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A MODEL OF *CULEX QUINQUEFASCIATUS* ABUNDANCE CONSTRUCTED USING ROUTINE SURVEILLANCE AND TREATMENT DATA IN TARRANT COUNTY, TEXAS

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ABSTRACT. Mosquito surveillance and pesticide treatment data can be combined in statistical models to provide insight into drivers of mosquito population dynamics. In cooperation with the county-based public health authority, multiple municipalities in Tarrant County, Texas, supplied surveillance and pesticide treatment data available from the 2014 mosquito season for analysis. With these data, general linear mixed modeling was used to model population dynamics of *Culex quinquefasciatus,* the primary vector for West Nile virus. Temporally lagged pesticide treatment information, weather data, and habitat variables were used as predictors of log + 1 transformed mosquito count data, and Akaike information criteria corrected for small sample sizes (AICc)-based model selection and multimodel averaging was used to produce a final model of mosquito abundance. The model revealed that mosquito counts were driven mainly by seasonally fluctuating temperature, precipitation, human population density, and treatment. In particular, interactions between temperature and treatment, and precipitation and human population density significantly contributed to the interpretation of the effects of the nonweather variables.

KEY WORDS *Culex quinquefasciatus*, model, mosquito control, surveillance

INTRODUCTION

In the United States, considerable effort is expended to control mosquito populations and their associated disease risk, mostly by an array of publicly funded mosquito control organizations (e.g., county and city health departments, mosquito abatement districts, and vector control divisions). These operations vary greatly, both regionally and operationally, but there are a few commonalities. First, the reduction of mosquito populations is implemented by targeting eggs, larvae, pupae, and adults through water management and pesticide applications (Connelly and Carlson 2009). Second, mosquito control programs survey mosquito populations using adult traps and larval sampling in order to decide where and when to apply mosquito control treatments (Connelly and Carlson 2009). These 2 aspects are important because they ultimately generate data that inform management decisions. However, these data also provide opportunities to more explicitly account for factors driving mosquito population dynamics via the use of quantitative modeling techniques and serve as the basis for the development of model-based management tools.

Statistical modeling techniques are particularly well suited to rapidly use information generated from mosquito control programs, since mosquito counts collected at traps can be modeled against associated factors such as weather and habitat information that is increasingly publicly available. Indeed, efforts in this regard have included landscape cover-based models (Diuk-Wasser et al. 2006, Schurich et al. 2014), temporally autoregressive models (Brown et al. 2011), and complex generalized linear models that account for temporal and spatial correlation using Bayesian estimation methods (Yoo 2014). Interestingly, few such models have used treatment as a prediction variable (for an exception, see Pawelek et al. 2014), despite the central role that treatment plays in mosquito control programs. This may be due to several reasons, including inconsistent or lacking curation of suitably detailed spatiotemporal information. However, the inclusion of treatment data to construct or validate quantitative models can provide valuable insight into the influence of vector control management on vector populations at landscape scales (Pawelek et al. 2014).

Tarrant County is in north-central Texas, USA, with its county seat located at Fort Worth. It is an urban county of 1.8 million people (Tarrant County, 2016). Within the county there are several species of mosquito that belong to the genus *Culex* that may be vectors of West Nile virus (WNV). These include *Culex quinquefasciatus* Say*, Cx. tarsalis* Coquillett*, Cx. restuans* Theobald, and *Cx. nigropalpus* Theobald. *Culex quinquefasciatus* are of particular concern since they are urban mosquitoes, breeding in small quantities of stagnant water, as well as water sources like wastewater lagoons (Zequi et al. 2014) and are known to be the primary vectors of WNV. Several municipalities operate independent mosquito control programs in the county (including the city of Fort Worth), while the Environmental Health Division of Tarrant

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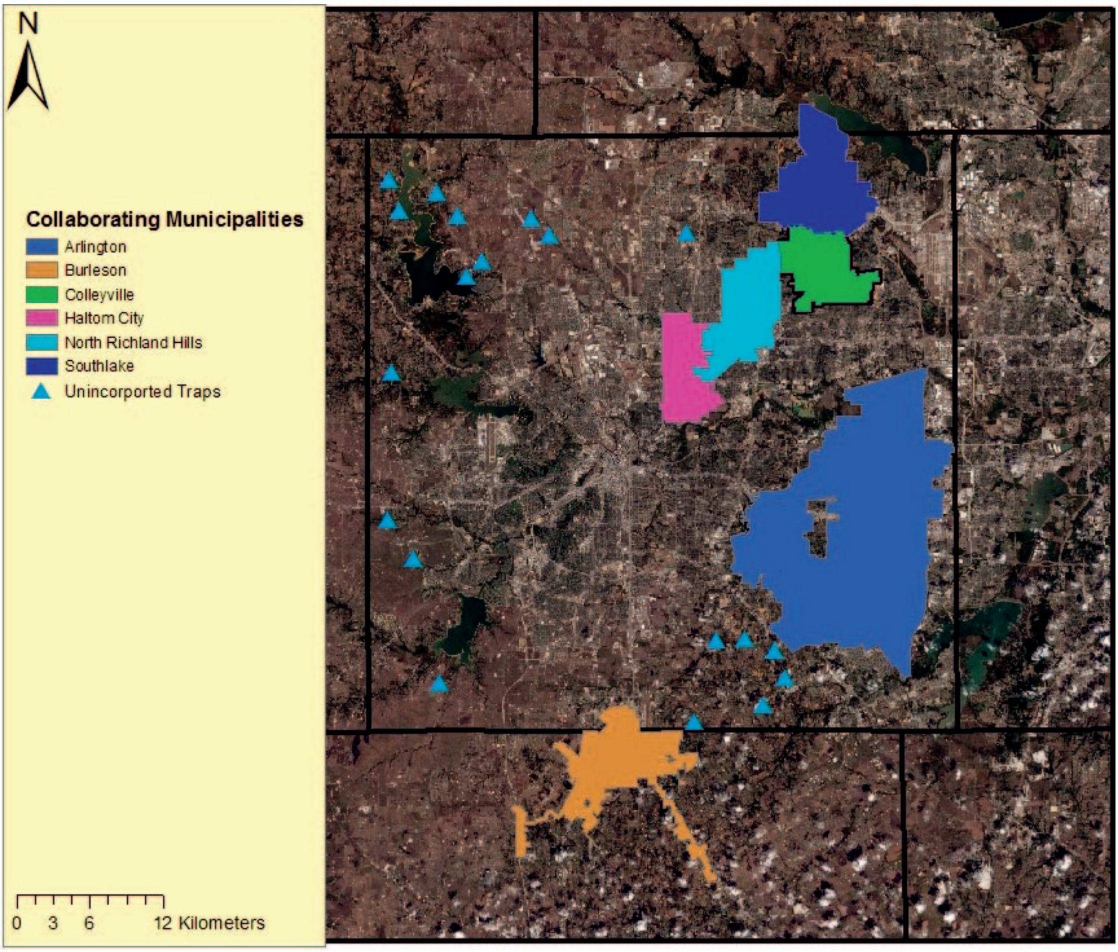

Fig. 1. Collaborating municipalities and traps in unincorporated Tarrant County, TX, operated by Tarrant County Public Health (TCPH). Some municipalities, including Burleson and Arlington overlap into adjacent counties.

County Public Health (TCPH) administers a mosquito control program that covers unincorporated Tarrant County. These entities maintain networks of adult mosquito surveillance traps and coordinate with the TCPH to manage vector-borne disease risks. Importantly, these entities also maintain spatially explicit treatment records, including both larvicide and adulticide applications. Thus, this dataset provided a rare opportunity to incorporate treatment information collected across organizations into a landscape-level statistical model of mosquito abundance.

MATERIALS AND METHODS

Data acquisition and processing

Mosquito surveillance and treatment data were obtained from TCPH following the 2014 mosquito season (April–October). The study area included a subset of participating municipalities within the county that administers mosquito control programs and unincorporated Tarrant County, in which the mosquito control program is operated by TCPH (Fig. 1). Collaborating municipalities included Arlington, Burleson, Colleyville, North Richland Hills, Southlake, and Haltom City.

The response variable of interest in this study was counts of female *Cx. quinquefasciatus* collected in Centers for Disease Control and Prevention (CDC) gravid traps (Reiter 1983) by both individual municipalities and TCPH, with data compiled by TCPH. Gravid traps are designed to attract gravid female *Culex* mosquitoes using water infused with organic materials. In the case of TCPH, that infusion is made from grass clippings fermented in water for 2 wk. In addition to being useful for surveilling viral infection rates in blood-fed females in general, gravid traps are known to be highly effective at attracting *Cx. quinquefasciatus* (DiMenna et al. 2006, White et al. 2009). Traps in the study area were operated on a weekly basis throughout the mosquito season, with some on a permanent basis, and some on a temporary basis. For the purposes of comparability, only data from permanent traps were used in this analysis.

Based on mosquito biology and previous efforts to model mosquito surveillance data (Schurich et al. 2014, Yoo 2014), it was hypothesized that mosquito abundance, as indicated by counts, could be modeled as a factor of 3 exogenous variable types (or a subset of them), including weather, mosquito control treatments, and habitat quality. Owing to their poikilothermic (i.e., cold-blooded) physiology and the necessity for standing water in which to breed, temperature and precipitation are known drivers of mosquito populations. Weather data, including precipitation and temperature records, were downloaded from the National Climatic Data Center website (NCEI 2015). These data were collected from 8 weather stations distributed around Tarrant County. Surveillance records were associated with weather data from the nearest weather station. A preliminary investigation using temperature data loggers at 20 trap locations around the county demonstrated that temperature data collected at weather stations closely aligned with temperatures at traps (data not shown).

Habitat variability was accounted for using the normalized difference vegetation index (NDVI) and human population density. The NDVI is an indicator of the vegetative vigor and potential water availability and is significantly associated with abundance (Yoo 2014) and distribution of mosquitoes (Diuk-Wasser et al. 2006). NDVI was calculated using the standard formula ([NIR − Red]/[Red + NIR]; NIR = near infrared) from spectral imagery downloaded from the US Geological Survey Global Visualization Viewer (USGS 2016) for 2 dates, July 1 and October 5, 2014. These dates had less than 10% cloud cover, were representative of warmer and cooler times of the study, and thus served as a representative sample of NDVI during the survey period.

Human population density was included as a variable here because *Cx. quinquefasciatus* is thought of as an anthropophilic mosquito (Murty et al., 2002) that uses small pools of standing water around human settlements (ditches, French drains, flower pots). Human population density has also been significantly associated with mosquito abundance in other species with affinity for humans (Yoo 2014). Density was calculated from census block information downloaded from the US Census Bureau (USCB 2016).

Mosquito control data included larviciding and adulticiding records collected and maintained by individual municipalities and TCPH. These data were compiled at the request of TCPH and released to the authors for the purposes of this study. Treatment data composition was heterogeneous between the collecting entity and ranged from hand-written descriptions of treatments with general descriptions of locations, and chemicals and quantities used (particularly for larvicide records), to high-resolution, geographic information system–generated maps of adulticide applications. All treatment data were digitized and migrated into ArcGIS 10.3. While adulticide information was area-based, larviciding information consisted of both point and spatial area information. To standardize data across sources, larvicide information was converted into an area context by extending 10 m polygon buffers around larviciding points. Owing to the heterogeneity of collected data, particularly larvicide records, application date was the only consistently associated auxiliary information and thus was used to indicate the influence of treatment in the model. Treatment measures included the total number of larviciding or adulticiding events within a time interval (e.g., total events in week 3) or the total areas treated with larvicide or adulticide within a time interval.

Mosquito populations are expected to respond to population drivers at a localized scale, but several traps in urban areas were near each other (i.e., less than 400 m apart). In order to maintain independence of data between spatially specific predictor variables, a 100-m buffer was extended around trap locations to extract habitat and treatment data. This buffer distance was within the spatial range of other studies examining the association of spatial variables and *Cx. quinquefasciatus* in urban environments (Landau and Leeuwen 2012, Leisnham et al. 2014). In addition, because we did not know the temporal lags that existed between treatment and weather variables and their influence on population dynamics in Tarrant county, treatment and weather information were aggregated into temporal intervals (1–4 wk) prior to any given surveillance record.

Prior to analysis, a quality assurance process was undertaken to improve the comparability of longitudinal data between trapping locations. The process included only traps that were categorized as "static" (as opposed to temporary) and that had a total number of data points (i.e., sample weeks) for the sample period that was at least 50% of the trap with the most data points (25). Trapping records were excluded where trap effectiveness was questionable, including trap malfunctions, high wind, or precipitation during trap setting. This resulted in a total of 53 traps and 1428 observations available for model construction.

Statistical analysis and model construction

Mosquito counts were modeled using general linear mixed modeling with the lme4 package (Bates et al. 2015) in program R (R Core Team 2017). Count data were log + 1 transformed (to include 0 observations) prior to inclusion in the modeling process. Although a Poisson or negative binomial regression approach would ostensibly be more appropriate, since the response variable (mosquito

Table 1. All variables included in the global model. Shown are category of the model term (fixed, interactive, random), class of variable (weather, habitat, treatment), and specific variable of interest. Note that all temporally varying variables except temperature included a representative of both the survey week and at the best supported longer term (2–4 wk).

Model term	Category	Variable
Fixed	Weather variables	$\text{Temperature}_{\text{wk 4}}$
		$\text{Precipitation}_{\text{survey wk}}$
		$\text{Precipitation}_{\text{wk 2}}$
	Habitat	NDVI
		Population density
	Treatment	$\text{Adulticide}_{\text{survey wk}}$
		$\text{Adulticide}_{\text{4 wk cumulative}}$
		$\text{Larvicide}_{\text{survey wk}}$
		$\text{Larvicide}_{\text{4 wk cumulative}}$
Interactive	Weather	$\text{Temperature}_{\text{wk 4}} \times \text{Precipitation}_{\text{wk2}}$
	Habitat	NDVI $\times$ Population density
	Weather and habitat	$\text{Precipitation}_{\text{wk 2}} \times$ NDVI
		$\text{Precipitation}_{\text{wk 2}} \times$ Population density
	Weather and treatment	$\text{Temperature}_{\text{wk 4}} \times \text{Adulticide}_{\text{survey wk}}$
		$\text{Temperature}_{\text{wk 4}} \times \text{Larvicide}_{\text{survey wk}}$
		$\text{Temperature}_{\text{wk 4}} \times \text{Larvicide}_{\text{4 wk cumulative}}$
		$\text{Temperature}_{\text{wk 4}} \times \text{Adulticide}_{\text{4 wk cumulative}}$
Random	Intercepts	Municipality
		Trap ID

counts) was discrete (Yoo 2014, Caputo et al. 2015), preliminary analyses using these methods produced poor model fit due to the large spread of count values (e.g., 0–2000). Previous modeling efforts of mosquito counts have included log transformed counts to improve model fit (Brown et al. 2011). Mixed modeling was used here to account for trap and municipality-specific dependencies. All predictor variables were centered and standardized by dividing variables by 2 times their standard deviation to facilitate numerical parameter estimation and to aid in model interpretation (Gelman 2008). Model comparison and selection was accomplished using the Akaike information criterion for small sample sizes (AICc; Anderson 2008, Ganser and Wisely 2013):

$$\text{AICc} = \text{AIC} + \frac{2k(k+1)}{N-k-1}, \tag{1}$$

with k equal to the number of parameters and N equal the number observations, to evaluate the relative fit of models at each step. Though the sample size was reasonably large in this study (1428 observations), AICc is generally superior to AIC (Anderson 2008, Ganser and Wisely 2014).

The model construction process started by identifying the best temporal aggregation of temporally varying variables (precipitation, temperature, adulticide, larvicide). This included considering predictors averaged within a week of surveys (to capture the influence of the predictor on capture rates), and 2–4 wk prior to count surveys. The best predictor from each group was determined by fitting univariate models at each temporal aggregation (average per week, or aggregation over 1 wk), and selecting the best supported model using AICc. Next, these variables were combined with variables considered constant over the study period (NDVI, human population density) into a global model.

With the global model, the best random structure was determined using restricted estimation maximum likelihood (Zuur et al. 2009; Table 1). From the global model, submodels were derived containing all combinations of variables with the following caveats. First, the most basic plausible model was considered to consist of only weather variables. Thus, all submodels considered included the best supported combination of weather variables (average precipitation over 2 wk prior to survey, average temperature 4 wk prior to survey, and their interaction). Second, because treatments largely occurred when mosquito populations and thus temperatures were higher, all models including adulticide and larvicide treatment terms also included interaction terms with temperature. These caveats resulted in the fitting of 416 unique models using maximum likelihood (Zuur et al. 2009).

A set of most supported submodels was determined by calculating AICc difference (e.g., dAICc) and selecting all sub models with dAICc ≤ 2. This resulted in 7 submodels (Table 1). To address model selection uncertainty, models in the final set were averaged by the "natural average" method described by Anderson (2008; Table 2) to produce a final average weighted model using the AICcmodavg package (Mazerolle 2016). Random intercept terms were included from the top model in this set. Diagnostics for the average model included a visual examination of the distribution of residuals for adequacy of fit, homogeneity of variance, and normality using graphical techniques.

The root mean square error (RMSE; Brown et al. 2011) was used to assess model performance, calculated as

Table 2. Parameter estimates for final, averaged model. The top table includes all fixed parameter estimates with their unconditional standard errors and the 95% CI. The bottom table includes standard errors for the estimated random effects for the intercepts for municipality and trap ID. A total sample size of 1428 observations was used to construct the final model.

Parameter	Estimate	Unconditional SE	95% CI Lower bound	95% CI Upper bound
(Intercept)	2.453	0.241	2.057	2.849
Adulticide$_{\text{survey wk}}$	0.312	0.252	−0.103	0.727
Larvicide$_{\text{survey wk}}$	0.109	0.098	−0.052	0.269
Larvicide$_{\text{4 wk cumulative}}$	0.271	0.125	0.065	0.476*
Adulticide$_{\text{4 wk cumulative}}$	0.233	0.142	0.0002	0.466*
Precipitation$_{\text{survey wk}}$	0.125	0.092	−0.027	0.276
Population density	−0.012	0.207	−0.353	0.329
NDVI	0.146	0.185	−0.159	0.451
Precipitation$_{\text{wk 2}}$	−0.668	0.091	−0.818	−0.518*
Temperature$_{\text{wk 4}}$	2.528	0.087	2.386	2.671*
Temperature$_{\text{wk 4}}$ × Adulticide$_{\text{survey wk}}$	−1.004	0.500	−1.827	−0.182
Temperature$_{\text{wk 4}}$ × Larvicide$_{\text{4 wk cumulative}}$	−1.205	0.295	−1.690	−0.720*
Temperature$_{\text{wk 4}}$ × Larvicide$_{\text{survey wk}}$	0.701	0.249	0.291	1.110*
Temperature$_{\text{wk 4}}$ × Precipitation$_{\text{wk 2}}$	0.296	0.189	−0.015	0.607
Precipitation$_{\text{wk 2}}$ × Population density	0.331	0.145	0.092	0.571*
Temperature$_{\text{wk 4}}$ × Adulticide$_{\text{4 wk cumulative}}$	−0.337	0.365	−0.936	0.263
Random intercepts	Std Dev.			
Municipality	0.578			
Trap ID	0.551			
Residual	1.316			

* Statistical significance at the $\alpha = 0.05$ level.

$$\text{RMSE} = \sqrt{\frac{\Sigma(\text{observed} - \text{predicted})^2}{n}},$$

with smaller values indicating better overall predictive ability. An overall RMSE was calculated for the model, as well as values for each municipality and trap location. To provide an estimate of model stability, a leave-one-out cross-validation procedure was performed in which the final average model was refit using all but a single data point, and the newly fit model is used to predict the missing data point. The process was repeated for all data points, and an RMSE was calculated between the predictions from the full data set (n) and the corresponding points in the $n - 1$ dataset.

RESULTS

The global model consisted of 9 variables, and 8 two-way interactions (Table 1). The best random structure included intercepts for both municipality and trap ID. When all submodels were compared using AICc, the best supported set of models ≤ 2 dAICc of the top model accounted for approximately 26% of overall AIC weight of the 416 models considered. Each of the 7 models in this set contained at least 1 representative of habitat and treatment variables along with required weather variables. When these 7 models were averaged, they produced the following final model:

$$\begin{aligned}
&\log(\text{Count} + 1) \\
&= \text{Intercept} + \text{Adulticide}_{\text{survey wk}} \\
&\quad + \text{Larvicide}_{\text{survey wk}} + \text{Precipitation}_{\text{survey wk}} \\
&\quad + \text{Larvicide}_{\text{4 wk cumulative}} + \text{Adulticide}_{\text{4 wk cumulative}} \\
&\quad + \text{Temperature}_{\text{wk 4 avg}} + \text{Precipitation}_{\text{wk 2 avg}} \\
&\quad + \text{Population Density} + \text{NDVI} \\
&\quad + \text{Temperature}_{\text{wk 4 avg}} \times \text{Preciptation}_{\text{wk 2 avg}} \\
&\quad + \text{Temperature}_{\text{wk 4 avg}} \times \text{Adulticide}_{\text{survey wk}} \\
&\quad + \text{Temperature}_{\text{wk 4 avg}} \times \text{Larvicide}_{\text{4 wk cumlative}} \\
&\quad + \text{Temperature}_{\text{wk 4 avg}} \times \text{Larvicide}_{\text{survey wk}} \\
&\quad + \text{Adulticide}_{\text{4 wk cumulative}} \times \text{Temperature}_{\text{wk 4 avg}} \\
&\quad + \text{Precipitation}_{\text{wk avg}} \times \text{Population Density} \\
&\quad + \text{Random Intercept}_{\text{municipality}} \\
&\quad + \text{Random Intercept}_{\text{Trap}} + \text{Error}.
\end{aligned}$$

Model coefficients, unconditional standard errors, and 95% confidence interval (CI) for each parameter in this model are shown in Table 2. Based on 95% CIs calculated via unconditional standard errors, there were 8 significant variables in the final average model, including the main effects for Larvacide$_{\text{4 wk cumulative}}$, Adulticide$_{\text{4 wk cumulative}}$, Precipitation$_{\text{wk 2}}$, Temperature$_{\text{wk 4}}$; and the interactions between Temperature$_{\text{wk 4}}$ and Larvicide$_{\text{4 wk cumulative}}$, Temperature$_{\text{wk 4}}$ and Larvicide$_{\text{survey wk}}$, Temperature$_{\text{wk4}}$ and Larvicide$_{\text{survey wk}}$, and Precipitation$_{\text{wk 2}}$ and Population Density.

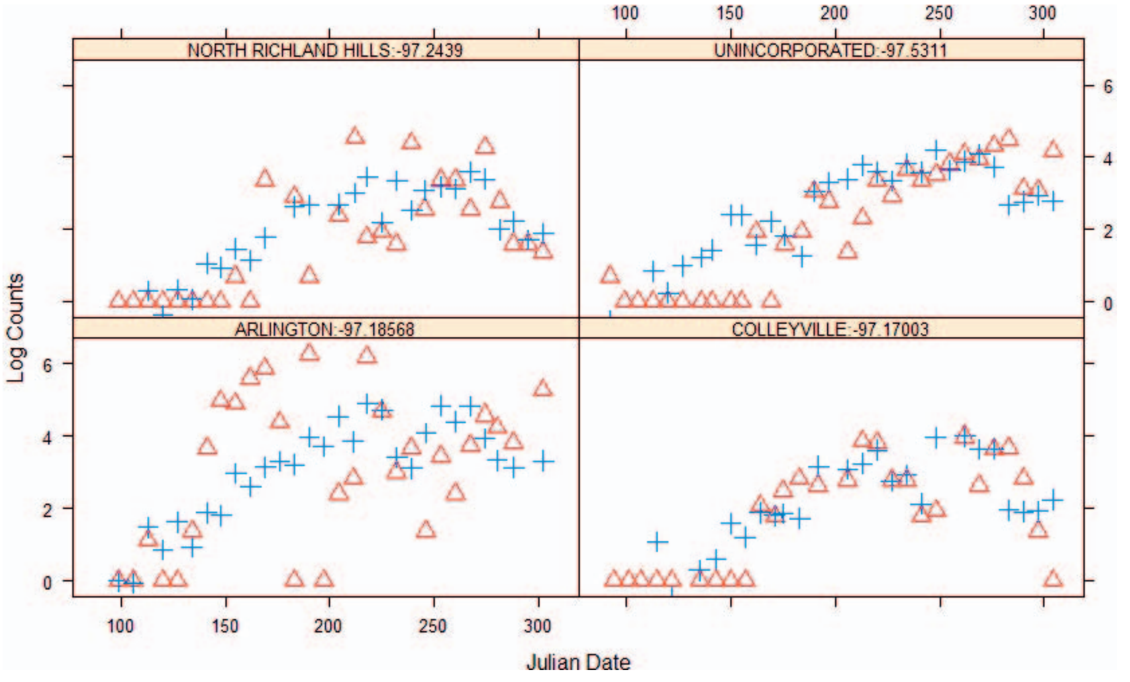

Fig. 2. Predicted log counts of *Cx. quinquefasciatus* (blue crosses) versus observations (red triangles) at 4 representative trap locations, including traps in North Richland Hills, a trap in unincorporated Tarrant County, Arlington, and Colleyville, over the calendar year 2014 (Julian date is indicated on the bottom left and top margins of the graph). Although all count predictions follow the general parabolic pattern based on temperature, accuracy of predictions depended upon trap location.

The main effects of significant treatment variables in the model were positive. The significant interactions of all treatment variables with temperature (i.e., $\text{Temperature}_{\text{wk 4 avg}}$) were negative except for the interaction with $\text{Larvicide}_{\text{survey wk}}$. This resulted in a temperature threshold of approximately 27°C, above which increasing treatment resulted in lower mosquito counts. Conversely, under this temperature threshold the model predicted higher counts with increasing treatment.

The average model had an overall RMSE of 1.296. Predicted counts at all locations followed the inverse parabolic pattern of observed counts, since mosquito abundance fluctuated with seasonal temperature (see Fig. 2 for predicted log counts versus observed log counts at a representative selection of traps). However, municipalities and individual traps varied in performance in RMSE from a low of 0.89 at a trap in South Lake Colleyville to a high of 2.03 at a trap in Arlington (Fig. 3). Lastly, the leave-one-out stability analysis resulted in a RMSE of 1.35 between the predicted counts and the observed counts.

DISCUSSION

The final average model of log counts was generally consistent with known correlates of mosquito population dynamics in general, and *Cx. quinquefasciatus* in particular. Temperature had the largest effect on log counts, as indicated by the relative size of the β coefficient in the model and the strong parabolic seasonal pattern of predictions across all locations (Fig. 2). Temperature is well recognized to influence mosquito ecology, including larval development and survival, gonotrophic cycle length, dispersal behavior, and adult survival (Clements, 1992, 1999). Increasing temperature increases larval development (Rueda et al. 1990, Ciota et al. 2014) and, within the range of 20°C–30°C (which includes approximately 69% of the observations of this study), increases survival in *Cx. quinquefasciatus* (Rueda et al. 1990). Although high temperatures (>30°C) have been shown to reduce survival and influence the blood-feeding patterns of *Cx. quinquefasciatus* and other *Culex* mosquitoes (Ciota et al., 2014), temperatures >30° only occurred <10% of the time. Thus, temperature in the model likely drove abundance patterns due to the influence of temperature on physiological processes. Interestingly, a significant reduction in abundance occurred at the end of the season in all locations (Fig. 2), which was not captured by the model. *Culex quinquefasciatus*, unlike congener *Cx. pipiens*, does not exhibit a seasonal diapause (Hayes 1975, Ciota et al. 2014, Meuti et al. 2015) but does exhibit seasonal quiescence in response to lower temperatures (Nelms et al. 2010, Diniz et al. 2017). The sharp reduction in activity here beyond what is predicted by tempera-

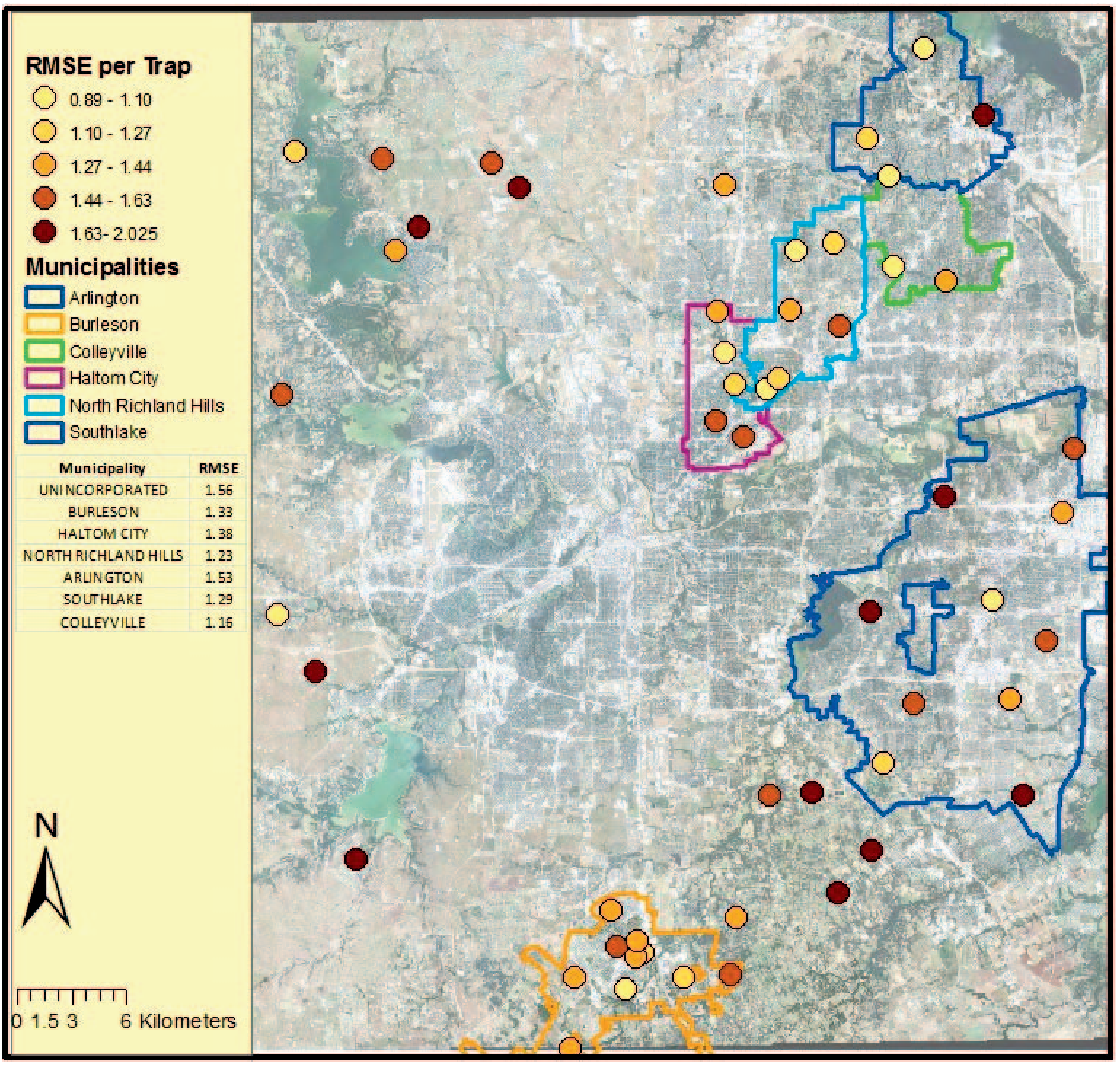

Fig. 3. Trap locations and their relative root mean square error (RMSE) rates. Light yellow colors indicate lower RMSE and better agreement with the model, and darker red colors indicate larger RMSE and worse agreement with the model. Municipality outlines are indicated. Trap locations not within a municipality are in unincorporated Tarrant County and monitored by the Tarrant County Department of Public Health.

ture likely indicates that other environmental drivers, such as photoperiod or humidity, may influence quiescence (Diniz et al. 2017).

Temperature also played an important role in how treatment variables influenced mosquito counts in the model (Table 2). Of note is that only interactive effects of some significant treatment variables ($\text{Adulticide}_{\text{survey wk}}$, $\text{Larvicide}_{4\text{ wk cumulative}}$) resulted in the prediction of lower mosquito counts with increasing treatment, and then only above a temperature threshold; a prediction of higher counts with increasing treatment resulted below the threshold. The reasons for these interactions are unclear. However, one hypothesis is that this is due to the influence of seasonal temperature on population dynamics. When average temperatures were higher than the identified threshold (27°C, approximately June–September), additional population growth due to temperature was limited, resulting in the expected negative relationship between mosquito counts and treatment. In contrast, when temperatures were below the threshold (especially earlier in the season), mosquito populations were naturally rising due to seasonal temperature increases. So, larviciding or adulticiding during this period may have resulted in an apparent association with higher counts. This may be especially the case for $\text{Larvicide}_{4\text{ wk cumulative}}$ and $\text{Adulticide}_{4\text{ wk cumulative}}$, since they represented aggregated treatment over 4 wk prior to surveys. It is also possible that there were actual changes in the relationship between vector control treatment and mosquito population dynamics over the course of the season, such as more effective targeting of source and adult populations as the season progressed. We plan to address these questions in future iterations of the model, particularly if additional years of data can be acquired.

Two-week lagged precipitation and its interaction with human population density were also significant terms in the model and likely represented the influence of larval habitat quality and availability on mosquito abundance. Like all mosquitoes, *Cx. quinquefasciatus* have a temperature-dependent development rate with a time of emergence that ranges from approximately 7 to 14 days in a temperature range of 30°C to 20°C, respectively (Rueda et al. 1990). Although other studies have found support for a 1-wk lag in precipitation prior to surveys as a weather predictor of mosquito counts (Ganser and Wisely 2014, Yoo 2014), a 2-wk lag here appears to better align with *Cx. quinquefasciatus* developmental biology (at least at warmer temperature ranges). Although a negative sign for the precipitation coefficient initially seems counterintuitive, mosquito counts can be negatively associated with precipitation in the short to intermediate term (i.e., weeks to months). This result is due to the dilution of nutrients in the aquatic habitats in which mosquitoes seek to lay eggs (Chaves and Kitron 2011, Jian et al. 2014) and the ability of heavy rains to flush eggs out of aquatic habitats (Koenraadt and Harrington 2008). Further, the production of *Cx. quinquefasciatus* is known to be associated with nutrient availability in the aquatic substrate (Noori et al. 2015), reflected by the aging of infusion media prior to use in CDC gravid traps (a length of time around 14 days for TCPH) to develop enough nutrient content.

Previous studies incorporating similar habitat predictors (Yoo 2014), as well as land-cover and other habitat features (Ganser and Wisely 2014, Leisnham et al. 2014, Schurich et al. 2014), found strong impacts of habitat factors, with oviposition habitat availability an especially important driver of *Cx. quinquefasciatus* abundance (Leisnham et al. 2014, Murty et al. 2002). In this model, the main effects of NDVI and human population density (used here as a proxy for anthropogenic habitat availability) were not significant, but a positive interaction between human population density and precipitation was significant. This suggests that, although greater human density does not by itself increase counts of *Cx. quinquefasciatus*, it may be a factor as precipitation increases. *Culex quinquefasciatus* are known to use a variety of standing water to oviposit, ranging from aboveground containers like flower pots in urban areas and cemeteries to natural and anthropogenic catch basins (Leisnham et al. 2014), including underground French drains (Nina Dacko, personal observation). Thus, such an effect is likely due to a greater abundance of anthropogenic oviposition habitat made available with precipitation in areas of higher human density. That the interactive effect is positive (in contrast to the negative main effect) suggests that increased habitat availability provided by urban area during times of high precipitation may partially offset negative influences of rainfall itself. For dry regions like north-central Texas where natural habitat may be scarce, this may represent a tradeoff that drives the use of urban habitats by *Cx. quinquefasciatus*.

Although overall model RMSE was relatively low (1.29) and the leave-one-out RSME indicated that the model was relatively stable, some locations were clearly better predicted than others (Figs. 2, 3). This may relate to insufficient characterization of oviposition site potential with the proxy habitat variables used here (Murty et al. 2002, Leisnham et al. 2014) Furthermore, precipitation and temperature information collected from weather stations may have been of insufficiently small scale to predict site-level heterogeneity. Although preliminary work demonstrated a high correlation between temperatures at trap locations and weather stations (unpublished data), precipitation, in particular, is prone to being highly variable across landscapes and is an important source of error in spatially explicit hydrological modeling (Tetzlaff and Uhlenbrook 2005).

The primary limitation of this model is that it was constructed using only a single year of data. This was due to the mosquito control chemical application data being relatively difficult to assemble due to different curation methods between organizations, an apparently common condition in the mosquito control community. It is also worth noting that many municipalities are reluctant to supply treatment data to outside entities because of concerns that it will be used to falsely portray the municipalities' efforts or to compare those efforts with those of another municipality (Nina Dacko, personal observation). Fortunately, there is increasing recognition regarding the importance of maintaining spatiotemporal records of mosquito surveillance and treatment records (Eisen and Eisen 2011, AMCA 2018). This is coupled with the commercial availability of both manual and automatically operated global positioning satellite–enabled technology that collects spatiotemporal information of treatment activity, particularly the application of adulticides dispersed from truck-mounted ultra–low volume spray devices. Thus, there are expanding opportunities to incorporate treatment information into statistical models of mosquito population dynamics.

This represents a first step in the use of data collected by mosquito control authorities in Tarrant County, Texas, toward 2 goals, namely, 1) providing quantitative inference into mosquito population dynamics in relation to environmental and treatment effects and 2) providing the basis for the development of operational tools. For the first goal, the model clearly establishes a biological basis for inferring population dynamics from environmental and anthropogenic drivers. Importantly, mosquito control treatment was predicted to reduce mosquito counts at the landscape scale under certain conditions. Regarding the second goal, inconsistency in predictive ability at different locations suggests site-level factors, such as oviposition habitat, may not have been adequately included in the current model. Future work will focus on the incorporation of additional habitat factors, as well additional years of surveillance and treatment information, to better model *Cx. quinquefasciatus* counts in Tarrant County.

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