MOSQUITO BITING AND MOVEMENT RATES AS AN EMERGENT COMMUNITY PROPERTY AND THE IMPLICATIONS FOR MALARIAL INTERVENTIONS

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ABSTRACT

Malaria, a mosquito-vectored disease, continues to be one of the most important scourges afflicting humankind. In this paper, we take a mosquito-centric approach by studying mosquito states (i.e., energy, neurological health, and toxin information state) to demonstrate how key parameters of malaria, biting and movement rates and mosquito survival, are all emergent properties of those states when considered in the context of the background community interactions. We do so as follows: First, we develop a dynamic state variable model of mosquito biting and movement decisions that maximize mosquito expected reproductive success (fitness), and then we embed those optimal policies in a Monte Carlo simulation wherein mosquitoes attempt to feed on human hosts at domiciles where insecticide-treated bednets (ITNs) and insecticidal residual wall sprays (IRSs) are used. We find that biting rates, at the domicile level, are not impacted by mosquito state but that emigration rates from domiciles are determined by an interaction between mosquito energy state, information state, and risk of predation. This means that malaria incidence, at the village level at least, may be best understood as a response of mosquitoes to their ecological community that includes nectar-bearing plants, predators, the spatial arrangement of homes, and the protection of humans in those homes.

Keywords: Mosquito, malaria, *Anopheles*, bednet, dynamic state variable, biting rate, Monte Carlo

INTRODUCTION

Malaria continues to be one of the most important diseases afflicting humankind. Indeed, nearly 1,000,000 childhood deaths were attributed to malaria in sub-Saharan African in the year 2000 (Rowe et al., 2006). As a result, many different malaria intervention strategies and tactics have been attempted. However, few of those tactics explicitly attempt to

exploit adult mosquito behavior and community interactions, even though *Plasmodium* transmission and subsequent malaria must be the result of mosquito (feeding) and movement (search) behaviors, and the surrounding sources of food and predators determine the life span of the mosquito.

In this paper, we show how biting and movement rates and associated behaviors are emergent properties of community interactions, and how to assess two major forms of ecological intervention for malaria control: Insecticidal residual wall sprays (IRSs) and insecticide-treated bednets (ITNs). The former was in the process of phase-out but has received increasing attention of late (e.g., Roberts et al., 2000; Kolaczinski et al., 2007), while the latter is considered to be a linchpin in the worldwide efforts to eradicate malaria.

It has been known since the classic work of Ross and MacDonald (MacDonald, 1957) that mosquito behavior is extremely important for understanding the population dynamics of the disease. For example, in the classic models, the basic reproductive rate of the disease R_0 is

$$R_0 = \frac{a^2}{r\mu} bc \frac{M_T}{H_T} \tag{1}$$

where *a* is the biting rate, r is the recovery rate of infected humans, μ is the death rate of mosquitoes, *b* is the fraction of bites by infectious mosquitoes on uninfected humans that lead to infections in humans, *c* is the comparable quantity for uninfected mosquitoes biting infected humans, and M_T and H_T are the sizes of the mosquito and human populations. In this elegant theory, key terms such as biting rate are constants; in what follows, we argue that they are in fact functions of mosquito response to internal states and the community setting. The classical theory is largely silent on movement rates, generally treating encounters between mosquitoes and hosts as a well-mixed system (but see Keeling and Gilligan's (2000) work on flea-vectored plague) and when movement and spatial heterogeneity is incorporated it is mostly done in a phenomenological manner (but see Roche et al., 2008). We will show how movement emerges from the community interactions of the mosquito.

Similarly, temporal and spatial patterns of rest periods and attack persistence will determine rates of exposure to wall and net-based adulticides, respectively. Currently, little is known regarding such behavior for *Anophelines* despite their importance as *Plasmodium* vectors (Anderson and Roitberg, 1999). However, little attention has been given to mosquito behavior or more specifically to flexibility in mosquito host seeking and host feeding behavior (but see Anderson and Roitberg, 1999; Takken, 2002). For example, a search through the Web of Science database from 1995–2007 using search words "phenotypic plasticity mosquito" and "behavior variability mosquito" yielded just 3 relevant papers. Admittedly, we know of other non-scored papers that do consider variable mosquito behavior (e.g., Foster and Takken, 2004) but they often view changes in behavior as parasite driven (e.g., Anderson et al., 1999; Schwartz and Koella, 2001) as opposed to mosquitoes acting in response to the ecological milieu. As such, it is difficult to know how mosquito behavior might be impacted by ecological interventions

and vice versa. To address the dearth of information regarding the behavior–intervention interface we develop a state-dependent (*sensu* Mangel and Clark, 1988; Houston and McNamara, 1999; Clark and Mangel, 2000) model of *Anopheles* host-seeking behavior. Our state-dependent approach is particularly appropriate for studying flexible behavior of *Anopheline* mosquitoes, which carry very few energy reserves (Walker, 2008) and have very few options in terms of energy transfer from soma to reserves and back again (e.g., Fernandes and Briegel, 2005; Ma and Roitberg, 2008). Thus, we expect that natural selection has honed energy-related behaviors in this genus. We will then use our model of energetically driven, host-seeking behaviors to investigate their impact on ecological intervention.

Communities are, of course, collections of populations, which themselves are collections of individuals. However, communities are also more than just the collection of the populations, because (sometimes unexpected) interactions emerge so that the whole is more than the sum of its parts. A major challenge of theory in community ecology is to understand what structures the emergence of properties that could not be expected from simply putting the populations together. There are many ways to do this; however, very little has been done to combine behavioral and population ecology as a means of informing community ecology (see Mangel and Wolf (2006) for another example), which is the novel approach that we take in this paper.

We consider that the community interactions have major effects on mosquito longevity (Fig. 1) and on search time for hosts (Fig. 2). Our goal is to first explain how biting
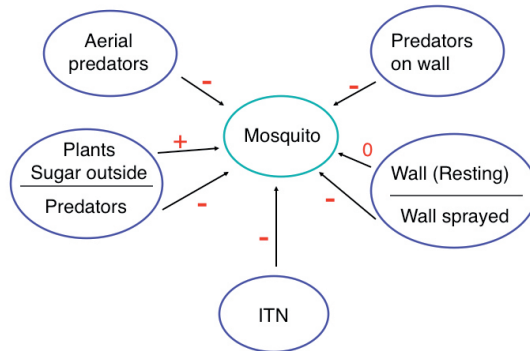

Fig. 1. Community interactions determining mosquito longevity. Beginning with plants outside the human domicile and moving clockwise: Plants provide sugar sources, which increase longevity (hence +) but may also harbor sit-and-wait or other predators (thus decreasing longevity, hence –); aerial predators—which mosquitoes encounter while flying—decrease longevity, as do predators on the wall of the domicile; when the mosquito rests on a wall that is not treated with insecticide, there is no effect on longevity (hence 0) but if the wall is treated, there is a negative effect on longevity; if the mosquito encounters a insecticide-treated net (ITN), there is a negative effect on longevity.
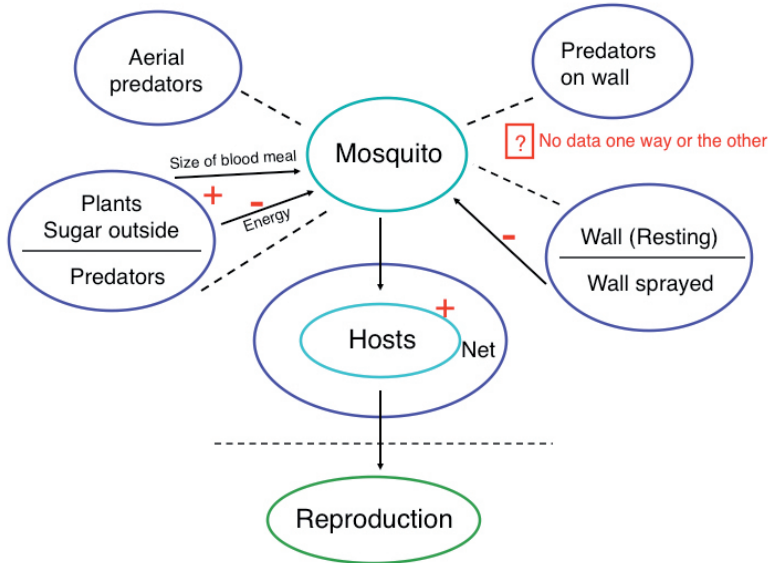
Fig. 2. Community interactions determining mosquito search times for blood meals. Following the same travel plan as in Fig. 1, predators on plants outside the domicile have no effect on mosquito search time for blood meals; sugar provides energy for searching (hence decreasing search time) but also fills up the crop which slows down search times; predators (either aerial or on the wall) have no direct effect on search times; there are no data for the effect of resting on a wall that is not treated with insecticide on search time, but clearly resting on a sprayed wall increases search times because of the need to repair damage induced by the toxin; and, of course, the presence of a bednet increases search times.

and movement rates and associated behaviors are emergent properties of the interaction of behavioral and community ecology. Then we will explore the efficacy of wall spraying and insecticide-treated nets on biting rates, mosquito survival, and movement of mosquitoes among domiciles.

MATERIALS AND METHODS

There are two parts to our model. First, we build a matrix of optimal decisions using a state-dependent life history model (Clark and Mangel, 2000) and then we use this matrix in Monte Carlo simulations in which individual females respond to internal (i.e., physiological) and external (i.e., community ecological) conditions according to the optimal decision matrix. As explained in detail below, by decision we mean responses to particular conditions but no cognitive processes are assumed. We choose *Anopheles gambiae* as our focal mosquito for several reasons: (i) it is the primary vector of human malaria in sub-Saharan Africa, (ii) it feeds almost exclusively on humans in homes (Qiu et al.,

2006), so that we can ignore other non-human mammals that might serve as alternate hosts and (iii) our current work in Kenya (Walker, 2008) provides data on energy reserve profiles for wild populations of *A. gambiae* in east Africa.

STATE DYNAMICS

We characterize an *A. gambiae* female by three states: energy reserves, neurological health state, and information state regarding domicile-based risk of toxins. These three states are important in the blood-host seeking process because they determine ability and efficacy of the host-seeking process, as well as the risk from remaining in a domicile. Thus, we consider

- Energy reserves $E(t)$ at time t: We assume that these reserves are used form somatic function and that their values vary from E_{min} to E_{max}. Should $E(t)$ fall below E_{min}, we assume that the animal starves. The dynamics of energy for all activities other than sugar feeding are

$$E(t + \tau_a) = E(t) - \tau_a \pi_a \qquad (2)$$

where τ_a is the time required to complete an activity a and π_a is the per unit time cost for performing activity a. The dynamics for energy acquisition activities (sugar, or blood feeding when the blood is not used to build eggs) are:

$$E(t + \tau_a) = E(t) + \kappa_s - \tau_a \pi_a \qquad (3)$$

where κ_s is the energy gained from source s from a single acquisition bout.

- Neurological damage $D(t)$ at time t: When individual *A. gambiae* females encounter IRSs on walls, they suffer concomitant damage to their nervous systems as typically occurs from exposure to chlorinated hydrocarbons, CHCs (Bloomquist, 1996). An individual with a completely healthy nervous system is characterized by $D(t) = D_{min}$; exposure to CHCs will cause an increase in $D(t)$. Damage to the nervous system reduces the probability that the damaged individual will locate a blood host accordingly. If $\lambda_b(d)$ represents the maximum probability that a mosquito with damage $D(t) = d$ locates a host, we assume

$$\lambda(d) = \lambda_b e^{-\theta d} \qquad (4)$$

where θ is a parameter. In addition, if damage exceeds a level D_{max} the individual dies due to loss of neurological control of vital functions. We assume that the mosquito recovers from damage at rate ρ via metabolic detoxification (e.g., Etang et al., 2007) per period but accrues damage via metabolic processes (e.g., oxidative stress generated by reactive oxygen species) ς, so that damage at time t and some time later $t+\tau$ are related by

$$D(t + \tau) = D(t) e^{(\varsigma - \rho)\tau} \qquad (5)$$

- A female mosquito cannot know whether a domicile harbors toxins unless she has encountered toxin odor or the compound itself. Exactly how mosquitoes assess environments on the basis of experience is largely unknown (Alonzo and Schuck-Paim, 2006); here we characterize informational state $I(t)$ at time t, as the probability that a hut contains pyrethroid insecticide given that none has been encountered thus far. When an individual enters a hut, its estimate of the probability that a pyrethroid toxin is present is based on the regional probability of pyrethroid presence, i_r. Over time however, the estimate for this domicile is updated whether a pyrethroid odor is or is not encountered, which occurs with probability c_p, given that the toxin is present (clearly there is no chance of encounter if the toxin is absent). When toxin is encountered, the estimate for that hut rises to 1.0 (certainty) but if toxin is not encountered, the updated information state is

$$I(t+1) = \left(\frac{I(t) \cdot (1 - c_p)}{I(t) \cdot (1 - c_p) + (1 - I(t))} \right) \tag{6}$$

We now describe a typical scenario. A female *A. gambiae* finds herself in a human domicile at time t on night n with $\{E(t) = e, D(t) = d, I(t) = i\}$. There are four possible behaviors.

1) *Seek a blood meal*. If she chooses to seek a blood host, she will successfully locate one with probability $\lambda_b(d)$. A blood meal will ensue and the mosquito acquires fitness f_b, discounted by the risk of death from blood seeking, blood feeding and ovipositing (see Table 1 for parameter values) and return 3 days later to begin again. We treat the size of the blood meal as a constant even though it too may be optimized (see Anderson and Roitberg (1999) for body size-energy state based theory of blood meal size). In addition, if the female's energy state is below the critical level for maturing eggs, then energy goes to the mosquito's energy reserves as described by eq 3. If a blood host is not located (with probability $1 - \lambda_b(d)$) several mutually exclusive events can occur. First, neither host nor pyrethroid odor may be encountered in which case energy changes according to eq 2, neurological state changes according to eq 3 and information state changes according to eq 6. Second, a host may not be encountered but a pyrethroid is encountered in which case $I(t+1) = 1$ (i.e., the new posterior estimate is certainty that a pyrethroid is present). Third, a pyrethroid may be encountered and the mosquito either dies directly with probability $e^{-\psi_p}$ or suffers from but then recovers from knockdown should it not die while knocked down for a period of τ_g. Recovered mosquitoes begin post-recovery with energy states $\{E(t+\tau_g) = E(t) - \pi_g, D(t+\tau_g) = D(t), I(t+\tau_g) = 1\}$.

2) *Move to the wall and rest until the next day*. The mosquito may move to the domicile wall and rest until next day. If the wall is treated with CHCs, which happens with probability κ, she will suffer damage according to

$$D(t + \tau_w) = D(t)e^{(\varsigma - \rho + \psi)\tau_w} \tag{7}$$

where τ_w and ψ are the rate of CHC intake per unit time while the mosquito rests on the wall; with probability i she encounters toxin. We assume that in the absence of senescence (Styer et al., 2007) that an individual fully recovers from CHC intoxication within 2 days (thus, the decision to rest overnight) and in the absence of recovery that continuous exposure to CHCs could kill an individual within 1 day. In addition to potential risks from CHCs while resting, we also assume that individuals are exposed to predators while resting so that the probability of mortality per unit time while resting is $e^{-\mu_w}$. In addition, energy reserves change according to

$$E(t+\tau_w) = \max[E(t)-\tau_w\pi_w,0] \qquad (8)$$

3) *Sugar feed outside the house*. The mosquito may choose to sugar feed outside the domicile, then return, followed by a move to the domicile wall and rest until next night. As such, we assume that the female will increase its energy state to some proportion v of maximum (i.e., there is an energetic cost of host plant seeking). Again, we assume there is a risk from predation per unit time is $e^{-\mu_s}$. Following the sugar feed, the mosquito returns to the domicile and rests on a wall and the dynamics proceed as above.

4) *Leave the current location entirely and seek another hut*. In nature, *A. gambiae* is as likely to enter pyrethroid-containing as pyrethroid-absent huts but is much more likely to leave the former (see Takken, 2002). The mechanism underlying this behavior is often referred to as excito-repellent (Mathenge et al., 2001; Kongmee et al., 2004)) though a recent paper by Cooperband and Allan (2009) suggests that pyrethroids are best described as locomotory stimulants because the exact mechanism underlying this response is not fully understood. In this case, the energetic cost of inter-hut flight and resetting of the information state must be considered. If the time it takes to find another hut is τ_h and the per unit time cost of inter-domicile flight is π_h then

$$E(t+\tau_h) = \max[E(t)-\tau_h\pi_h,0] \qquad (9)$$

and

$$I(t+\tau_h) = i_r \qquad (10)$$

The future fitness associated with inter-domicile flight must be discounted by the risk of predation $e^{-\mu_h\tau_h}$ while traveling between huts. There are few data on predation on adult female mosquitoes (see Mogi, 2007) or on mosquito response to such risk, even though we know that mosquitoes respond to larval predators (e.g., Eitam and Blustein, 2004). Thus, we assume that mosquitoes cannot perceive differences in predator densities among sites and therefore μ_h is a global estimate of predation risk. Further, we assume that all huts provide the same access to bloodmeals. Thus, it will never be optimal to leave a hut unless a pyrethroid odor has been encountered or a knockdown has occurred; this is because all huts are equally valuable. On the other hand, they can vary in terms of perceived danger from toxins.

Finally, we assume that mosquitoes have not (yet) evolved with specific reference to bednets nor synthetic pyrethroids, i.e., the response to the latter is simply to natural toxins that they might encounter in the wild. Therefore, our behavioral model does not include a bednet mortality term. We will, however, consider bednets in the forward iteration.

DYNAMIC PROGRAMMING EQUATIONS

We consider a single gonotrophic cycle that consists of N nights with n indexing a particular night. Within a night, we consider T periods, with t indexing a particular period within a particular night. Thus, the state variables E, D, and I must now be indexed by both n and t We define

$$F(e,d,i,t,n) = \text{Maximum accumulated fitness from blood meals,}$$
$$\text{given that } E(t,n) = e, D(t,n) = d, I(t,n) = i \qquad (11)$$

At the last period at the end of this gonotrophic cycle we, no more fitness can be accumulated so that

$$F(e,d,i,T,N) = 0 \qquad (12)$$

For previous times, we compute the fitness values of seeking a blood meal, resting on the wall, sugar feeding or moving to a new hut, which we denote by $V_b(e,d,i,t,n)$, $V_r(e,d,i,t,n)$, $V_f(e,d,i,t,n)$ and $V_h(e,d,i,t,n)$ respectively. They are given by

$$V_b(e,d,i,t,n) = \lambda \left(d \left[f_b + e^{-\mu_b-\mu_f-\mu_o} F(e_1,d_1,i,t+1,n+3) \right] \right)$$
$$+ \left(1-\lambda(d)\right) \begin{bmatrix} \lambda_p e^{-\mu_g-\tau_g} F(e_2,d_2,1,t+\tau_g,n) \\ + \left(1-\lambda_p\right) e^{-\mu_b} F(e_1,d_1,i,t+1,n) \end{bmatrix} \qquad (13)$$

$$V_r(e,d,i,t,n) = e^{-\mu_w} \left[\left\{ \kappa F(e_3,d_3,i,1,n+1) \right\} + \left\{ (1-\kappa) F(e_3,d_4,i,1,n+1) \right\} \right] \qquad (14)$$

$$V_f(e,d,i,t,n) = e^{-\mu_w-\mu_s} \left[\left\{ \kappa F(e_4,d_3,i,1,n+1) \right\} + \left\{ (1-\kappa) F(e_4,d_4,i,1,n+1) \right\} \right] \qquad (15)$$

$$V_h(e,d,i,t,n) = e^{-\mu_h \tau_h} F(e_5,d_5,i_r,t+\tau_h,n) \qquad (16)$$

in these eqs e_j and d_j, $j = 1,...,5$ are the energy and damage states at the subsequent time, given $E(t,n) = e$ and $D(t,n) = d$ and the associated behavior. These new states are determined from eqs 2–7. Once the computations in eqs 13–16 are completed we compute

$$F(e,d,i,t,n) = \max\{V_b(e,d,i,t,n), V_r(e,d,i,t,n), V_f(e,d,i,t,n), V_h(e,d,i,t,n)\} \qquad (17)$$
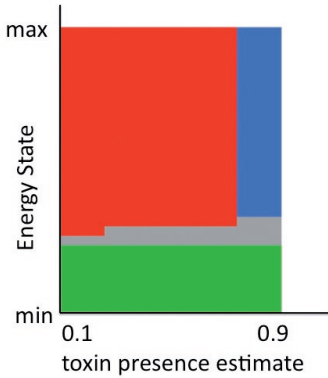
Fig. 3. Decision space for an individual female mosquito as a function of its current estimate of probability that a pyrethroid toxin is present and its current energy state. The colored regions refer to: green—seek nectar meal outside the domicile, grey—rest, red—seek a blood meal, and blue—emigrate from the current domicile and seek another one.

DECISION MATRIX

We generated an optimal decision matrix for all combinations of energy, neurological health and information state as described above. Figure 3 shows a slice through the 3-dimensional decision matrix at midnight when neurological health state is 0.5 D_{max}. There are several interesting features of this plot. First, a large portion of this decision space goes to bloodseeking decisions, so long as energy is sufficient. Recall, that many searches will expend energy that does not lead to host finding. As such, it may be optimal to seek sugar when energy state is low and search efficacy is low due to neurological state. Second, emigration decisions are also energy and toxin-risk dependent. It is only when energy is sufficient to support search for a domicile and the danger from remaining exceeds that from emigrating that a domicile-leaving decision is optimal. At intermediate energy states, rest is the optimal activity wherein the individual can recover from neurological damage and increase its search efficacy before host-seeking. Notice that the optimal-risk decision space increases with toxin risk. Our interpretation is that danger while foraging increases with toxin risk but at low energy state it is too costly to exit the domicile, thus the best thing to do is rest and recover thus increasing efficiency and reducing overall risk while foraging in the future. Finally, feeding decisions seem to be capped at a constant low-energy state and independent of toxin risk. Of course, the size of the state space should depend upon the predation risk from sugar feeding, which we set as a constant as discussed above. When this is the case, the interaction between energy state and toxin estimate occurs with the resting decision, due to the recovery process, and not the sugar seeking decision.

MONTE CARLO MARKOV CHAIN FORWARD ITERATION AND BEHAVIORAL PREDICTION

With the optimal decision matrix in place, we can now examine the impact of community-level parameters on mosquito performance that we index as bloodfeeding success and emigration from the current domicile. We "experimentally" modified two key parameters shown in Fig. 1: non-blood energy sources (i.e., nectar) and predators. To do this, we use a Monte Carlo simulation in which 200 individual *A. gambiae* females, not infected with *Plasmodium* (but see Anderson et al., 1999) search independently

for blood hosts. The simulations proceeded as follows: A female arrives at a domicile with energy state drawn from a beta density (Mangel, 2006) with parameters α and β so that the mean of the energy state is $\frac{\alpha}{\alpha+\beta}$. We explored three choices of parameters: $\alpha = \beta = 1.5$ for a symmetrical distribution; $\alpha = 1.5$, $\beta = 3.0$ for a right-skewed distribution; and $\alpha = 3.0$, $\beta = 1.5$ for a left-skewed distribution. We set information state at arrival at the regional probability of pyethroid presence at i_r (0.2) and initial neurological damage at D_{min} (1.0).

At the onset of each 20-minute period, a mosquito follows the optimal behavioral decision from the decision matrix computed from eq 17 above. She continues to move through time periods until one of the following events occurs: (1) she dies while host or sugar seeking, host feeding or resting; (2) she obtains a blood meal, (3) she abandons the current hut or (4) she runs out of time, i.e., she is still blood host seeking after >7 nights. Each of the mortality values (Table 1) was compared against a value randomly drawn from a uniform distribution (0,1).

Table 1
Parameters used in the Model, their definition and values

Parameter	Definition	Value
E	Energy state	(150,1)
D	Neurological state	(20,1)
I	Information state	(1,0)
t	Time unit in minutes	20
τ	Number of time units to complete an activity	(71,1)
λ	Baseline probability that a mosquito will locate a blood host during a single period of search	0.24
ρ	Rate at which mosquito recovers from neurological damage	0.021
ψ	Rate at which mosquito accrues neurological damage from contact with CHC toxins	0.03
ς	Rate at which mosquitoes senesces	0.001
i_r	Regional probability that pyrethroid toxin is present	0.2
f_b	Fitness from eggs matured following a bloodmeal	80
μ_b	Death rate while seeking a blood host	0.105
μ_f	Death rate while feeding on a blood host	0.2
μ_O	Death rate while maturing eggs and ovipositing	0.125
μ_p	Probability of dying following contact with pyrethroid	0.8
μ_g	Death rate while knocked down following contact with pyrethroid	0.34
μ_s	Death rate while seeking sugar	0.2
μ_p	Death rate while flying to a new domicile	0.06
τ_h	Number of time units to locate new domicile	2
π	Energetic cost of engaging in different activities per unit time	1

To test for the effects of floral energy and predators, we performed the following manipulations: For energy, we drew from the three aforementioned distributions of energy states upon arrival at the domicile. Walker (2008) showed that most females are highly bereft of energy upon emergence from nursery pools in west Kenya. Thus, nectar availability can dramatically impact energy state upon arrival at domiciles. As such, our manipulations mimic low, moderate, and high levels of flowering plants in the mosquito's community.

To test for the effect of predators, we manipulated the term that describes survival while sugar seeking and feeding to reflect different natural levels of predators that operate within the plant community. Here, we multiplied μ_s by either 0.2 (a low predation community) or 5.0 (a high predation community).

RESULTS

In our Monte Carlo simulations we evaluated bloodfeeding rates as a function of floral energy and predator density. There is no obvious or consistent effect from either (range of successful mosquitoes from the cohort of 200 arrivers across all 9 combinations of energy and predator manipulations (16,20)). On the other hand, we can see that both of these parameters do impact emigration rates (Fig. 4). Our interpretation is that since mosquito behavior has evolved to maximize fitness via offspring production, that once in a hut and not hampered by energy state, such females will maximize most opportunities for getting to and feeding on bloodhosts; the large decision space devoted to host search means that biting rates will be similar across a range of individuals that do not
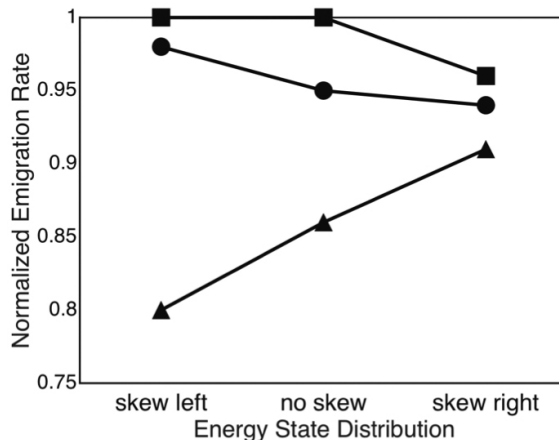

Fig. 4. Normalized emigration rates for mosquitoes as a function of 3 levels of predator risk (0.2 ■, 1●, 5▲) outside the domicile and only interacting with mosquitoes when they seek nectar. The three energy states in the x axis refer to different distributions of energy states for populations when they arrive at the focal domicile.

encounter pyrethroids, as we observed. Abandoning huts however does require energy and sugar feeding can incur high predation and thus reduce emigration rates. Finally, if we remove the bednets from our simulations, bloodfeeding rates increase dramatically (8.5×).

DISCUSSION

Our results are consistent with evidence that untreated bednets provide less protection than treated ones (Burkot et al., 1990). Our models predict that *A. gambiae* do not enter houses in lower numbers in ITN-provided rooms compared with houses with untreated nets (Mathenge et al., 2001), but the proportion of unfed and exiting mosquitoes will be significantly greater in treated houses than untreated ones. Thus, ITN users are protected because both fewer mosquitoes land on the net and many will leave the house.

We have developed a framework for bringing behavioral, community, and evolutionary considerations into mosquito control. Such control is almost guaranteed to fail without the aforementioned considerations (Feachem, 2009). The models that we use are complicated, but no more complicated than necessary, and the parameters in the models can be estimated and computations are relatively easy. The mosquito decision space can be understood and, most broadly, we have shown that bednets increase emigration and decrease bloodmeals.

We emphasize that our framework is only a first attempt at a theory of biting rate that comprises both mosquito behavior and community interactions. We have made a number of common sense assumptions that require validation. For example, we assume that females cannot evaluate local risk from predation, so we entered it as a constant. There is a relatively large literature showing that female adults can discriminate among larval nursery sites that vary in presence of predators or competitors, so why shouldn't adults recognize their own predators and, if so, does that matter? The terrestrial guild that attacks adults is likely far broader than the aquatic guild that attacks larvae, making it difficult to recognize specific enemies. In addition, terrestrial sites comprise much greater volume than nursery sites, especially for Anopheline species that frequently exploit breeding sites as small as water-filled hoofprints. In addition, turbulence is generally far greater in the air-based terrestrial system that at aquatic nursery sites. Taken together, we conclude that enemys' odors would spread rapidly and be found at much reduced concentrations in air than at nursery sites (Koehl, 2006).

Suppose, however, that mosquitoes have evolved the ability to estimate local risk of predation; how might that affect our interpretation of the importance of community interactions? First, as noted in the Results section, within-hut decisions are relatively insensitive to danger so we would not expect any effects there. On the other hand, if we were to seed a habitat with predators and their presence was recognized, there would be less sugar feeding but at a higher death rate for those doing so and, as a consequence, fewer emigration attempts. By contrast, reducing the recognized risk of sugar feeding should increase both attempts and success, thus increasing emigration rates again in non-linear ways that depend upon nectar availability, the other important community

element (Fig. 4). These non-obvious patterns emerge as a consequence of embedding our individual behavior model into a community setting.

In an analogous fashion, we have set nectar-finding rates at a global constant. Of course, flower densities could vary dramatically among sites and this could greatly impact sugar finding, blood feeding, and inter-site movement rates (see Ma and Roitberg, 2008). There are two ways in which such plant community inter-site variability could impact our results and our current interpretation. First, with regard to the decision matrix, including a local estimate of flower density would alter the decision spaces, but to a limited degree. Feeding decisions are largely energy-state-based, so not much change there, but we would expect that resting decisions would be most affected. For this effect to hold, mosquitoes would need to make estimates of current nectar availability from inside the domicile; this might be very difficult to achieve, though it is possible that estimates could be made and retained from previous forays (see Jhumur et al., 2006; Tomberlin et al., 2006). Second, with regard to our simulations, we assumed a fixed time to locate nectar plants whereas this parameter could be further developed to include a mean and variance based upon local conditions. We expect that the greatest impact here would be via predation risk because mosquitoes could mitigate energy losses while foraging via nectar intake modulation. This provides managers with opportunities for managing malaria via community manipulation via plants and predators. Area-wide reduction in mosquito-favored plants (Manda et al., 2007) skews populations to the left and would reduce inter-domicile movement and/or increase resting and encounters with predators via increased sugar foraging.

Our results have some similarities with Ma and Roitberg (2008), who also used a dynamic-state variable model to study blood and sugar feeding decisions in female mosquitoes, but in the absence of ITNs and also with much greater detail devoted to physiological processing of somatic and gametic resources, as well as explicit relationship between bloodmeal size and mortality risk (see Roitberg et al., 2003). Their results also show that blood-feeding decisions are generally invariable to sugar availability. This is not surprising because the only way to garner fitness is via bloodfeeding. However, as blood host availability declines (e.g., via nets) mosquitoes spend more time outside sugar feeding and here, as discussed above, the nectar availability–predator complex likely plays a role causing overall (i.e., village level via movement among huts) blood-feeding rates to emerge in a non-obvious manner.

The use of ITNs must also be evaluated in the context of evolving resistance to pyrethroids (Chandre et al., 1999; Guillet et al., 2001) and may threaten the basis for the presently adopted malaria control strategy (Takken, 2002). Our methods provide a framework for such evaluation. The strength of our approach is that we consider mosquito biting and movement by linking behavioral, physiological, and community ecology. The recent call by the Gates Foundation to eradicate malaria using current tools and new high tech approaches acknowledges that serious improvements to infrastructure are needed. However, nobody disputes that ITNs work in reducing the biting rate. Even untreated nets protect against mosquitoes, at least until they tear. And the treated versions work even when they are torn, because they not only block contact but also repel or kill the mosquitoes that

transmit the malaria parasite. Little is known about the factors affecting attack persistence by *Anopheline* females however experimental analysis by Roitberg et al. (2010) showed that it is complex function of size and energy state as suggested here.

Our work also shares some elements with Vonesh and Kraus (2009) who reported that habitat selection and thus community structure were impacted by the presence of pesticides. Vonesh and Kraus (2009) make the point that habitat selection is not random yet this is often a default assumption in metapopulation models. Here we showed that leaving rates may differ among domiciles, but in a non-obvious manner that is driven by state dependence and the presence or absence of pesticides.

Our model has focused on the single domicile and we found (not surprising in retrospect) that biting rates do not vary too much as a function of predators and nectar but that emigration rates do in a non-linear manner. If between-hut movements factor into biting rates within and among huts, then we have an important missing link in the connection between (state dependent) behavior and malaria in an ecological context. This suggests that the next step in our work is the development of a metapopulation model (in which each hut represents a "local population") for the mosquito population dynamics. At this level, the emergent properties of biting and movement rates as a result of community interactions will become apparent.

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