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VECTOR-BORNE AND ZOONOTIC DISEASES
Volume 5, Number 3, 2005

Research Paper

Cross Correlation Maps: A Tool for Visualizing and Modeling Time Lagged Associations

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ABSTRACT

It has long been recognized that arthropod populations fluctuate with changes in environmental conditions and these changes occur at various spatial and temporal scales. Empirical studies that have explored associations between vector abundance and the environment often considered meterological events as leading indicators with their effects traditionally restricted to single points in time, such as precipitation 12 days prior to trapping. Field experience, however, suggests that the duration of these environmental effects on vectors often extends over a range or interval of time. Such a scenario is not directly interpretable from cross correlation plots routinely employed to visualize and identify time lag associations. Cross correlation maps are introduced as a way to generalize cross correlation plots and to visualize the effects of environmental conditions over intervals of time. This graphical method is flexible and can include different characterizations of environmental effects, as well as interactions among environmental variables. A time series of daily trapped female *Ochlerotatus sollicitans* mosquitos and leading meterologic conditions were used for demonstration. Associations shown in cross correlation maps were consistent with the arthropod biology and trapping efficacy and were also stronger than those identified at single time points using cross correlation plots. Poisson regression models for vector abundance built using meterological variables with both single and interval based leading time lags were compared. The approach based on the leading meterological events allowed to extend over time intervals reproduced the *Oc. sollicitans* daily population dynamics better than the traditional approach. Key Words: Correlation—Mosquito—Poisson regression—Population dynamics. Vector-Borne Zoonotic Dis. 5, 267–275.

INTRODUCTION

It has long been recognized that arthropod populations fluctuate with changes in environmental conditions and these changes occur at various spatial and temporal scales (Curtis 1985, Moore 1985). Changes in meterological conditions, such as temperature, precipitation events, insolation, relative humidity, and wind speed, can impact both the population size (through changes in survival and reproduction) as well as the ability to sample individuals in the vector populations. For example, Ailes (1998) postulated low temperatures affected both individual survival/reproduction, as well as flight activity of *Aedes sollicitans* and *Ae. taeniorhynchus*. Other meterological factors, such as increasing wind speed or cloud cover, may have similar effects (Ailes 1998).

The apparent relationship between previous and current environmental factors and the abundance of arthropods, such as mosquitoes has led workers to use environmental conditions as leading indicators of vector abundance, with the goal

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of predicting or modeling vector abundances. These attempts have used numerous analytical approaches, and aggregated their data to various spatial and temporal scales (e.g., some used daily time steps while others averaged variables over months) and they have met with varying degrees of success. For example, Hacker et al. (1973) examined cross-covariance functions of daily counts of *Culex tarsalis*, and *Aedes vexans* with minimum daily temperatures, and rainfall for a three-year period. They found strong positive associations of vector abundance and minimum temperature on the day of sampling and a second peak 12–15 days previously. Numbers sampled were positively associated with precipitation of 16–17 days and 33–36 days prior to sampling. Takeda et al. (2003) aggregated data annually over a 6-year period to examine the relationship between arbovirus activity in mosquito pools and variation in precipitation and temperature aggregated as deviations of total rainfall, and deviations of monthly average temperatures from 30-year averages. They reported significant correlations between viral activity levels and some of these environmental variables but not for others. Ailes (1998) found significant associations between precipitation, tides and temperature, aggregated to various time scales and the numbers of *Ae. sollicitans* and *Ae. taeniorhynchus* captured (approximately) each week for a 9-year period. There were highly significant associations among many of the leading environmental variables and the captures. However, when these variables were used in multiple regression models to predict an additional 2 years worth of data, the results were less than satisfactory.

A common thread in these cited analyses is that the attempts to associate vector abundance with leading meterological conditions are restricted to single times. Exceptions include the studies by Gleiser et al. (2000) and Mbogo et al. (2003). Even if all other climatic conditions could be controlled, the biology of many species would suggest the effects of a known environmental indicator such as precipitation likely extends over an interval of time rather than at a single point in time. Or conversely, the same amount of precipitation occurring 2 weeks prior to sampling could have the same impact on vector populations as precipitation happening 12 days prior to sampling.

One of the key limitations with previous analytical methods is that they fail to capture the inherent variability in population responses to climatic events that observational studies tell us occur. Thus, the relatively low correlation coefficients that are often reported (Maelzer et al. 1996, Ailes 1998, Takeda 2003) reflect traditional statistical approaches that incorporate this biological "fuzziness" into the error term of the analysis. Current statistical approaches require us to assume that the effects of a particular environmental variable remain the same. Even with more sophisticated time series analysis it is assumed that the impact of environmental variables at time t are constant compared to their effects at time $t + h$, for non-zero temporal shift h.

It would be more flexible, and realistic, if we could identify a time period over which the environmental factor could act and still have a similar impact on the vector population. For example, being able to account for a relationship between rainfall amounts at any time during the past ten days to two weeks, and vector abundance might improve our abilities to forecast vector abundance and more closely capture the biology of the system. Similarly, the ability to aggregate the environmental data in various ways, such as total precipitation, maximum precipitation, or average precipitation during a time interval could better capture the interplay between the biology of the vector and the environment.

In this paper, we propose a graphical method to explore relationships between vector population dynamics and environmental variation. This method captures the essence of field experience that the duration of environmental effects on vectors often extends over an interval of time rather than a single point in time. It also demonstrates that different characterizations of the environmental effects (data aggregation), as well as interactions among environmental variables (conditional effects) can be incorporated. The graphical method proposed, called cross correlation maps, is shown to be a generalization of cross correlation plots, which are often used to display lag associations at single points in time. Cross correlation maps are also demonstrated in identifying key antecedent environmental conditions, their timing, and duration for developing predictive models of vector abundances.

MATERIALS AND METHODS

Mosquito and meterological data

The Maryland Department of Agriculture has archived mosquito surveillance data from 1956 to 1989 in which New Jersey light traps were employed nightly at a large number of sites in 23 countries surrounding the Chesapeake Bay (Shone et al. 2004). The numbers of male and female mosquitos of each species collected were recorded. For demonstration purposes we select the site located in Cambridge, Maryland (76.079°W, 38.558°N), and consider the 1965 data for mosquitos trapped nightly between June 1 and September 19 of that year.

Accompanying meterological data included total daily precipitation (in hundredths of an inch) and maximum and minimum temperature (in degrees Fahrenheit), obtained from the Cooperative Summary of the Day TD3200 data set from the National Climatic Data Center (NCDC) <http://lwf.ncdc.noaa.gov/oa/ncdc.html>. A cooling degree day variable was calculated by subtracting 65°F from the daily mean temperature. Mean temperature levels were determined by averaging daily maximum and minimum values. The TD3200 weather station located at the Cambridge Water Treatment Plant, 3.9 miles from the Cambridge mosquito sampling site, was used to acquire this data. Maximum and minimum relative humidity (in percent) and wind speed (in meters per second) were obtained from the Solar and Meterorological Surface Observation Network (SAMSON) database available at NCDC <http://lwf.ncdc.noaa.gov/oa/ncdc.html>. The SAMSON data were collected at Baltimore Washington International airport. Since the Cambridge, Maryland, site is located adjacent to a salt marsh along the Chesapeake Bay, maximum and minimum daily tide data for the Chesapeake Bay provided by the National Oceanic and Atmospheric Administration Center for Operational Oceanographic Product and Services <http://tidesonline.nos.noaa.gov> was included. The tide levels, recorded at the United States Naval Academy in Annapolis, Maryland, were reported as feet relative to mean lower low water, where mean lower low water is the average of the minimum low tides of each tidal day observed over the National Tidal Datum Epoch.

Visualizing time-dependent associations

Time plots and plots of cross correlations are common procedures for visualizing associations in multivariate time series data. For the discussion to follow we let Y_i represent the time series of daily recorded mosquito trap counts at the Cambridge site with time index $i = 1, \ldots, 111$ representing the consecutive trapped days from June 1, 1965 through September 19, 1965 and let X_i denote a corresponding meteorological series of interest, say total daily precipitation.

To explore the bivariate association between mosquito abundance and precipitation one can calculate lagged correlations $corr(Y_i, X_{i-k})$, where $k > 0$ represents the preceding daily lag and *corr* denotes Pearson product moment correlation. So $corr(Y_i, X_{i-10})$ denotes the correlation between mosquito trap counts and precipitation ten days prior. A plot of these correlations for a sequence of lags k produces the cross correlation plot (Diggle 1990). A disadvantage of this approach is that associations that extend over a range or interval of time lags cannot be directly interpreted from the single lags displayed in the cross correlation plots. For example, total precipitation accumulated between fourteen and seven days prior to trapping may represent a more biologically plausible scenario when exploring associations between mosquito abundance and precipitation than precipitation on any one given day.

To extend the cross correlation plot we introduce an interval time lag comprised of consecutive days and consider the correlation between mosquito abundance and some aggregate summary of a meterological variable within this interval lag. We can represent this interval lag cross correlation with $corr(Y_i, f(X_{i-j,i-k}))$, for positive lags j, k with $j \geq k$ and some aggregate summary function $f(\cdot)$. For example, $corr(Y_i, Avg(X_{i-14,i-7}))$ provides the notation representing the correlation between mosquito abundance and average precipitation accumulated during a seven to fourteen day preceding time frame.

For a given aggregate summary function, interval lag cross correlations can be visualized with a cross correlation map, where the time lags j and k (used to define the interval lag) range along the two axes with colors or shading employed to represent the corresponding interval lag cross correlation. The cross correlation map thus provides the analogue to cross correlation plots for interval based lag structures. Further, for $j = k$ the interval lag structure reduces to the single lag so information in a cross correlation plot can be obtained from the cross correlation map.

Modeling vector abundance

Cross correlation maps are useful in visualizing stratified bivariate associations between mosquito abundance and interval based time lagged meterological conditions. Further statistical analysis of mosquito data may seek to understand and possibly predict the impact of several meterological conditions and their potential interactions simultaneously on mosquito abundance. This can be accomplished with a regression model.

For the trapped mosquito count data, Y_i, we propose the following Poisson regression model where the daily expected count (shown below as λ_i) is parameterized as a log linear function of meterological conditions

$$Y_i \sim Pois(\lambda_i)$$

$$\log \lambda_i = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p. \qquad (1)$$

In model (1) above, variables $X_1, \ldots, X_p$ represent meterological conditions (and possible interactions) based on either a single or interval based preceding lag and $\beta_1, \ldots, \beta_p$ their associated effects with β_0 representing the baseline null effect. For notation brevity the time index on the variables $X_1, \ldots, X_p$ is suppressed although as stated these variables are defined with single or interval based preceding lags.

For demonstration we consider two modeling approaches for daily counts of mosquitoes during the 1965 sampling at the Cambridge, Maryland, site. The first approach allows the effect of meterological variables to be realized over an interval time lag of consecutive days. Cross correlation maps are used to identify key meterological conditions, their timing, duration, and aggregate summary of association.

The second approach considers a traditional approach relating meterological variables restricted to lags at single points in time (a day) with mosquito vectors (Hacker et al. 1973a,b, Evans et al. 1987). Cross correlation plots are used to identify key meterological conditions and their time lags. More sophisticated techniques for modeling vector abundance certainly exist. These two approaches are compared primarily to demonstrate the utility of cross correlation maps as a graphical tool for visualizing time lagged associations and how that may impact modeling.

Statistical analysis

The two resulting models are primarily compared with visual inspection as to their ability to reproduce the observed dynamics in the mosquito population. Goodness-of-fit statistics based on Pearson standardized residuals:

$$X^2 = \sum_{i=1}^{N} \frac{(Y_i - \hat{\mu}_i)^2}{\hat{\mu}_i},$$

where N and $\hat{\mu}_i$ denote sample size and fitted counts respectively, and AIC, Akaike's Information Criterion (Akaike 1973) are also used to evaluate and compare models. Note X^2 has an approximate χ^2 distribution so that large values, greater than $N - p$, with p being the total number of model parameters, is an indication of over-dispersion (McCullagh and Nelder 1989). This chi-squared approximation however depends on the majority of fitted counts $\hat{\mu}_i$ being greater than 5. For the given data set this assumption is questionable and the X^2 statistic is therefore reported only as exploratory indicator of model fit.

RESULTS

A total of 1,341 female *Oc. sollicitans* were caught at the Cambridge, Maryland, site from June 1, 1965 to September 19, 1965. Time plots

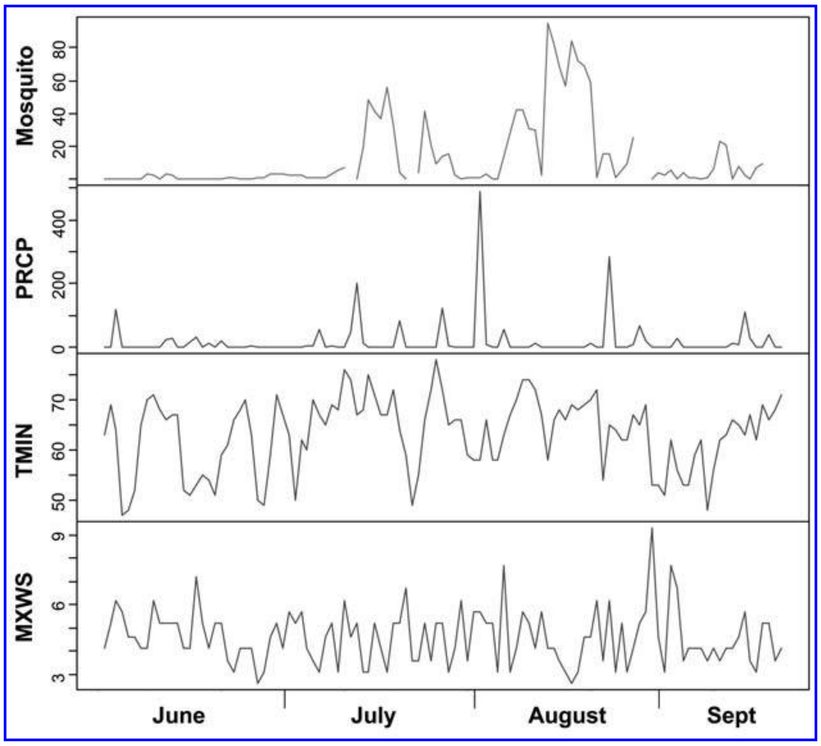

FIG. 1. Time plots of daily captures of female *Oc. sollicitans* (**top panel**) trapped at the Cambridge, Maryland site from June 1, 1965 to September 19, 1965. Stacked below are the corresponding series of total daily precipitation (PRCP) in hundredths of an inch, minimum daily temperature (TMIN) in degrees Fahrenheit, and maximum daily wind speed (MXWS) in meters per second. Line breaks in the top panel represents a total of 6 days with missing mosquito captures.

of trap counts indicate two major broods of *Oc. sollicitans* in July and August with only sporadic activity prior to that time (Fig. 1). The corresponding meterological series of total daily precipitation, daily minimum temperature, and daily average wind speed indicate no striking associations between leading meterological conditions and *Oc. sollicitans* captures.

To investigate less obvious associations, cross correlation plots for the $\log_e$ transformed trap counts and daily meterologic conditions were performed up to 4 weeks prior to sampling. Total daily precipitation (Fig. 2A) for single time lags extending back 4 weeks had its strongest association, a correlation of 0.21, at a lag of 12 days prior to trapping. The pattern of these single lag cross correlations with precipitation is biologically consistent with positive correlations during a one to three week lag, which is the typical length of the aquatic life cycle. The consecutive negative correlations close to the day of trapping is indicative of reduced trap efficacy due to rainfall.

The cross correlation map extends the cross correlation plot for for average daily precipitation because it examines all possible intervals for the same four week preceding time frame (Fig. 2B) with the axes defining the interval lags. For example, the correlation between $\log_e$ trap counts and average precipitation from 21 days to 4 days, which we represent by (21,4) and shown highlighted in Figure 2B, is 0.57. The map reveals consistently higher correlations (greater than 0.50) for total accumulated precipitation beginning three to four weeks out and extending into the week prior to trapping.

The cross correlation map is triangle shaped by design because time lag 1 is always greater than or equal to time lag 2. The correlations for intervals when time lag 1 is identical to time lag 2 (i.e., a single lag) are the diagonal of the triangle (Fig. 2B) and are the correlations displayed in the cross correlation plot (Fig. 2A).

Cross correlation maps for the highest minimum temperature and highest low tide are shown in Figure 3A,B. Strong associations for both appear at three to four weeks prior to sampling and extend into the week prior to trapping. For highest minimum temperature, strong associations are also evident extending

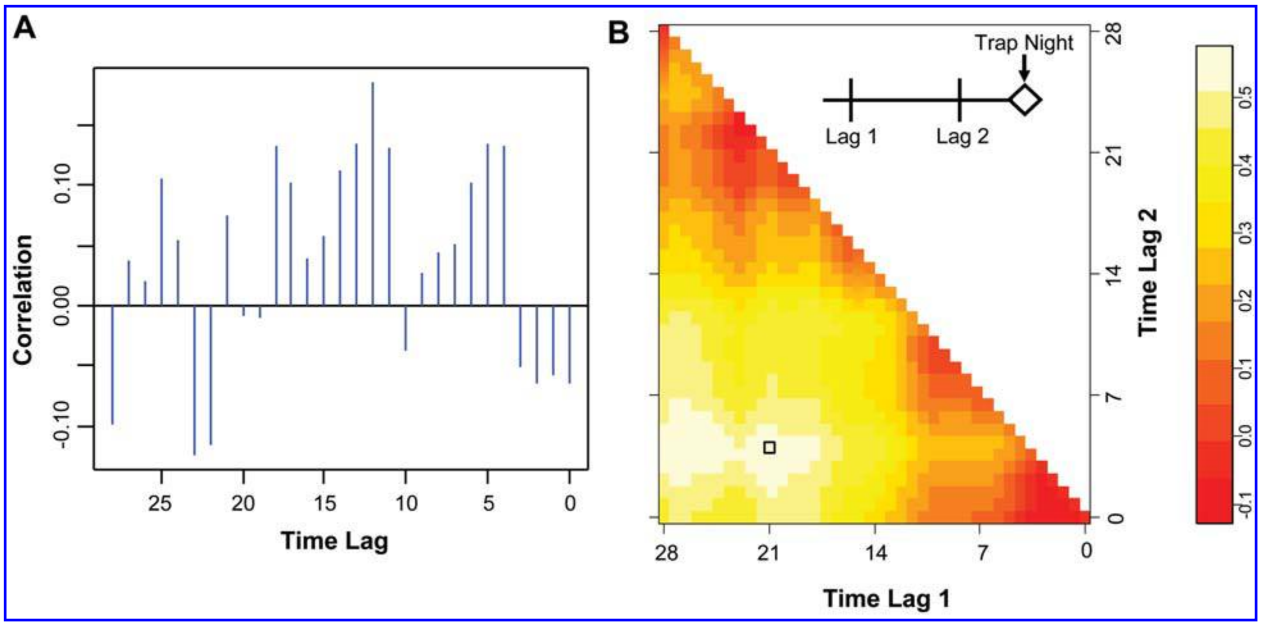

FIG. 2. (**A**) The cross correlation plot for $\log_e$ transformed female *Oc. sollicitans* daily captures and total daily precipitation. (**B**) A cross correlation map showing correlations between $\log_e$ transformed female *Oc. sollicitans* daily captures and average daily precipitation experienced within all possible interval lags. Shown highlighted is the correlation of 0.57 for average precipitation experienced during a 21 to 4 day preceding lag, represented as (21,4). Both plots include a four week preceding time frame.

from three to four weeks to only about the second week prior to trapping. Data can be aggregated over time using alternate summaries as part of exploratory data analysis. Figure 3C displays the interval lag cross correlations for minimum temperature but considers the average (instead of the highest) as the aggregate summary measure of association. Associations between average minimum temperature and mosquito counts are not as large as when highest minimum temperature is used (Fig. 3C vs. Fig. 3A) and, consequently, were not selected for the model.

As part of model building it is useful to be able to control for effects of previously included variables. The cross correlations for average maximum wind speed (Fig. 3D) represent partial correlations (Draper and Smith 1998), conditioned on associations of other variables. These were calculated by considering the added effect average maximum wind speed would have in a linear regression model for the $\log_e$ transformed counts that already included the interval lagged meterological conditions average precipitation (21,4), highest minimum temperature (25,0), and highest low tide (25,5). Evidence that trapping efficacy is affected by wind speed after controlling for biological factors is indicated by the stronger negative correlations experienced during or just prior to the day of trapping.

Cross correlation maps were used to select meterological variables, their interval lag structures, and aggregate summaries for inclusion in the Poisson regression model (1) (Table 1). Both maximum wind speed and precipitation for the day of trapping were included as trapping efficacy conditions. For the second modeling approach, which restricted variables to single daily lags, we considered the same meterological variables and chose the lag that yielded the maximum association as read off corresponding cross correlation plots (or equivalently diagonals of cross correlation maps). The final Poisson regression models for each approach also included all pairwise interactions among the main effects (Table 1).

Results from modeling the female *Oc. sollicitans* daily population dynamics for both approaches are shown in Figure 4. Visual inspection of these results favor the approach based on interval lag structures. The ability to better capture the two emerging states occurring in mid July and mid August is apparent as is the

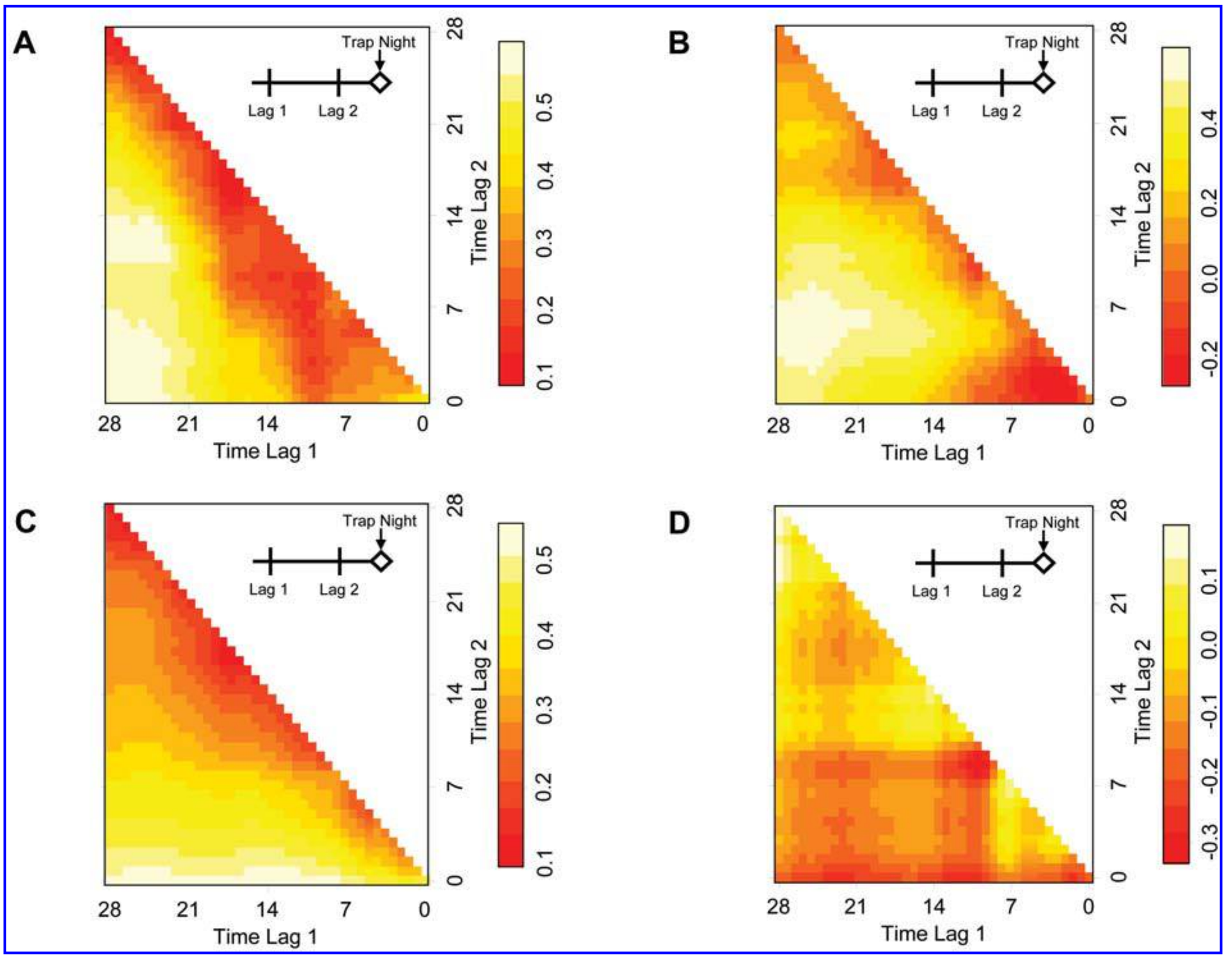

FIG. 3. Cross correlation maps for $\log_e$ transformed female *Oc. sollicitans* daily captures with highest minimum daily temperature (**A**), highest daily low tide (**B**), and average minimum daily temperature (**C**). (**D**) The map displays partial correlations for average maximum daily wind speed controlling for average precipitation (21,4), highest minimum daily temperature between (25,0), and highest daily low tide between (25,5).

striking ability to better reproduce the nonemergence of female *Oc. sollicitans* at the beginning of the season (June to mid-July). Further support is provided by the goodness-of-fit statistic, $X^2 = 633.9$ for interval lag based model and $X^2 = 2530.4$ for single time point lag model. Both models exhibit over-dispersion, but was far less severe, by about 75%, for the interval lag approach. The AIC for the interval lag based model was 958.3, an approximate 50% improvement compared to the AIC of 1990.3 for the single time point lag model.

DISCUSSION

Cross correlation maps were introduced as a tool for visualizing bivariate time lag associations where the effects of an environmental variable are allowed to extend over a time interval. This graphical method is a generalization of the commonly used cross correlation plots and includes information on single time lag associations as a special case. Cross correlation maps and variants on this idea were demonstrated to be effective for exploratory data analysis and statistical model building.

In exploring the association between daily captures of female *Oc. sollicitans* and leading meteorologic conditions, cross correlation maps revealed interval lag structures indicating both the timing and duration of these effects. Correlation coefficients for log transformed daily captures were approximately double in magnitude with interval based lags compared to their single daily lag counterparts. Importantly, these

TABLE 1. METEOROLIGICAL CONDITIONS, AGGREGATE SUMMARY MEASURES OF ASSOCIATION, TIMING, AND DURATIONS DEFINED VIA INTERVAL LAGS (LAG 1, LAG 2) FOR THE MAIN EFFECT VARIABLES INCLUDED IN THE POISSON REGRESSION MODELS

Daily meteorological condition	*Aggregate summary*	*Interval lag model (Lag 1, Lag 2)*	*Single lag model (Lag)*
Total precipitation	Average	(21,4)	12
Minimum temperature	Highest	(25,0)	5
Low tide	Highest	(25,5)	3
Maximum wind speed	NA	(1,1)	1
Maximum precipitation	NA	(1,1)	1

N/A, not applicable.

Aggregate summary measures of association do not apply to meteorological conditions defined over single daily lags (last column), including interval lags defined as single daily lags such as with maximum wind speed and precipitation.

results also are biologically consistent with the mosquito's life cycle, providing empirical evidence for what has long been conjectured regarding this species.

Flexibility in the use of cross correlation maps as applied to the *Oc. sollicitans* data were demonstrated in several ways. Different summary measures of environmental effects were explored, for example, stronger interval lag associations were revealed with the highest compared to the average minimum daily temperature (Fig. 3C vs. Fig. 3A). The partial association of wind speed on the log transformed daily captures conditional on the effects of precipitation, temperature, and tide (Fig. 3D) exemplified the relationship between wind speed and trapping efficacy.

Partial association analysis is a useful tool for variable selection in building statistical regression models and can be certainly applied to single time lag data as well via cross correlation plots. The model approach based on interval lag structures demonstrates a smoother fit (Fig. 4A) than the model based on a single point lag

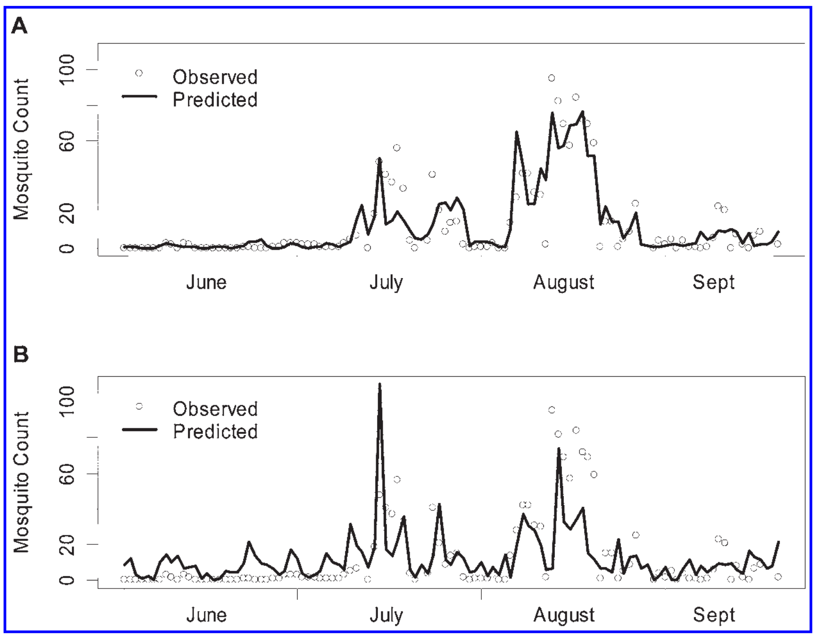

FIG. 4. Observed counts for female *Oc. sollicitans* daily captures trapped at the Cambridge, Maryland site from June 1, 1965 to September 19, 1965 versus predicted counts from Poisson regression models with meterological conditions allowed to extend over interval time lags (**A**) and restricted to single daily lags (**B**). Days with missing capture data are displayed with predicted counts from the respective fitted regression models.

structure (Fig. 4B). This is expected because the variability in the lagged environmental variables is reduced due to aggregation over a time interval. Although single time point lag models perform well for individual years, their lags may vary over time and space. Interval lag structures are more prone to remain fixed which is appealing in working towards a generalized time or space-time model.

The idea behind cross correlation maps (and cross correlation plots for that matter) is not restricted to using *correlation* as the measure of association. For example, the Poisson regression analysis might be better served by considering goodness-of-fit statistics like reduction in model deviance for generalized linear models or Akaikes Information Criterion (AIC). Partial associations based on these goodness-of-fit summaries then relate more directly to the variable selection process. These concepts are further explored in Shone (2005) with more comprehensive mosquito capture data.

ACKNOWLEDGMENTS

Support for this study was provided by grants from the U.S. National Oceanic and Atmospheric Administration Office of Global Programs Climate and Societal Interactions Project (NA16GP2631), the Defense Advanced Research Projects Agency (F3060201C0184), and the Johns Hopkins Malaria Research Institute. We also extend our sincere appreciation to the employees of the mosquito control section at the Maryland Department of Agriculture, including Cyrus Lesser, Stan Joseph, and Bob Berry, who collected and supplied the mosquito data. We also thank Thomas Yu who helped convert the data from paper to electronic format.

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