Vector-Borne Diseases, Surveillance, Prevention

An Investigation of Human–Mosquito Contact Using Surveys and Its Application in Assessing Dengue Viral Transmission Risk

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Abstract

Aedes-borne viral diseases such as dengue fever are surging in incidence in recent years. To investigate viral transmission risks, the availability of local transmission parameters is essential. One of the most important factors directly determining infection risk is human-mosquito contact. Yet the contact rate is not often characterized, compared with other risk metrics such as vector density, because of the limited research tool options. In this study, human-mosquito contact was assessed in two study sites in the Southern United States using selfadministered standardized survey instruments. The fraction of mosquito bites attributed to important vector species was estimated by human landing sampling. The survey participants reported a significantly higher outdoor mosquito bite exposure than indoor. The reported bite number was positively correlated with outdoor time during at-risk periods. There was also a significant effect of the study site on outdoor bite exposure, possibly due to the differing vector density. Thus, the levels of human-mosquito contact in this study were influenced both by the mosquito density and human behaviors. A dengue virus transmission model demonstrated that the observed difference in the contact rates results in differential virus transmission risks. Our findings highlight the practicality of using surveys to investigate human-mosquito contact in a setting where bite exposure levels differ substantially, and serve as a basis for further evaluations. This study underscores a new avenue that can be used in combination with other field methods to understand how changes in human behavior may influence mosquito bite exposure which drives mosquito-borne virus transmission.

Key words: human-mosquito contact, dengue virus, SEIR model, Aedes aegypti, Aedes albopictus

Globally, mosquito-borne viral diseases are on the rise. In the past few decades, diseases such as dengue, West Nile, chikungunya, and Zika have emerged and persisted in the parts of the world where their mosquito vectors thrive (Weaver and Reisen 2010, Roehrig 2013, Baud et al. 2017, Castro et al. 2017, Wahid et al. 2017). Among these diseases, dengue fever is the most common and widespread (Wilder-Smith et al. 2017). According to a recent study (Bhatt et al. 2014) about 390 million dengue viral infections occurred in 2010. A majority of dengue cases either are asymptomatic or present with a cluster of mild symptoms. However, severe dengue, with manifestations such as hemorrhage and hypovolemic shock, can be life-threatening and is becoming more common (Kuno 2009).

Dengue virus (DENV) can be transmitted by two species of mosquito vectors in the genus *Aedes: Aedes aegypti* (Linnaeus) (Diptera: Culicidae), the Yellow Fever mosquito, and *Aedes albopictus* (Skuse) (Diptera: Culicidae), the Asian Tiger mosquito (Gubler 2011). Both species are widespread in residential settings of tropical and subtropical parts of Asia, Latin America, Africa, and the Pacific (Santos and Meneses 2017). Because of a warming climate and suitable habitats, both *Aedes* species have gained a foothold in the Southern United States and Southern Europe (Šebesta et al. 2012, Oter et al. 2013, Hahn et al. 2016). This, in combination with increases in international travel, results in a possibility that DENV may emerge in these areas.

Mathematical models can help guide the design of disease prevention and control programs (Katzelnick et al. 2017). For these models to be effective, they require estimates of local transmission parameter values. One of the most important parameters determining virus transmission is the human–mosquito contact rate, which we define as the total number of times all humans in an area of interest are bitten by the vector species of interest each day (Manore et al. 2014). Unfortunately, the human-mosquito contact is not often characterized, when compared to other measures such as vector density, because the gold standard field method, the Human Landing Capture (HLC), can be impractical or unethical (Lima et al. 2014). The paucity of contact data hinders our progress in understanding how changing environments and human behaviors drive mosquito-borne virus transmission. We need to know how often, and under what circumstances, humans are exposed to mosquito bites to plan effective mitigation strategies.

To date, only a few approaches have been used to approximate contact patterns in the field. HLC is the traditional gold standard method to monitor human-vector contact patterns in malaria transmission (Wong et al. 2013, Kenea et al. 2016). This method involves human volunteers collecting mosquitoes that land on them to feed, typically at night, when malaria vectors seek blood meals. A well-designed HLC study could potentially be used to approximate the contact rate in this situation where *Anopheles* mosquitoes bite sleeping humans. However, *Aedes* spp. bite during the day when humans could actively interrupt or avoid bites. This could result in a potential bias for the HLC estimates because the *Aedes*-human contact rate depends heavily on housing infrastructure, human behaviors, and lifestyle differences that cannot be captured easily by an HLC experiment (Reiter et al. 2003, Haenchen et al. 2016, Ndenga et al. 2017).

Thus, other field methods to assess the contact rate between *Aedes* spp. and humans are needed. Ideally, the methods should take into account the heterogeneity in human factors that may influence contact rate, and generate estimates that are useful for mathematical modeling of virus transmission. The goals of this study are to 1) test the feasibility of using questionnaire-based surveys to estimate human–mosquito contact rates, 2) understand how environmental factors and human behaviors may influence mosquito bite exposure, and 3) model how changes in human–mosquito contact rates impact pathogen transmission outcomes.

Methods

We assessed the contact rates between *Aedes* spp. and humans in the Greater New Orleans Region using a self-administered standardized survey and a small-scale HLC experiment. An HLC study was performed to determine the proportion of mosquito bites that belong to either *Ae. aegypti* or *Ae. albopictus*. Next, the contact rates between humans and the *Aedes* species were calculated. Finally, a deterministic compartmental SEIR (Susceptible, Exposed, Infected, Recovered) model describing DENV transmission by *Ae. aegypti* and *Ae. albopictus* was used to compare how the model predictions are influenced by the locally characterized human–mosquito contact rates from the two distinct locations.

Study Sites and Survey Methods

We designed two questionnaires in the form of door hangers. We designed short questionnaires to encourage participation. The first questionnaire (Supp Data 1 [online only]) was used in a preliminary survey to explore the range of bite exposure and to estimate the return rate. The research participants were asked to indicate the number of mosquito bites they received within the past 7 d, the locations in which they experienced mosquito bites most often, and the frequency of mosquito bite exposures inside homes. All questions in this questionnaire were in a multiple-choice format.

The second questionnaire (Supp Data 2 [online only]) was designed after the preliminary survey. The questions included

open-ended questions inquiring about the number of mosquito bites participants received both indoors and outdoors, where they had received the outdoor bites, and the time spent outside in the past 24 h. The questionnaire also collected demographic data, including age range, gender, and the number of people in their household.

In the preliminary survey, the questionnaires were distributed in August and September of 2016 in three study sites: the Bywater and 7th Ward neighborhoods of Orleans Parish (ORL), the Bridge City neighborhood of Jefferson Parish (JEF), and the Oak Harbor and Eden Isle neighborhoods of St. Tammany Parish (TAM). Four street blocks were randomly chosen per month from each of the three study sites. The questionnaires were distributed to all addresses in the chosen blocks and collected back the next day.

In the second survey, only two study sites, ORL and TAM, were included. In order to have a large enough sample size, JEF, farther away and had the lowest response rate, was dropped while the numbers of residential blocks included in ORL and TAM were increased. The study period was from April to August 2017. In each month, four street blocks from each study site were randomly selected, without replacement, to receive the questionnaires on Sundays, and another four blocks on either Wednesdays or Thursdays. The questionnaires were distributed to all addresses in the chosen blocks and retrieved back the next day. No identifying information or addresses were collected from the study subjects, and the Tulane University's Internal Review Board (IRB) approved the full-review exempt status of both surveys (IRB reference number: 16-923467E).

The ORL site was in an urban environment close to New Orleans city's downtown area. Compared to the other two study sites, ORL's residents were younger and lived in a smaller household (almost 40% of all households were a 1-person household; U.S. 2010 Census). Its population median age was 38 (40 in JEF, and 50 in TAM; U.S. 2010 Census). ORL was a racially mixed neighborhood (52.85% African American and 41.86% White; U.S. 2010 Census). JEF and TAM are located further away from the city's downtown area in a more suburban environment. TAM had the highest average household income (\$96,415; 2016 American Community Survey 5-yr estimates) compared to ORL (\$55,709), and JEF (\$49,928). TAM also had the highest percentage of households that were classified as 'Family Household' (76.40%; U.S. 2010 census). Racial diversity was lowest in TAM (89.18% of the total population were White). The population variables of the study sites are shown in detail in Supp Table 1 (online only).

Human Landing Catch

HLC experiments were performed in ORL and TAM to investigate the species composition of host-seeking mosquitoes from April to August 2017. Two locations were chosen within the perimeter of each study site based on their accessibility. These locations were either empty lots or backyards of properties accessed after obtaining verbal permission from landowners. They were the same throughout the survey period and were shaded outdoor areas. In each location and month, HLC was performed once in the morning and once in the evening on two separate days. Each collection consisted of two 45-min capturing sessions with an up to 15-min break in between. The morning collection started within 30 min after sunrise, and the evening collection stopped within 30 min before sunset. The collector was seated on a chair with the legs exposed from the shoes up to the knees, and the lower arms were exposed from the elbows down. Collection of landing mosquitoes from the collector's own body was done using a portable aspirator, and the mosquitoes were either identified

on-site or transported back to the laboratory for further identification using a microscope. A single collector took part in all the HLC sessions.

Survey and HLC Data Analysis and Statistical Tests

Because the first survey was a preliminary data collection with a small sample size, only the data from the second survey was analyzed with statistical tests. In the second survey, the sampling method was a two-stage stratified cluster sampling. To account for the differential probabilities of selection due to the study design and to ensure more accurate estimates, a sampling weight for each participant was calculated based on the selection probability proportional to size. The population cohort was defined as persons aged >18 yr old who lived in one of the two study sites at the time of sampling. The Primary Sampling Unit (PSU) was at a residential block level. The sampling probability of each block was $1/B_p$, where B_i is the total number of blocks in study site *i*. The Secondary Sampling Unit (SSU) was at the research participant level. The probability that a person in each household was selected was $1/P_p$, where P_j was the household size for address *j*.

All data analysis was done using R (version 3.3.3) and R studio. The data and weights were defined to create a Survey Object using Survey package (Lumley 2004). The sampling weight for each data point was calculated as the inverse of the probability of selection. Specifically, weight for each data point was equal to $(1/B_i + 1/P_i)^{-1}$. All statistical tests downstream of the weighting procedure were analyzed with the functions within the Survey package. The Wilcoxon Rank Sum tests were used to compare the numbers of reported bites and the time spent outside within the past 24 h between groups. Spearman's correlation tests were used to determine the correlation between the time spent outside at each time interval, and the numbers of reported bites received outdoors.

Two generalized linear models assuming quasi-Poisson distribution as the probability distribution function of the response variable, with log link function, were created to analyze the data. The first model used the total time spent outside between 5 pm to 6 am (evening and nighttime) as a response variable. In this model, the independent variables included the age range and gender of research participants, weekend/weekday setting, and study sites. The second model used numbers of reported bites received outdoors within the past 24 h as a response variable. The independent variables included in this model were the time spent outside within the past 24 h, the gender of research participants, the month of data collection, and the weekend/weekday setting.

For HLC data analysis, comparisons between the numbers of landed *Ae. aegypti* or *Ae. albopictus* between study sites and between times of collection were determined using the Wilcoxon Rank Sum test. The proportions of *Ae. aegypti* and *Ae. albopictus* from HLC were calculated based on the average values of landing mosquito types across all HLC sessions for both study sites.

Dengue Epidemiological Compartmental Model Description and Assumption

Our compartmental mathematical model described the transmission of one serotype of DENV by both vector species: *Ae. aegypti* and *Ae. albopictus*. We used this model to estimate and predict quantities of interest at the initial epidemic spread. This model was adapted from a mathematical mosquito-borne disease model published in a study by Manore et al. (2014). We defined human-mosquito *contact rate* (B) as the number of biting events that occurred by all mosquitoes of a given species on the human population in the area of interest within a 24-h period. Note that we defined the mosquito's *biting rate* as a *per capita* rate of bites that a typical single mosquito may give to humans per unit time.

The human population was divided into four compartments: susceptible (S_h) , exposed (E_h) , infectious (I_h) , and recovered/immune (R_h) . The *Ae. aegypti* and *Ae. albopictus* mosquito populations were divided into three compartments: susceptible $(S_g \text{ and } S_b, \text{ respectively})$, exposed $(E_g \text{ and } E_b, \text{ respectively})$, and infectious $(I_g \text{ and } I_b, \text{ respectively})$. The total population sizes for *Ae. aegypti*, *Ae. albopictus*, and humans were $N_g = S_g + E_g + I_g$, $N_b = S_b + E_b + I_b$, and $N_h = S_h + E_h + I_h + R_h$, respectively. We assumed that the carrying capacities of the two species were independent of each other. Supplementary Fig. 1 (online only) shows a diagram of the model.

Humans entered the susceptible class S_{μ} with a per capita birth rate $\Psi_{\rm h}$. Humans were bitten by Ae. aegypti with a rate of $B_{\rm g}/N_{\rm h}$ (bites per person per day) or by Ae. albopictus with a rate of $B_{\rm b}/N_{\rm b}$. These biting Ae. aegypti or Ae. albopictus had a probability of I_o/N_o , or $I_{\rm h}/N_{\rm h}$, of being infectious, respectively. If a mosquito was infectious, then there was a probability of $\beta_{\rm b}$ that the person will become infected. When a human was infected, they moved from susceptible class $S_{\rm h}$ to the exposed class $E_{\rm h}$. After an average intrinsic incubation period of $1/v_{h}$ days, they moved to the infectious class I_{h} . Humans in the infectious class can infect other mosquitoes upon contact. After an average recovery time $1/\gamma_{\rm b}$ days, the infectious humans recovered and moved to class R_1 . Recovered persons were assumed to have immunity to the infecting DENV serotype for the entire period of the simulation. Also, humans of all status left the population through a per capita natural death rate μ_{μ} . The death rate due to disease was assumed to be very low and negligible. The human population size was assumed to be stable ($\Psi_{\rm b} = \mu_{\rm b}$), and the migration of mosquitoes and humans was low and negligible.

When a susceptible Ae. aegypti mosquito bit humans at a biting rate of B_g/N_g (bites per mosquito per day), there was a probability I_h/N_h that the persons being bitten were infectious. If the person was infectious, then the biting Ae. aegypti mosquito in the class S_g became infected with a probability β_g and moved to the exposed class E_g . After an average extrinsic incubation period $1/v_g$ days, the mosquito advanced to the infectious class I_g . Similarly, when a susceptible Ae. albopictus mosquito bit humans at a biting rate of B_b/N_b , there is a probability I_h/N_h that the persons were infectious and a probability β_b that the mosquito became infected and advanced to the exposed class E_b . After an extrinsic incubation period $1/v_b$ days, the Ae. albopictus mosquito advanced to the infectious class I_b . Both mosquito species remained infectious for life.

Female mosquitoes entered the susceptible class through recruitment from the pupal stage. The recruitment term for mosquitoes was proportional to the egg-laying rate of adult female mosquitoes and accounted for the hatching rate of eggs and survival of larvae and pupae. The aquatic stages were not explicitly included in the model and were approximated by a density-dependent recruitment (birth) rate. We assumed that all adult female *Ae. aegypti* and *Ae. albopictus* mosquitoes had the same per capita natural death rate μ_g and μ_b , respectively. In this model, dengue infection did not affect the mosquito death rate or biting rate.

Model Equations

Our ordinary differential compartmental equations modeling dengue transmission were:

$$\frac{dS_b}{dt} = \Psi_b H_0 - \lambda_b S_b - \mu_b S_b \tag{1a}$$

$$\frac{dE_b}{dt} = \lambda_b S_b - \nu_b E_b - \mu_b E_b \tag{1b}$$

$$\frac{dI_b}{dt} = \nu_b E_b - \gamma_b I_b - \mu_b I_b \tag{1c}$$

$$\frac{dI_h}{dt} = \nu_h E_h - \gamma_h I_h - \mu_h I_h \tag{1d}$$

$$\frac{dS_g}{dt} = \eta_g N_g - \lambda_g S_g - \mu_g S_g \tag{1e}$$

$$\frac{dE_g}{dt} = \lambda_g S_g - \nu_g E_g - \mu_g E_g \tag{1f}$$

$$\frac{dE_g}{dt} = \lambda_g S_g - \nu_g E_g - \mu_g E_g \tag{1g}$$

$$\frac{dE_g}{dt} = \lambda_g S_g - \nu_g E_g - \mu_g E_g \tag{1h}$$

$$\frac{dE_b}{dt} = \lambda_b S_b - \nu_b E_b - \mu_b E_b \tag{1i}$$

$$\frac{dI_b}{dt} = \nu_b E_b - \mu_b I_b \tag{1j}$$

The female Ae. aegypti and Ae. albopictus recruitment rates were:

$$\eta_g = \psi_g - r_g \frac{N_g}{K_g} \tag{2}$$

and

 μ_{g}

 $\mu_{\rm h}$

$$\eta_b = \psi_b - r_b \frac{N_b}{K_b} \tag{3}$$

Here, Ψ_{a} and Ψ_{b} were the per capita natural birth rates of female Ae. aegypti and Ae. albopictus, respectively. In the absence of density

Per capita death and birth rate for human

Per capita death rate for Ae. aegypti

Per capita death rate for Ae. albopictus

Table 1.	Model	parameters,	their	baseline	values ar	nd ranges	, and sources
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Parameter Unit Value Range Source U.S. census 2016 estimates H_0 Human population size, ORL Human 10,157 _ Human population size, TAM 7,385 Ae. aegypti-human contact rate, ORL Day-1 26,389 17,094-From this study B 35,684 Ae. aegypti-human contact rate, TAM 5,484 3.777-7.197 $B_{\rm h}$ Ae. albopictus-human contact rate, ORL 40,916 26,504-55,329 9,834 Ae. albopictus-human contact rate, TAM 6.773-12.895 Probability of transmission from mosquito 0.33 0.10-0.75 Manore et al. (2014), $\beta_{\rm h}$ to human given an infectious bite Newton and Reiter (1992)Vector competence for Ae. aegypti 0.25 0.03-0.76 Richards et al. (2012), Guo β_{g} et al. (2013) 0.06 Richards et al. (2012), Guo Vector competence for Ae. albopictus 0.01 - 0.56 $\beta_{\rm h}$ et al. (2013) 1/vEIP for Ae. aegypti Day 6.5 2-33 Chan and Johansson (2012) EIP for Ae. albopictus $1/v_{h}$ $1/v_{h}$ IIP Day 3-10 Gubler et al. (1981) 6 3.89-5.97 Ψ Per capita recruitment rate of Ae. aegypti Day-1 4.93 Delatte et al. (2009) ΨĽ Per capita recruitment rate of Ae. albopictus K_{g} Mosquito Carrying capacity of Ae. aegypti $10H_{0}$ $3H_0 - 17H_0$ Estimated K_{b}° Carrying capacity of Ae. albopictus $1/\gamma_{h}$ Day 5 4-14 Gubler et al. (1981), Busch Viremic period in human et al. (2016) $\mu_h = \Psi_k$ 1/75.7 1/74.9-1/81.3 CDC's wonder database

Year-1

Day-1

1/18

dependence, r_{e} and r_{h} were the intrinsic growth rates of female Ae. *aegypti* and *Ae. albopictus*, respectively, where $r_{g} = \Psi_{g} - \mu_{g}$ and $r_{\rm b} = \Psi_{\rm b} - \mu_{\rm b}$. $K_{\rm c}$ and $K_{\rm b}$ were the carrying capacity of the female Ae. aegypti and Ae. albopictus, respectively, in the area of interest.

The force of infection from mosquitoes to humans (λ_{h}) was the product of the average number of bites a person received from mosquitoes per day $(B_{a}/N_{b}$ and B_{b}/N_{b}), the probability that the mosquito was infectious (I_{a}/N_{a}) and I_{b}/N_{b} , and the probability of virus transmission from the biting and infectious mosquito to the human (β_{i}) ,

$$\lambda_b = \frac{B_g}{N_b} \beta_b \frac{I_g}{N_g} + \frac{B_b}{N_b} \beta_b \frac{I_b}{N_b}$$
(4)

The force of infection from humans to Ae. aegypti and to Ae. *albopictus* (λ_a and λ_b , respectively) were the product of the number of bites per mosquito per day (B_{ρ}/N_{ρ}) and B_{h}/N_{h} , respectively), the probability that the bitten human was infectious $(I_{\rm b}/N_{\rm b})$, and the probability of pathogen transmission from an infected human to the biting mosquito (β_a and β_b , respectively).

$$\lambda_g = \frac{B_g}{N_g} \beta_g \frac{I_h}{N_h} \tag{5}$$

$$\lambda_b = \frac{B_b}{N_b} \beta_b \frac{I_b}{N_b} \tag{6}$$

Model Parameters

The contact rates of humans and Ae. aegypti (B_a) or Ae. albopictus $(B_{\rm h})$ were obtained from this study. Other parameters were obtained from other sources (Table 1).

The bite number, $\rho_{\rm b}$, was the total number of bites a typical human received per person per day, regardless of mosquito species, and was estimated from our survey. The proportion of bites, p_{i} , that belonged to mosquito species v was estimated from HLC data. The

1/11-1/55

Busch et al. (2016), Styer

et al. (2007)

number of mosquito bites that belonged to mosquito species v that humans received per person per day (or the bite exposure rate) was

$$\rho_{h\nu} = \rho_h \cdot p_\nu \tag{7}$$

If H_0 was the human population size, then, the number of mosquito bites from mosquito species v that all humans in the population received per day (or the contact rate) is

$$B_{\nu} = \rho_{h\nu} \cdot H_0 \tag{8}$$

The Basic Reproductive Number (R_0)

The calculations and model analyses were done in MATLAB R2018a (version 9.4.0). The model outcomes of interest were 1) the initial rate of disease spread by evaluating the basic reproduction number (R_0) and 2) the initial transient disease dynamics by evaluating the timing and magnitude of the first epidemic peak.

In a homogeneously mixed population, R_0 is the expected number of secondary infections that one infectious individual would cause over the duration of the infectious period in a fully susceptible population (Heffernan et al. 2005). From this definition, it can be logically interpreted that when $R_0 < 1$, each infectious individual produces less than one new infected individual on average and the pathogen transmission 'dies out' from the population. Conversely, if $R_0 > 1$, the pathogen is able to invade the susceptible population.

The next generation operator approach was used to calculate R_0 (Diekmann et al. 1990). The derivation of R_0 using the next generation operator and the interpretation of R_0 expression are described in the Supp Text (online only). The R_0 equation is:

$$R_{0} = \sqrt{\frac{\beta_{b}B_{g}\nu_{g}}{K_{g}\mu_{g}(\mu_{g}+\nu_{g})} \cdot \frac{\beta_{g}B_{g}\nu_{b}}{H_{0}(\mu_{b}+\nu_{b})(\mu_{b}+\gamma_{b})}} + \frac{\beta_{b}B_{b}\nu_{b}}{K_{b}\mu_{b}(\mu_{b}+\nu_{b})} \cdot \frac{\beta_{b}B_{b}\nu_{b}}{H_{0}(\mu_{b}+\nu_{b})(\mu_{b}+\gamma_{b})}$$
(9)

Sensitivity Analysis

Because the transmission parameters are only known approximately, it is important to understand how variations in these parameters affect model outcomes. Our analysis includes local sensitivity analysis, an extended sensitivity analysis, and global sensitivity analysis to quantify the impact of changes in parameters on R_0 .

In the local sensitivity analysis, sensitivity indices were derived to quantify how small changes in the parameter of interest p caused variability in the model output of interest q. If an input parameter pchanged by $x^{\%}$, then the output quantity q changed by $S_p^q \cdot x^{\%}$. As such, the sensitivity index's magnitude determines the relative importance of the model parameters on the model predictions. The sign of the sensitivity index indicates the direction of change of the output in response to the parameter change. The sensitivity indices of R_0 were analytically computed by evaluating partial derivatives of R_0 (equation 9) with respect to each parameter of interest at the baseline value, multiplied by a scaling factor ($S_p^q = \frac{\partial q}{\partial p} \cdot \frac{b}{q}$). As a result, the local sensitivity indices are valid only at a small range around the parameter baseline values.

In the extended sensitivity analysis, the responses of R_0 to the variations in each parameter of interest are calculated over the entire possible range of that parameter (Table 1), while fixing all other parameters at their baseline. The extended local sensitivity analysis curves were plotted to depict the derivative of R_0 as a function of the model parameter of interest at all values within its possible range.

In the global sensitivity quantification, the values of R_0 were calculated using multiple combinations over the full range of all the

parameters. The parameters were treated as random variables (all parameters can simultaneously take any values within their possible ranges), and R_0 had a distribution, which depended on the distributions of parameters. In this analysis, each of the model parameters was assumed to vary independently from each other and has a uniform distribution. The description of sensitivity analyses was given in more detail in the previous publication (Manore et al. 2014). All sensitivity analyses were done in MATLAB R2018a (version 9.4.0).

Results

Exploratory Survey of Mosquito Bite Exposure in Adults in the Greater New Orleans Region

In the preliminary survey, the total number of retrieved questionnaires was 104 (ORL, 33; JEF, 24; TAM, 47). The average return rate across study sites was 20.7%. The results are shown in Fig. 1.

The preliminary results suggested variations between study sites. Research participants in JEF reported higher exposure to mosquito bites than research participants in ORL and TAM. In TAM, around 40% of research participants indicated that they did not receive any mosquito bites in the past 7 d. While in ORL, 38% of research participants chose '1–5' bites in the past 7 d. In JEF, equal proportions (23%) of research participants reported being bitten more than 10 times, 5–10 times, 1–5 times, and none in the past 7 d.

When asked how often they experienced mosquito bites inside of their homes, 19% of research participants from JEF chose 'often' as the answer, higher than the other two study sites (both were <5%). In all study sites, the place where people most often experienced outdoor mosquito bites was around their homes (78%, 72%, 56% for TAM, JEF, and ORL, respectively). In ORL, 'public space' was also reported as a place where people most often experienced mosquito bites (32%).

Mosquito Bite Exposure Rates in Adults in the Greater New Orleans Region

For the second survey, a total of 941 and 801 questionnaires were distributed in ORL and TAM, respectively. The average numbers of addresses per block were 23.5 (SD = 7.9) for ORL and 20.0 (SD = 3.4) for TAM. In ORL, a total of 91 questionnaires were retrieved, with an average return rate of 10.0% (SD = 6.5%) per block. In TAM, a total of 94 questionnaires were retrieved, with an average return rate of 11.4% (SD = 8.3%) per block.

The average numbers of adults (>18 yr old) per household were 1.8 for ORL (SD = 0.7) and 2.1 for TAM (SD = 0.6). Graphs showing the gender and age distribution of research participants in both study sites are shown in Supp Fig. 2 (online only). In total, research participants included 90 females, 70 males, and 25 individuals who did not indicate their gender. Of these, one person was between 18–25 yr old, 38 were between 26–40 yr old, 78 were between 41–65 yr old, 63 were more than 65 yr old, and 5 failed to indicate their age range.

Overall, the reported numbers of mosquito bites that occurred outdoors and indoors within the past 24 h in ORL, after adjustment with sampling weights, were 5.5 (SE = 0.9) and 1.7 (SE = 0.5), respectively. The reported numbers of bites that occurred outdoors and indoors within the past 24 h in TAM, after adjustment with sampling weights, were 2.3 (SE = 0.3) and 0.3 (SE = 0.1), respectively. In both study sites, the average numbers of reported bites that occurred outdoors were significantly higher than indoors (Wilcoxon Rank Sum test, ORL: df = 34, *P*-value < 0.001, TAM: df = 30, *P*-value < 0.001). In addition, the reported numbers of bites were significantly



Mosquito bite exposure inside home

Fig. 1. Results from the preliminary survey showing the frequency of bite exposure inside homes and the estimated numbers of bites research participants experienced in the past 7 d. The percentages of participants choosing each answer of the multiple-choice questions are shown.



Fig. 2. The average numbers of mosquito bites per person, after adjustment with sampling weights, in the past 24 h that research participants reported are shown by sites and month of data collection. The circles represent the outdoor bites and the triangles represent indoor bites. Error bars represent the standard errors

higher in ORL compared to TAM for both outdoor and indoor settings (Wilcoxon Rank Sum test, outdoors: df = 66, P-value = 0.003; indoors: df = 66, *P*-value < 0.001). The average reported numbers of bites that occurred outdoors and indoors, after adjustment with sampling weights, within the past 24 h in both study sites across months are shown in Fig. 2.

Factors Affecting Bite Exposure in Adults in the **Greater New Orleans Region**

For research participants who reported receiving outdoor mosquito bites within the past 24 h, they were asked to indicate the locations

that they experienced these bites. In TAM, 47 participants or around 90% reported being bitten around their homes (answers such as 'front yard', 'backyard', 'sitting in my open garage'). Five participants (~10%) reported being bitten both around their homes and at public spaces (answers such as 'backyard and dog park' and 'yard and during a walk'). In ORL, 33 participants (~59%) reported being bitten around their homes (answers such as 'backyard' and 'front porch'), 6 participants or 11% reported being bitten at public spaces (answers such as 'outside while at work' and 'while walking the dog'), and 17 participants (30%) reported being bitten both around their homes and at public spaces (answers such as 'backyard, while out walking').

Information about the time spent outdoors within the past 24 h was collected from survey participants (Supp Fig. 3 [online only]). After adjustment with sampling weights, research participants in ORL spent 41.8 min (SE = 7.4) and 67.5 min (SE = 6.9) outdoor during the weekday and weekend on average, respectively. After adjustment with sampling weights, research participants in TAM spent 54.3 min (SE = 5.5) and 51.0 min (SE = 8.2) outside during the weekday and weekend on average, respectively. The difference of the time spent outside between the weekend and weekday was significant for research participants in ORL (Wilcoxon Rank Sum test, df = 34, P-value = 0.02) but not for research participants in TAM (Wilcoxon Rank Sum test, df = 30, P-value = 0.3). In addition, the difference of the time spent outside between research participants in ORL and TAM was statistically significant for the weekend (Wilcoxon Rank Sum test, df = 32, *P*-value = 0.02) but not during the weekday (Wilcoxon Rank Sum test, df = 32, P-value = 0.3).

The time spent outside during the time period between 5:00 p.m. to 8:00 p.m. (or evening time), and 8:00 p.m. to 6:00 a.m. (or nighttime) showed significant correlations with reported bite numbers using Spearman's correlation test. The correlation coefficient was 0.25 (*P*-value = 0.003) and 0.28 (*P*-value < 0.001) for the evening and nighttime, respectively. The time spent outside during the time period between 6:00 a.m. to 10:00 a.m. (or morning time), and 10:00 a.m. to 5:00 p.m. (or daytime) did not show significant correlations with reported bite numbers (Spearman's correlation test; *P*-value = 0.078 and 0.975, respectively).

A generalized linear model analysis was used to determine which variables are associated with how much time the research participants reported spending outside in the evenings and at night. A table showing the model's result is shown in Supp Table 2 (online only). Only the age range of research participants and the weekend/weekday setting showed significant associations with the time participants reported spending outside in the evening and night. Specifically, older participants spent less time outside in the evening and night than younger participants. Research participants also spent less time outside on weekdays than on weekends.

Another generalized linear model analysis was used to determine the effect of the study site, the month of data collection, total time spent outside in the evening and night, and gender of research participants on the reported numbers of outdoor bites. The results, detailed in Supp Table 3 (online only), indicated that the time spent outside in the evening and night, the month of data collection (May, July, and August), and study site show significant associations with the reported outdoor bite numbers. The results show that, when controlled for other variables, including the time they spent outside, research participants in ORL reported experiencing higher mosquito bites than participants from TAM. Gender did not show a significant association with the reported bite numbers (*P*-value = 0.053).

Determining Mosquito Species Contributing to Bite Exposure in the Greater New Orleans Using HLC

The average composition of female mosquito species and types captured during HLC in both study sites are shown in the top graphs of Fig. 3. In ORL, on average 56.0% of landed female mosquitoes were *Ae. albopictus* and 36.1% were *Ae. aegypti*. In TAM, on average, 51.0% of landed mosquitoes were *Ae. albopictus* and 28.4% were *Ae. aegypti*. In ORL, species other than *Ae. aegypti* and *Ae. albopictus* that were captured included: *Ae. taeniorhynchus*, *Ae. vexans*, *Mansonia titillans*, and *Ae. infirmatus*. In TAM, other species included: *An. bradleyi*, *Cx. salinarius*, *Cx. restuans*, *Ae. taeniorhynchus*, and *Ae. sollicitans*.

The average numbers of female *Ae. aegypti* and *Ae. albopictus* landed during 40 HLC sessions are shown in the bottom graph of Fig. 3. In ORL, the average numbers of landed female *Ae. aegypti* in the morning and evening HLC session (1.5 h) were 1.9 (SD = 1.4)

Average composition of mosquito types from HLC in ORL

Average composition of mosquito types from HLC in TAM



Fig. 3. Top: pie graphs showing the average composition of mosquito types captured during HLC in ORL and TAM. Bottom: average numbers of landed female *Ae. aegypti* and *Ae. albopictus* in ORL and TAM during the 1.5 h of HLC sessions in the morning and evening.

and 4.1 (SD = 2.0), respectively. The average numbers of landed female Ae. albopictus in the morning and evening HLC sessions were 3.7 (SD = 7.0) and 6.7 (SD = 11.6), respectively. In TAM, the average numbers of landed female Ae. aegypti in the morning and evening HLC sessions were 0.8 (SD = 1.3) and 2.0 (SD = 3.4), respectively. The average numbers of landed female Ae. albopictus in the morning and evening HLC sessions were 1.4 (SD = 2.0) and 3.3 (SD = 5.1), respectively. Averaging data from both study sites, the number of landed mosquitoes was higher in the evening than in the morning for both Aedes species. However, the difference is statistically significant only for Ae. aegypti and not for Ae. albopictus (Wilcoxon Rank Sum test, P-value = 0.04 and 0.08, respectively). In addition, averaging data from both morning and evening sessions, the number of landed mosquitoes in ORL was significantly higher than in TAM for Ae. aegypti but not for Ae. albopictus (Wilcoxon Rank Sum test, P-value = 0.002 and 0.2, respectively).

Basic Reproductive Number (R_0) and the Initial Transmission of DENV

The model analysis simulated a situation where one infectious human was introduced into fully susceptible populations of humans and mosquitoes. Table 2 shows the result from the model analysis using different values of local human–mosquito contact rates, calculated using equations 7 and 8, while holding other parameters at baseline values. The output of interest includes R_0 , the percentage of infected and recovered humans at their peaks, and the number of days before the number of infected and recovered humans reach their peaks.

For the human–mosquito contact rates acquired from both study sites, only the R_0 during the initial DENV transmission in ORL exceeds 1. When using the baseline value of the human–mosquito contact rate from ORL, the calculated R_0 for DENV transmission in the area was 2.41, and the infected human number peaked at day 188th after the virus introduction. When using the minimum value for the contact rate from ORL, R_0 was greater than 1 even though the outbreak was less explosive. The infected human number peaked at day 510th after the initial virus introduction. R_0 value was highest (3.26) for the maximum value of the contact rate from ORL, and the number of infected humans peaked at day 124th. However, none of the human–mosquito contact rate values quantified in TAM resulted in an R_0 exceeding 1, and therefore a small initial infection would die out.

Given the baseline value of the human-mosquito contact rate in ORL, the number of infected *Ae. aegypti* at its peak was 4,647. This is higher than the infected *Ae. albopictus*, where their number at the peak was 182 (Fig. 4). When using the maximum value of the human-mosquito contact rate in ORL, the number of infected *Ae. aegypti* and *Ae. albopictus* at their peaks were 8,779 and 360, respectively. Finally, when using the minimum value of the human-mosquito contact rate in ORL, the number of infected *Ae. aegypti* and *Ae. albopictus* at their peaks were 713 and 27, respectively.

Local Sensitivity Analysis

The local sensitivity indices of R_0 with respect to model parameters are shown in Table 3. For both transmission scenarios in ORL and TAM, the R_0 is most sensitive to 1) *Ae. aegypti* contact rate (B_g) , 2) the probability of DENV transmission from a mosquito to a human given an infectious bite (β_h) , and 3) the recovery rate of the human (or the inverse of viremic period; γ_h), evaluated at their baseline values. At the baseline values, the basic reproductive number is least sensitive to the inverse of the intrinsic incubation period (v_h) and the human death rate (μ_h) .

The sign of the sensitivity index indicates the relationship between the direction of changes in R_0 and model parameters. For example, the sensitivity indices of R_0 with respect to human-mosquito contact rates (both B_g and B_b), evaluated at their baseline values, are positive. Therefore, as the contact rate between mosquito and human increases, the R_0 also increases. On the contrary, the sensitivity indices of R_0 with respect to γ_h , evaluated at their baseline values, are negative. As a result, as the human recovery rate increases (i.e., viremic period decreases), the R_0 decreases. Another observation is the negative value of the sensitivity indices of R_0 with respect to the mosquito carrying capacity (both K_g and K_b), evaluated at their baseline values. This can be interpreted that as the mosquito carrying capacity increases, the R_0 decreases. The mathematical explanation for this unexpected relationship is discussed in the Discussion section.

The relative ranking of the parameter importance was almost the same between the two scenarios (Table 3). The only exception is that $B_{\rm b}$, or *Ae. albopictus* contact rate with humans, becomes relatively less important at determining R_0 in the ORL scenario compared to TAM. This results from the assumption that *Ae. albopictus* has a lower vector competence than *Ae. aegypti*, and *Ae. aegypti* has a higher contact rate with humans in the ORL.

Extended Sensitivity Analysis

The extended sensitivity analysis plots of R_0 with respect to the mosquito-human contact rate for the transmission scenario in ORL are shown in Fig. 5. The extended sensitivity analysis plots of R_0 to other selected model parameters for ORL and TAM are shown in Supp Figs. 4 and 5 (online only), respectively.

First, consider the top two graphs of Fig. 5, which show how the R_0 value changes in response to changes in the humans' contact rates with *Ae. aegypti* (B_g ; top left panel) and *Ae. albopictus* (B_b ;

Table 2. Results from the model analysis using different values of local human-mosquito contact rates

Parameter	R ₀	Infected human a	at its peak	Recovered human at its peak		
		Percentage over total population	Time at the peak (day)	Percentage over total population	Time at the peak (day)	
Using human-mosquito co	ontact rates from OR	L				
Baseline values	2.41	6.53%	188	97.00%	332	
Minimum values	1.56	1.30%	510	64.70%	907	
Maximum values	3.26	10.83%	124	99.67%	213	
Using human-mosquito co	ntact rates from TA	M				
Baseline values	0.73	-	-	_	-	
Minimum values	0.50	-	-	_	-	
Maximum values	0.96	-	-	-	-	



Fig. 4. Model analysis of DENV transmission in ORL using baseline value of human-mosquito contact rate.

Table 3. Sensitivity indices of R_0 with respect to model parameters at the baseline values

Parameter	ORL $(R_0 = 2.41)$	TAM $(R_0 = 0.73)$	
B	0.63	0.56	
β _b	0.50	0.50	
γ _h	-0.50	-0.50	
μ	-0.40	-0.36	
B	0.37	0.44	
K _e	-0.32	-0.28	
β	0.32	0.28	
μ	-0.23	-0.28	
K _b	-0.18	-0.22	
β	0.18	0.22	
ν	0.08	0.07	
vb	0.05	0.06	
μ _h	-2.0×10^{-4}	-2.0×10^{-4}	
v _h	1.1×10^{-4}	1.1×10^{-4}	

top right panel), while holding all other parameters at their baseline values. Both plots show curves with positive trends, indicating that a decrease in the contact rate, while holding other parameters at their baselines, will cause R_0 to decrease. However, this relationship is not linear; as the contact rate decreases, the slope becomes smaller. That is, the reduction in human–mosquito contact rate, when focused on only one vector species at a time, becomes less effective at reducing R_0 when the contact rate is already low. In fact, in the ORL scenario, reducing the contact rate between humans and only one vector species at a time will fail to reduce R_0 below 1. This is because the contact rate between humans and the other vector species is high enough to maintain the transmission.

Next, consider the bottom graph in Fig. 5, which shows how R_0 changes in response to the changes in both B_g and B_b simultaneously while holding other parameters at their baseline values. In this case, the reduction of both B_g and B_b at the same time below certain threshold values will result in $R_0 < 1$.

Global Sensitivity Analysis

Figure 6 shows the distribution of R_0 calculated from combinations of model parameter values, which were sampled uniformly and independently within their possible ranges. The R_0 distribution for the ORL scenario was wider at the base and had a longer tailed distribution, indicating that there was a higher variation in the outcomes. The percentage of scenarios (or the combinations of parameter values) that resulted in an $R_0 > 1$ indicated how likely DENV was to spread in either location. In the ORL case, 74.52% of scenarios resulted in an $R_0 > 1$. In TAM, 68.80% of scenarios resulted in an $R_0 > 1$. As such, ORL was more receptive to an initial outbreak of DENV than TAM.

Discussion

Mosquito bite exposure was investigated using a questionnaire survey to ask survey participants about their past experience receiving mosquito bites. We found that the mosquito bite exposure on research participants occurred more frequently in the outdoors than indoors in both study sites. The location that research participants most often reported being exposed to mosquito bites was around their homes. We quantified the correlation between the reported bite number and the time spent outside in the evenings and at night. After controlling for the time duration spent outside, there was a significant effect of study site on the outdoor biting rate, where participants in ORL reported receiving more mosquito bites than participants in TAM. In places such as the Greater New Orleans Region where the mosquito bite exposure between indoors and outdoors may be different, the human-mosquito contact rate depends on the density of host-seeking female mosquitoes and human behavior, such as the time spent outside.

Interestingly, the indoor bite exposure rate was also higher for ORL than in TAM. The potential reason for this difference was not investigated in this study. According to the 2016 American Community Survey 5-yr estimates, the median household income in TAM is 42% higher than in ORL (Supp Table 1 [online only]). It is possible that factors such as the integrity of the wall, the availability of air conditioners, combined with human behaviors (keeping doors or windows open), determine the difference in indoor bite exposure rate (Mburu et al. 2018). Future study is needed to investigate the relative importance of these factors on indoor mosquito bite exposure.

Only a few other studies have used surveys to investigate mosquito bite exposure. A study by Dowling et al. asked research participants in suburbs of Washington, DC, how often they were bitten by mosquitoes, and found that almost half chose 'Everyday' (Dowling et al. 2013). A similar study by Halasa et al. interviewed residents in two counties of New Jersey and found that during a typical summer week, large percentages of respondents reported being bitten at least once, and while outdoors (Halasa et al. 2014). In Halasa's study, bite exposure occurred most often in the evening, followed by at night and late afternoon. Read et al. performed a unique study to compare the number of mosquito bites that participants thought they received while sitting outside for 5 min with the number of mosquitoes captured concurrently on a staff person using a Whole Person



Fig. 5. The extended sensitivity analysis plots of R_0 with respect to the human–mosquito contact rate for the model analysis of DENV transmission in ORL. In the top graphs, the dots represent the R_0 at the contact rate baseline values. In the bottom graph, the horizontal plane represents where $R_0 = 1$ and the lines represent the R_0 values at baseline contact rates of each of the two *Aedes* species and humans. The point where the two lines meet represents the R_0 value at the baseline contact rates of both *Aedes* species and humans.



Fig. 6. The frequency distribution of R_0 values calculated from combinations of model parameter values sampling uniformly and independently. The vertical dashed line at $R_0 = 1$ indicates the threshold value for an outbreak.

Bag Sampler (Read et al. 1994). They showed that respondents' reported bites received during the 5-min blinded test time increased with increasing trap count.

Even though this study was not designed to compare the bite survey to HLC, the observations from both methods were congruous. For example, the higher reported mosquito bite exposure in ORL mirrored the higher number of host-seeking mosquitoes in that site, compared to TAM. In addition, the correlation between the reported outdoors time and the number of mosquito bites was found only in the evening and nighttime, but not in the morning. This finding was consistent with our HLC data and other studies, which found higher numbers of host-seeking *Ae. aegypti* in the evenings than in the mornings (Chadee 1988, Ndenga et al. 2017). Future study is needed to investigate the correlation between the reported bite exposure level from surveys and the number of landed mosquitoes from HLC experiments.

Our model analysis showed that the human-mosquito contact rate played an important role in determining contrasting outcomes in dengue transmission simulated in the two study sites. The local sensitivity indices indicated that the contact rate between humans and *Ae. aegypti* was the most important parameter determining the R_0 , and was more important than the contact rate between humans and *Ae. albopictus*. This was because of the difference in the vector competence between the two species. *Aedes aegypti* is thought to be a more competent vector (Lambrechts et al. 2010), and we set its vector competence value to be higher.

Interestingly, changes in the carrying capacity of mosquitoes (which controlled their population size) showed an inverse relationship with the changes in R_0 , while holding other parameters at their baselines. This is counterintuitive because one may expect the

risk of an outbreak to be smaller when the vector density is low. However, the assumption of this model is that the contact rate does *not* depend on human or mosquito density. This assumption may be valid when human, and mosquito variables contribute to a fixed amount of bites that is compromised by both the mosquito's desire to blood-feed and the number of bites humans can tolerate. Under this assumption, the biting rate *per mosquito* (B_g/K_g and B_b/K_b) would increase as the carrying capacity (K_g and K_b) of mosquitoes decreases. The increase in this biting rate *per mosquito* results in a higher outbreak potential. Even though this explanation is justifiable mathematically, the real-world mechanisms will likely be more complicated and may result in a different outcome.

Mathematical models are a simplified simulation of a real-world complex process. As such, the models are biased and limited by their assumptions and parameter values. In our model, we assumed uniform distributions of human and mosquito density in both space and time. In reality, this is unlikely to hold true. For example, the mosquito population size in the Southern United States fluctuates significantly as a response to seasons. When the simulated time period spans across several seasons, then the model parameters need to account for the fluctuating mosquito's carrying capacity and death rate.

In addition, a deterministic model was utilized. Even though this model type has been applied in many disease systems due to its simplicity and clarity (Cheng et al. 2016, Tang et al. 2016), it ignores heterogeneity and stochasticity inherent in natural disease transmission. Early in the disease invasion stage, when there are only a few infectious hosts, stochasticity, and chance events often play an important role in determining the transmission course (Britton and Lindenstrand 2009). For example, infectious hosts can all heal or die due to chance alone before transmission can take off even when R_0 is above 1.

We also assumed that the contacts were evenly distributed among individuals. This assumption rarely applies in the real world. Often, only a small fraction of individuals, known as super-spreaders, contribute significantly to contacts and transmission events (Stein 2011). Studies have shown that mosquito biting and bite exposure are associated with many variables such as human body size, alcohol consumption, skin odor, housing type, or proximity to mosquito habitats (Perkins et al. 2013). In addition, behavioral changes that may be associated with more severe human cases (e.g., houseridden individuals) could result in differential bite exposure rates. Questionnaire-based surveys may be a valuable tool that could be feasibly used to investigate how these factors impact heterogeneity in mosquito bite exposure among individuals.

Another important factor determining the accuracy of the model's predictions is the accuracy of the parameters' values. The human-mosquito contact rate is not often characterized in the field and among the least known parameters in mosquito-borne disease transmission. HLC has been the traditional gold standard method, but its use is often impractical (Lima et al. 2014), and does not take into account human lifestyles or other innate human variables.

Molecular approaches to profile the mosquito blood meal were often used to identify host types or individuals, but not rate (Chow-Shaffer et al. 2000, De Benedictis et al. 2003, Harrington et al. 2014). In order to be used for the estimation of R_0 , the contact data would need to be in form of a *rate*, thus requiring the estimation of the time denominator. A histological technique was used to analyze blood-fed mosquitoes' abdomens, and obtain contact rate by estimating the time of blood-feeding based on the appearance of blood and ovarian development when compared to known laboratory standards (Scott et al. 2000). Bloodmeal analysis method that can give an estimate

time since blood-feeding, such as one by Scott et al. (2000), can provide an objective blood-feeding rate to support or validate bite exposure data from questionnaire-based surveys in future studies. With further validation, the use of questionnaire-based surveys can provide a low-cost, fast, and feasible alternative.

Despite their benefits, using surveys to approximate human-mosquito contact rates may result in some biases. For example, in an attempt to get a full blood meal, a mosquito may repeatedly probe the host (Ribeiro 2000). As a result, a person may report being bitten multiple times, but the contacts were with only one mosquito. In addition, the bites research participants received could be from arthropods other than mosquitoes. Even though the participants were asked to indicate the number of mosquito bites within the past 24 h (instead of the past 7 d, as was done in the preliminary survey), it is likely that there was a recall bias. To reduce this bias, a prospective cohort study design could be used in future studies. In addition, only a small portion (~10%) of the targeted population participated in the study. This may cause selection bias because the decision to participate in the study may reflect the inherent characteristics of the participants. By using other sampling methods or increasing sample size, selection bias could be reduced.

The small scale of our HLC to characterize the mosquito compositions only at crepuscular periods limits the uncertainty of conclusions to other situations. Also, the diversity of mosquitoes that can contribute to bites during nighttime was not characterized. We expected that nighttime biters such as *Culex* spp. and *Anopheles* spp. may contribute considerably to bites during this period.

Computational uncertainties are unavoidable in predicting the dynamics of an epidemic. The baseline model parameters in Table 1, together with the human–mosquito contact rates obtained through the survey, are only our best-guess estimates of the model parameters. Such uncertainties in the parameters could affect the reliability of the model predictions. It is important to emphasize that the quantitative values of the model outputs, such as R_0 , should *not* be taken at face value. They only give us insight into the potential outcomes of disease spreads. Fortunately, the qualitative aspects of the model, such as the relative importance of the different factors are usually robust and less sensitive to these assumptions.

The probability of disease emerging in a new geographical area encompasses two qualitative attributes: vulnerability and receptivity (Le Menach et al. 2011). Vulnerability indicates the influx of infected individuals into an area of interest, while receptivity reflects the local conditions that are conducive for disease transmission. In this study, the risk of DENV outbreak was investigated only at the level of receptivity. In Louisiana, a total of 45 imported cases were reported from 1980 to 2015 (Dengue Annual Report, Louisiana Office of Public Health, 2015). In general, despite the highly receptive condition, the probability of a DENV outbreak could be lower due to its low vulnerability.

In conclusion, we found that the use of a questionnaire-based survey is a feasible method to investigate human-mosquito contact. It can be used to compare mosquito bite exposure levels between contrasting settings. Most importantly, it may provide an avenue to investigate how changes in human characteristics such as behaviors, lifestyles, use of clothing and personal protection, and other innate variables affect mosquito bite exposure and the risk of infection in a way that is very difficult to do with HLC. This information is indispensable if we want to predict how the changing environment, such as urbanization, poverty, and climate change impacts human behaviors that may drive mosquitoborne disease transmission. In addition, the use of mathematical models to simulate disease transmission produces valuable information that helps us understand how changes in the transmission variables may impact disease transmission. This type of knowledge facilitates the planning of cost-effective disease prevention programs to target the most important transmission factor, which may lead to the largest reduction in transmission risk.

Supplementary Data

Supplementary data are available at Journal of Medical Entomology online.

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