A Simple Model to Predict the Potential Abundance of *Aedes aegypti* Mosquitoes One Month in Advance

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Abstract. The mosquito *Aedes (Stegomyia) aegypti* (L.) is the primary vector of dengue, chikungunya, and Zika viruses in the United States. Surveillance for adult *Ae. aegypti* is limited, hindering understanding of the mosquito's seasonal patterns and predictions of areas at elevated risk for autochthonous virus transmission. We developed a simple, intuitive empirical model that uses readily available temperature and humidity variables to predict environmental suitability for low, medium, or high potential abundance of adult *Ae. aegypti* in a given city 1 month in advance. Potential abundance was correctly predicted in 73% of months in arid Phoenix, AZ (over a 10-year period), and 63% of months in humid Miami, FL (over a 2-year period). The monthly model predictions can be updated daily, weekly, or monthly and thus may be applied to forecast suitable conditions for *Ae. aegypti* to inform vector-control activities and guide household-level actions to reduce mosquito habitat and human exposure.

Aedes (Stegomyia) aegypti (L.) is the primary vector of dengue, chikungunya, and Zika viruses in the United States.¹ Surveillance for adult *Ae. aegypti* is limited: its presence has only been recorded in 291 counties of 1,443–2,209 counties deemed environmentally suitable.^{2,3} Few records document the mosquito's temporal fluctuations, hindering understanding of its seasonal patterns and periods of elevated risk for autochthonous virus transmission.⁴

The seasonal presence and abundance of *Ae. aegypti* in the United States is limited by cool and/or dry meteorological conditions.⁵ With many of the weather-influenced bionomics of *Ae. aegypti* known,⁶ surveillance gaps could potentially be addressed using weather-driven dynamic mosquito simulation models^{7,8} to estimate the seasonality of *Ae. aegypti* abundance across geographic locations.⁴ However, implementing dynamic models is challenging because of computational expense, required expertise, and uncertain model parameters.⁹ Here, we describe a simple empirical model that uses readily available temperature and humidity variables to predict environmental suitability for low, medium, or high abundance of adult *Ae. aegypti* in a given city 1 month in advance. The model may be used to forecast suitable conditions for *Ae. aegypti* to inform public health and vector-control activities and guide resident actions to reduce vector habitat and human exposure.

Two available temporal *Ae. aegypti* abundance records were used for model fitting and evaluation. Coauthor KAS et al. collected a 10-year (January 2006–December 2015) surveillance record of monthly aggregated weekly adult abundance from ~750 Centers for Disease Control and Prevention light traps across Maricopa County (Phoenix, AZ). Coauthor MHR et al. collected a 2-year (June 2006–June 2008) record of monthly egg abundance from 30 ovitraps across a 650 km² area of Palm Beach County (near Miami, FL).¹⁰ The Phoenix record is longer and draws on more traps and thus was used

for model fitting. The Miami record is shorter, draws on fewer traps, and measures egg rather than adult abundance and thus was used for model evaluation. Both records consist of aggregated counts across all traps by city-month. The trap records are not directly comparable across locations because of uncertainty arising from species specificity, malfunctions, and catch loss.¹¹ We thus computed the relative abundance across seasons for each city by setting the maximum monthly aggregate trap count in each record to 1,000 and proportionally rescaling other months. Next, base 10 logs of the monthly counts ("*log(aegypti)*") were computed because the log-transformed values have linear relationships with meteorological variables. The logs of values between 1 and 1,000 conveniently vary between 0 and 3, allowing categorization of results into "low" (0–1), "medium" (1–2), and "high" (2–3) potential abundance categories.

Daily meteorological fields were obtained from the North American Land Data Assimilation System (NLDAS) V2 forcing dataset.¹² Time series of rainfall, relative humidity, vapor pressure, minimum temperature, maximum temperature, and mean temperature were bilinearly interpolated for the coordinates of Phoenix and Miami for 2006–2015. Previous studies have associated these variables with *Ae. aegypti* suitability.^{2,7} Next, for each month for which *log(aegypti)* was to be predicted, the 30-day mean of each meteorological variable was computed for the prior month, allowing for a 3-day lag. For example, to predict *log(aegypti)* for a month beginning on July 1, one would compute the 30-day average meteorological fields from May 29 to June 27. This "lag" approach recognizes that there is often a several-day delay before meteorological fields become available to users. Sensitivity tests indicate that the model fit is insensitive to a 3-day versus 0-day lag, so users can also simply use monthly average meteorological variables from, for example, June to predict July. Monthly average periods approximate the duration of the combined immature life stages and adult gonotrophic cycle.⁷

Gaussian, Poisson, and negative binomial models of *log(aegypti)* were fit with combinations of the meteorological variables with an iterative process accounting for collinearity, removal of model components, attempts to use quadratic and interaction terms, and monthly random effects (see

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TABLE 1
Fit statistics for model shown in eq. (1)

Regression statistics					
<i>R</i> Square (marginal)	0.75				
<i>R</i> Square (conditional)	0.78				
Standard Error	0.38				
Observations	120				
	Coefficients	Standard error	<i>P</i> -value	Lower 95%	Upper 95%
Intercept	−0.634	0.135	0.000	−0.910	−0.358
<i>e</i>	0.065	0.021	0.003	0.006	0.110
<i>T</i> _{min}	0.064	0.010	0.000	0.057	0.084

Supplemental Text 1). Because of its combination of simplicity and accuracy, we selected a Gaussian mixed effects model for $\log(aegypti)$ in month n that included vapor pressure (e ; hPa) and minimum temperature ($T_{\min}$; °C) from month $n - 1$ as predictors:

$$\log(aegypti)_n = -0.634 + 0.065 \times e_{n-1} + 0.064 \times T_{\min n-1} + \text{ranef}_n, \quad [1]$$

where the values of random effect, ranef_n , vary by month (−0.076, −0.012, −0.022, 0.013, 0.155, 0.194, 0.078, −0.132, −0.078, −0.072, 0.040, and −0.088 for January through

December). Predicted $\log(aegypti)$ is termed “potential abundance” because it essentially estimates environmental suitability for levels of *Ae. aegypti* abundance, rather than explicitly predicting abundance. The standard error of regression is 0.38 and the model explains 78% of the variation in $\log(aegypti)$ in Phoenix (Table 1). Observed and predicted year-to-year monthly and 10-year average monthly variations are shown in Figure 1A and B. Over the entire 10-year period ($n = 120$), the predicted potential abundance categories (“high,” “medium,” and “low”) match those observed in 72.5% of months, are lower in 16.7% of months, and are higher in 10.8% of months. Under-predictions are most common in May (40% of months), June

PHOENIX

MIAMI

FIGURE 1. Phoenix (left) and Miami (right) observed vs. predicted: (A, C) $\log(aegypti)$ by year and month; (B, D) multiyear average $\log(aegypti)$ by month. Labels adjacent to the lines indicate for each month the percentage of years in which the potential abundance category was correctly predicted; the potential abundance categories are indicated by the background colors (“low” = blue, “medium” = green, and “high” = red). This figure appears in color at www.ajtmh.org.

(30%), August (30%), and November (30%); over-predictions are common in August (30%) and September (30%).

The model predictions for Miami are shown in Figure 1C and D. Over the 2-year period ($n = 25$), the predicted categories match those observed in 62.5% of months, are lower in 0.0% of months, and are higher in 37.5% of months. The over-prediction occurs in the non-summer months when observed *Ae. aegypti* abundance is lower and is related to the humidity term in the model. Because the model was developed for Phoenix—where humidity is comparatively lower than Miami—the slope for e may be larger than it would be if adequate *Ae. aegypti* trap counts from other climatic regions were available for model fitting. This shortcoming should be considered when applying the model to humid areas. However, the model predictions for Miami were still more accurate than those of the corresponding null model, suggesting there is some predictive skill outside arid regions.

The model was next used to explore the seasonality of *Ae. aegypti* across the contiguous United States (Figure 2).

The 10-year average NLDAS meteorological fields were used as model inputs. Because winter conditions limit the northernmost range of *Ae. aegypti*¹³—which the model does not explicitly account for—results were masked with an observation-constrained environmental suitability map for *Ae. aegypti* presence.² The resulting maps indicate areas of high potential abundance in the Southeast from June to November. In south Florida and southernmost Texas, where local transmission of *Aedes*-borne viruses has occurred recently,^{1,4} potential abundance is at least moderate year-round. In California where *Ae. aegypti* has spread since detection in 2013,¹⁴ potential abundance is moderate across broad areas from July to October. Promisingly, despite having higher suitability in the Southeast, the simple model produces similar seasonal patterns of potential abundance compared with independent estimates from complex dynamic mosquito simulation models⁴ (compare Supplemental Figure 1 with Figure 2).

Several limitations are noted. The model was fit using abundance records from traps in Phoenix not specifically

FIGURE 2. 2006–2015 average monthly $\log(aegypti)$ in the United States, predicted using the average meteorological fields from the prior month per eq. (1). For example, average August $\log(aegypti)$ is based on average meteorological conditions in July. The $\log(aegypti)$ values are color-coded into their respective potential abundance categories including “low” (blue), “medium” (green), and “high” (red). This figure appears in color at www.ajtmh.org.

designed for *Ae. aegypti*. Phoenix is arid and differs from humid environments where *Ae. aegypti* is common,¹³ which may lead to over-prediction of potential abundance during non-summer months in warm, humid areas such as Miami. Conversely, the seasonal representativeness of the Miami validation data may be affected by the use of ovitraps rather than adult traps, the short record, and being in an area of active mosquito control.¹⁰ The “low,” “medium,” and “high” potential abundance categories are relative and do not indicate specific *Ae. aegypti* thresholds having biological or epidemiological relevance. In addition, they may not fully represent differences across locations. Although rainfall was not a significant predictor, it can be an important water source for immature *Ae. aegypti*.⁸ It is probable that vapor pressure is an adequate proxy of rainfall in the model. Temperatures in Phoenix regularly exceed 40°C in summer and are not typical of many environments where *Ae. aegypti* is present.¹³ Using minimum temperature in the model partially addresses this difference as enhanced nighttime cooling in arid cities such as Phoenix can generate average minimum temperatures comparable with humid cities such as Miami. Using 1-month meteorological averages as predictors may limit detection of fluctuations in *Ae. aegypti* populations related to episodic events such as hurricanes or heatwaves. The model does not account for interspecies competition,¹⁰ adaptation,¹⁵ winter egg survival,¹⁶ or diel temperature fluctuations.¹⁷ Finally, the model neglects non-climatic factors important for supporting *Ae. aegypti* such as vector control, the presence of humans and availability of container habitats.¹⁸

Despite its simplicity and limitations, the model predicts patterns of seasonal *Ae. aegypti* potential abundance across the United States that are similar to dynamic model simulations.⁴ Regions where predicted *Ae. aegypti* potential abundance is moderate or high nearly year-round coincide with areas of recent arbovirus transmission.^{1,4} The model was designed for rapid, low-cost implementation, and the monthly predictions can be updated daily, weekly, or monthly using readily available meteorological data (see Supplemental Text 2 for details). It may be most beneficial for forecasting locally suitable conditions for *Ae. aegypti* a month in advance to inform timing of surveillance in areas without a current program, trigger mobilization of vector-control activities, and initiate public educational campaigns to prepare households for the season.

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