activity and increase with population size. These habitats include unkept flower pots, discarded tires, water containers, and other trash.

### 2.3 EMOD

Developed by the Institute for Disease Modeling (IDM), EMOD is a proprietary epidemiological modeling software package designed to determine the combination of interventions that may eventually lead to disease eradication (Eckhoff 2011, Wenger and Eckhoff 2013). As an agent-based model, EMOD directly models the humans *and* the mosquitoes in the system, i.e. all humans and mosquitoes are individuals with their own properties. In order to run, EMOD requires demographic, weather, mosquito, and parasite parameters as input. EMOD also allows for the definition of almost all available malaria interventions.

### 2.4 Other Related Models

There are some models that simulate the mosquito components by simply creating adult mosquito populations mathematically (Smith, Maire, Ross, Penny, Chitnis, Schapira, Studer, Genton, Lengeler, Tediosi, De Savigny, and Tanner 2008, Chitnis, Hardy, and Smith 2012). The most notable of these today, OpenMalaria, was developed by the Swiss Tropical and Public Health Institute. OpenMalaria is an open source program designed to simulate malaria epidemiology and the effects of interventions (Smith, Maire, Ross, Penny, Chitnis, Schapira, Studer, Genton, Lengeler, Tediosi, De Savigny, and Tanner 2008). Although OpenMalaria is an agent-based model, it does not model the mosquitoes that transmit the disease as individuals. So, to create adult mosquito populations, OpenMalaria uses an estimation of infection rates that the user provides. Although users typically create this estimation based on weather patterns, the simulation does not require these patterns internally. This approach, along with others, allows for a simpler set of inputs, but requires the user to have direct knowledge about the weather or infections throughout the year.

Some other models provide habitats for mosquito larvae to develop before being added to the adult population (Arifin, Zhou, Davis, Gentile, Madey, and Collins 2014, Arifin, Madey, and Collins 2016, Eckhoff 2011, Bomblies, Duchemin, and Eltahir 2008, Griffin, Hollingsworth, Okell, Churcher, White, Hinsley, Bousema, Drakeley, Ferguson, Basáñez, et al. 2010). Arifin *et al.* model the entire larval development cycle within the habitat in detail, and the habitat itself uses rainfall data to determine capacity (Arifin, Zhou, Davis, Gentile, Madey, and Collins 2014). Eckhoff *et al.* created the EMOD model, discussed more above (Eckhoff 2011). EMOD models larval habitat by combining a set of various habitat type equations that are partially defined by the user and rely on daily weather data as input. Bomblies *et al.* created a uniquely detailed, yet generalized mosquito habitat model using hydrology models as a basis (Bomblies, Duchemin, and Eltahir 2008). Their model was unique in that it used the exact dimensions of the puddles, lakes, etc. that the simulation required, which could be set to fit any location. Griffin *et al.* built a sophisticated malaria transmission model that included climate-based mosquito larval habitats; however they only created habitats available in Sub-Saharan Africa (Griffin, Hollingsworth, Okell, Churcher, White, Hinsley, Bousema, Drakeley, Ferguson, Basáñez, et al. 2010). All these approaches mostly use climate data to maintain the larval habitats. However, only Bomblies *et al.* uses a generalized model for multiple habitats, but the inputs required are difficult to obtain for most applications.

## 3 CURRENT EMOD MODEL

In this section, we give a description of the equations for the EMOD model habitats (version 2.0). These are the equations that are needed to try to replicate certain environments. One mosquito species is allowed any combination of these habitats (Eckhoff 2011).

### 3.1 Temporary Rainfall Habitat

The temporary rainfall habitat is used to recreate temporary habitats in the system, such as puddles and crevices.

$$H_{temp} += (K_{temp} * D_{cell}^2 * P_{rain}) - ((1/\tau) * H_{temp}),$$

where

- $H_{temp}$ is Current Larval Habitat Carrying Capacity (capacity)
- $K_{temp}$ is Required Habitat Factor (the maximum larvae per unit volume) (capacity/$m^3$)
- $D_{cell}$ is Half of the Node Grid Size (the grid diameter) (m)
- $P_{rain}$ is Current Daily Rainfall (m).

and

$$(1/\tau) = (5.1x1011) * (-5628.1/T) * k_{temp-decay} * \sqrt{0.018/2 * \pi * R * T} * (1 - RH),$$

where

- $(1/\tau)$ is Temporary Decay Rate (-)
- $T$ is Current Air Temperature (K)
- $k_{temp-decay}$ is Temporary Decay Factor (-)
- $R$ is the Specific Gas Constant for Dry Air (287.058 J/(kg*K))
- $RH$ is Current Relative Humidity (-).

### 3.2 Water Vegetation Habitat

The water vegetation habitat is used to recreate semi-permanent habitats in the system, such as lake and river edges.

$$H_{semi} += (K_{semi} * D_{cell}^2 * P_{rain}) - (k_{semi-decay} * H_{semi}),$$

where

- $H_{semi}$ is Current Larval Habitat Carrying Capacity (capacity)
- $K_{semi}$ is Required Habitat Factor (the maximum larvae per unit volume) (capacity/$m^3$)
- $D_{cell}$ is Half of the Node Grid Size (the grid diameter) (m)
- $P_{rain}$ is Current Daily Rainfall (m)
- $k_{semi-decay}$ is Semipermanent Decay Rate (-)

### 3.3 Brackish Swamp Habitat

The brackish swamp habitat is used to recreate semi-permanent habitats that have a chance to overflow.

$$H_{semi} += (K_{semi} * D_{cell}^2 * P_{rain}) - (k_{semi-decay} * H_{semi}),$$

where

- $H_{semi}$ is Current Larval Habitat Carrying Capacity (capacity)
- $K_{semi}$ is Required Habitat Factor (the maximum larvae per unit volume) (capacity/$m^3$)
- $D_{cell}$ is Half of the Node Grid Size (the grid diameter) (m)
- $P_{rain}$ is Current Daily Rainfall (m)
- $k_{semi-decay}$ is Semipermanent Decay Rate (-)
- Maximum carrying capacity defined by Rainfall-To-Fill-Swamp: If $H_{semi}$ > ( $K_{semi}$ * $D_{cell}^2$ * Rainfall-To-Fill-Swamp ), $H_{semi}$ = ( $K_{semi}$ * $D_{cell}^2$ * Rainfall-To-Fill-Swamp ) and larval mortality occurs.

### 3.4 Human Population Habitat

The human population habitat is used to recreate pseudo-permanent habitats that fluctuate with the available human population, such as water storage containers and tires. This is not affected by climate, but can be combined with climate-driven habitats to provide a minimum capacity.

$$H_{pop} = K_{pop} * P_{pop},$$

where

- $H_{pop}$ is Current Larval Habitat Carrying Capacity (capacity)
- $K_{pop}$ is Required Habitat Factor (the maximum larvae per person) (capacity/person)
- $P_{pop}$ is Current Human Population (person).

### 3.5 Constant Habitat

The constant habitat is used to allow for a permanent supply of adult mosquitoes in the system, regardless of climate factors. This is not affected by climate, but can be combined with climate-driven habitats to provide a minimum capacity.

$$H_{const} = K_{const} * D_{cell}^2,$$

where

- $H_{const}$ is Constant Larval Habitat Carrying Capacity (capacity)
- $K_{const}$ is Required Habitat Factor (the maximum larvae per unit area) (capacity/$m^2$)
- $D_{cell}$ is Half of the Node Grid Size (the grid diameter) (m).

## 4 OUR NEW MODEL

In this section, we give a description of the equation and inputs for our new habitat model.

### 4.1 Climate-Based Habitat

Our new climate-based habitat equation is a combination of several widely-accepted climate equations meant to track water entering and exiting the system. Mainly incorporating the FAO Penman-Monteith (Allen, Pereira, Raes, Smith, et al. 1998, Zotarelli, Dukes, Romero, Migliaccio, and Morgan 2010) equation, it also includes additional cloud cover (Depinay, Mbogo, Killeen, Knols, Beier, Carlson, Dushoff, Billingsley, Mwambi, Githure, et al. 2004), interception (Savenije 2004), infiltration (Tarboton 2003), and runoff (COMET 2015) equations.

$$H_{climate} = (W_d/1000) * A * K,$$

where

- $H_{climate}$ is Current Larval Habitat Carrying Capacity (capacity)
- $W_d$ is Current Water Depth (mm)
- $A$ is Habitat Area ($m^2$)
- $K$ is Larval Potential (the amount of possible larvae per unit volume) (capacity/$m^3$),

$$W_d = W_p + W_t,$$

where

- $W_p$ is Minimum Water Level (mm)
- $W_t$ is Current Temporary Water Level (mm) and $W_t >= 0$,

$$W_t += (IIR * P) - ET,$$

where

- $P$ is Current Daily Rainfall (mm)
- $ET$ is EvapoTranspiration (mm)
- $IIR$ is Environmental Loss (-)
- If $W_d$ > Maximum Water Level, BRACKISH-SWAMP-like overflow occurs,

$$ET = ((0.408 * \delta * R_n) + (\gamma * (900/(T + 273.15)) * u_2 * (es - ea)))/(\delta + (\gamma * (1 + (0.34 * u_2))))$$

where

- $ET$ is EvapoTranspiration (mm) [2, 3]
- $\delta$ is Slope Vapor Pressure Curve (kPa/C)
- $R_n$ is Net Radiation at Surface (J)
- $\gamma$ is Psychrometric Constant (kPa/C)
- $T$ is Current Air Temperature (C)
- $u_2$ is Wind Speed at 2 meters (m/sec)
- $es$ is Saturation Vapor Pressure (kPa)
- $ea$ is Actual Vapor Pressure (kPa),

and

$$IIR = (1 - L_i) * (1 - L_f) * (1 - L_r)$$

where

- $IIR$ is Environmental Loss (-)
- $L_i$ is Interception Factor (-)
- $L_f$ is Infiltration Factor (-)
- $L_r$ is Runoff Factor (-).

## 4.2 Input Definitions

In this section, we provide a brief description of the inputs needed for our new habitat. Any inputs mentioned here that are not directly mentioned in the equations above are part of the environmental loss equations.

### 4.2.1 Climate

*Rainfall:* Daily Rainfall in millimeters per day for the location. This input is gathered from weather station data. For EMOD, it must be in meters per day, then converted from a csv file to a binary file in order to be used in the simulation. Example set of values: ‘0.001, 0.023, 0.05, 0.13, 1.204, 0.89, 0.42’.

*Temperature:* Air Temperature in degrees Celsius per day for the location. This input is gathered from weather station data. For EMOD, it must be converted from a csv file to a binary file in order to be used in the simulation. Example set of values: ‘24, 25, 27, 22, 25, 23, 20’.

*Humidity:* Relative Humidity as a decimal (between 0 and 1) per day for the location. This input is gathered from weather station data. For EMOD, it must be converted from a csv file to a binary file in order to be used in the simulation. Example set of values: ‘0.20, 0.25, 0.40, 0.35, 0.85, 0.75, 0.60’.

#### 4.2.2 Location

*Center Point:* The latitude and longitude of the center of the habitat. This input is gathered from map data. Example value: ‘(12.433789, 9.181599)’.

*Elevation:* The elevation in meters of the habitat. This is gathered from map data. Example value: ‘377’.

*Portion of Area:* The portion of the total location area that the habitat consists of as a decimal (between 0 and 1). This input is gathered from satellite map data. Example value: ‘0.33’.

#### 4.2.3 Vegetation

*Types:* The predominant types of vegetation in and around the habitat represented as an official IGBP land-type phrase. This input is determined by knowledge of the location. Example value: ‘Shrubland’.

*Coverage:* The portion of the habitat covered by vegetation represented as a decimal (between 0 and 1). This input can be estimated by satellite map data or more precisely determined by knowledge of the location. Example value: ‘0.35’.

#### 4.2.4 Soil

*Type:* The soil texture of the habitat as determined by portions of clay, silt, and sand represented by an official UN-FAO soil-type. This input is gathered from satellite map data. Example value: ‘Sandy Loam’.

#### 4.2.5 Slope

*Gradient:* The predominant gradient of the slope of the habitat area represented by an official USDA slope phrase. This input is determined by knowledge of the location. Example value: ‘Gently Sloping’.

#### 4.2.6 Water

*Minimum:* The amount of water in millimeters that represents the water that remains within the habitat regardless of climate data. This input can be estimated from satellite map data or more precisely determined by knowledge of location. Example value: ‘0.01’.

*Maximum:* The amount of water in millimeters that represents the total amount of water that a habitat can hold before it overflows. This input can be estimated from satellite map data or more precisely determined by knowledge of location. Example value: ‘6.0’.

## 5 TESTING AND VALIDATION

In this section, we describe the methodology behind the testing and validation of the climate-based habitat model. We also briefly describe the implementation of the model *in silico*.

### 5.1 Prototype

Since it is a more complicated model, we first built an external prototype in Python before implementing the habitat and its components entirely in EMOD. For purposes of this prototype, we used a limited form of climate data, as well as a much smaller agent-based model. Basically, we made the entire model only contain the habitat module itself, with a module that fed inputs and a module that consumed outputs. This limited prototype only simulated artificial larval development and only produced output on larval population; however, with this prototype, we were able to preliminarily test, and re-design as needed, our new climate model before going through the extensive process of a full implementation.

### 5.2 Testing

In order to properly test our new habitat model, especially with comparison to EMOD's current habitats, the new habitat was added to the EMOD v2.0 C++ larval habitat module. This allowed for the running of simulations in EMOD for all the original and new habitats. We made the addition in such a way, that the currently existing connections to the module did not need to be edited. Therefore, the way climate data was inserted and outputs were extracted remained intact. This allowed for a better comparison and for a faster testing and validation process. This did, however, require that many of the new climate and environment variables needed for our new habitat be hard-coded into the module. This would be a necessary change for future work and adaptation.

### 5.3 Validation

After running the simulations in EMOD, we inspect the outputs from both the original and new habitats. For these experiments, the specific outputs we are looking at for correctness and comparison are the Larval Mosquito Population and the Adult Mosquito Population. By viewing these outputs for each simulation run in both graphical and tabular form, we can determine the face validity of both the similarity and differences of these habitat models. For the sake of space, we exclude the tabular data from this manuscript. As we continue to change the inputs of these two models, we continue to re-analyze the outputs and re-determine the amount of face-validity between these models.

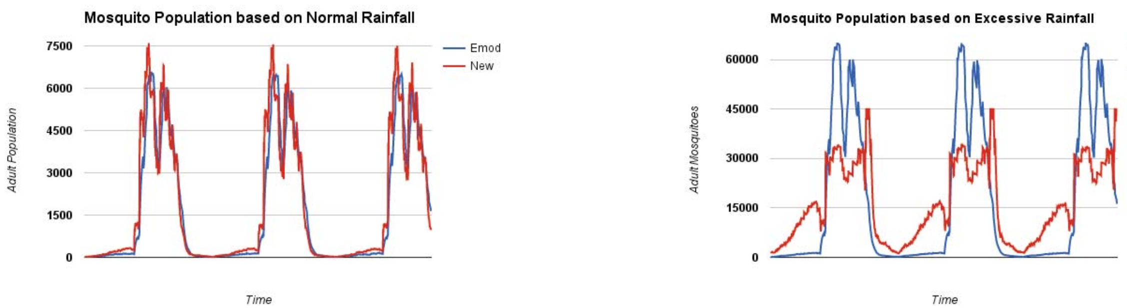
## 6 RESULTS

In this section, we describe the results of testing of the integrated model in EMOD, along with the validation.

### 6.1 Artificial Data

We first tested our model on a hypothetical location provided as a tutorial with the EMOD tool (IDM 2015). EMOD includes both the inputs for the habitats and the expected outputs for the tutorial run. We were able to use this to do simple comparisons between the EMOD habitats and our new generalized habitat. We first calibrated our habitat to match the habitats represented in the hypothetical location. Then we experimented with how the different habitats react to varying weather inputs.

Figure 2 shows two of the more apparent comparisons between the EMOD habitat model and our habitat model. Due to space restrictions, we limit our discussion to these examples. Figure 2a shows the results of the two models under normal weather conditions. As can be seen, with these inputs, our model almost completely replicates the EMOD model built for this situation. Figure 2b shows the results of the two models under overly rainy conditions, as might be seen during monsoon season, which EMOD's habitats were not originally designed to be used for. From expert face-validity, our model is better able to follow a pattern consistent with those rainy weather conditions, as confirmed by expert face-validity. We believe these examples, along with our other comparisons, are convincing evidence of the usefulness of our new habitat model.




(a) Normal Weather

(b) Overly Rainy Weather

Figure 2: The comparison results using artificial data, measured in adult mosquito population over time.

### 6.2 Real Data

After comparing EMOD's habitats with the new habitat using artificial data, we then modeled a real location that the original models have had some difficulty modeling to see if our habitat could model it more effectively. This real location is a well-studied malaria transmission site in Nigeria, Africa, then known as the Garki District (Molineaux and Gramiccia 1980, ND 2016). This location has a small set of mosquito data collected over a 3 year period (from 1970 to 1973) that we used for comparison. For our simulations, we first gathered all of the input data we needed for this location. Then we calibrated the best combination of EMOD habitats we could for this data set. Finally, we ran both habitat setups through an EMOD simulation for 3 years to gather our data and scale it allow a comparison to the real study.

As can be seen in Figure 3, our habitat model, although not exactly fitting the real data set, follows the real data trend more closely than the calibrated EMOD habitats. Since the dataset is small, we do not expect our habitat to follow it perfectly, but the improvement upon the original habitat is promising. Additionally, since our habitat model is more generalized than the EMOD habitats, we believe this also helps show the value in the generalizable model approach over the more directly-defined approach.

## 7 FUTURE WORK

With this version of the habitat model only partially built-in to a fully functional disease transmission model, a logical next step would be to fully integrate the model into EMOD in order to perform further verification. Also, after being integrated, a thorough suite of simulation tests with both artificial and real data should be run to ensure the validity of the model in a simulated setting. With this complete verification and validation, this generalized model could be extended to be placed in other mosquito-driven individual-based models.

Additionally, in this paper, we presented a model to represent all possible climate-driven mosquito larval habitats. However, mosquitoes live in several types of habitats that are not climate-driven. Therefore, a future work is to formulate models for these additional habitats. These include human-driven habitats, such as barrels and tires; agriculture-driven habitats, such as rice fields and maize fields; and permanent habitats,

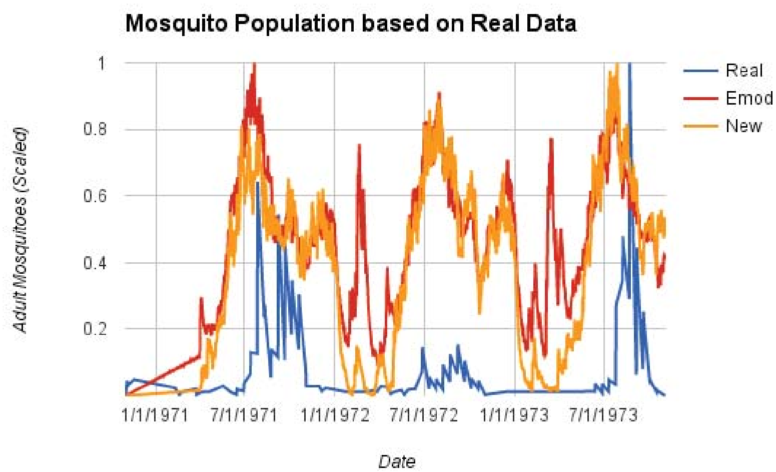



Figure 3: The comparison results using real data, measured in adult mosquito population over time, scaled from 0 to 1.

such as private ponds and community reservoirs. There will also need to be more testing to determine the possible side-affects of the interaction between all of these habitat types.

## 8 CONCLUSION

In this paper, we present a model intended to represent all of the possible climate-driven larval habitats available throughout the world. In order to evaluate the new model, we replaced EMOD's current mosquito larval habitat module with our custom module. Then we ran several scenarios with our model in EMOD as normal and compared the results to both EMOD results using its original module and real-world data. The results showed that our module improved upon the existing EMOD module by subsuming the original capabilities, while also allowing for more types of habitats. They also showed that our new model is capable of modeling natural, real-world habitats. Furthermore, we believe our new model reveals the value in creating more generalized models within preexisting tools as these tools become more shareable and widely used.

## ACKNOWLEDGEMENTS

We thank the Institute for Disease Modeling for their help with using and exploring EMOD. We also thank Salvador Aguinaga and Reagan Meredith at the University of Notre Dame for their consultation during our model creation. We would especially like to thank Dr. Frank Collins at the University of Notre Dame Biology Department for his expert knowledge and validity checking during our model experiments. Finally, we also thank the VecNet group and Notre Dame's Center for Research Computing who assisted with the setup and execution of these simulations on their computing cluster.

## REFERENCES

Allen, R. G., L. S. Pereira, D. Raes, M. Smith et al. 1998. "Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56". *FAO, Rome* vol. 300 (9).

Arifin, S., Y. Zhou, G. J. Davis, J. E. Gentile, G. R. Madey, and F. H. Collins. 2014. "An agent-based model of the population dynamics of Anopheles gambiae.". In *Malaria Journal 13*.

Arifin, S. N., G. R. Madey, and F. H. Collins. 2016. *Spatial agent-based simulation modeling in public health: design, implementation, and applications for malaria epidemiology*. John Wiley & Sons.

Bomblies, A., J.-B. Duchemin, and E. A. Eltahir. 2008. "Hydrology of malaria: Model development and application to a Sahelian village". *Water Resources Research* vol. 44 (12).

Chitnis, N., D. Hardy, and T. Smith. 2012. "A Periodically-Forced Mathematical Model for the Seasonal Dynamics of Malaria in Mosquitoes". *Bulletin of Mathematical Biology* vol. 74 (5), pp. 1098–1124.

Chitnis, N., A. Schapira, T. Smith, and R. Steketee. 2010. "Comparing the Effectiveness of Malaria Vector-Control Interventions Through a Mathematical Model". *The American Journal of Tropical Medicine and Hygiene* vol. 83 (2), pp. 230–240.

COMET 2015. "Runoff Processes: International Edition". www.meted.ucar.edu/hydro/basic_int/runoff/.

Depinay, J.-M. O., C. M. Mbogo, G. Killeen, B. Knols, J. Beier, J. Carlson, J. Dushoff, P. Billingsley, H. Mwambi, J. Githure et al. 2004. "A simulation model of African Anopheles ecology and population dynamics for the analysis of malaria transmission". *Malaria journal* vol. 3 (1), pp. 1.

Eckhoff, P. 2011. "A malaria transmission-directed model of mosquito life cycle and ecology". *Malaria Journal* vol. 10 (1), pp. 303.

Griffin, J. T., T. D. Hollingsworth, L. C. Okell, T. S. Churcher, M. White, W. Hinsley, T. Bousema, C. J. Drakeley, N. M. Ferguson, M.-G. Basáñez et al. 2010. "Reducing Plasmodium falciparum malaria transmission in Africa: a model-based evaluation of intervention strategies". *PLoS Med* vol. 7 (8).

IDM 2015. "EMOD Garki Tutorial". http://idmod.org/idmdoc/#EMOD/DiseaseTutorials/.

Molineaux, L., and G. Gramiccia. 1980. "The Garki project: research on the epidemiology and control of malaria in the Sudan savanna of West Africa".

ND 2016. "The Garki Project". http://garkiproject.nd.edu/.

Savenije, H. H. 2004. "The importance of interception and why we should delete the term evapotranspiration from our vocabulary". *Hydrological Processes* vol. 18 (8), pp. 1507–1511.

Smith, T., N. Maire, A. Ross, M. Penny, N. Chitnis, A. Schapira, A. Studer, B. Genton, C. Lengeler, F. Tediosi, D. De Savigny, and M. Tanner. 2008, 11. "Towards a comprehensive simulation model of malaria epidemiology and control". *Parasitology* vol. 135, pp. 1507–1516.

Tarboton, D. G. 2003. "Rainfall-runoff processes". *Utah State University*.

Wenger, E., and P. Eckhoff. 2013. "A mathematical model of the impact of present and future malaria vaccines". *Malaria Journal* vol. 12 (1), pp. 126.

Zotarelli, L., M. D. Dukes, C. C. Romero, K. W. Migliaccio, and K. T. Morgan. 2010. "Step by step calculation of the Penman-Monteith Evapotranspiration (FAO-56 Method)". *Institute of Food and Agricultural Sciences. University of Florida*.

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