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The Impact of Weather Conditions on *Culex pipiens* and *Culex restuans* (Diptera: Culicidae) Abundance: A Case Study in Peel Region

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ABSTRACT Mosquito populations are sensitive to long-term variations in climate and short-term variations in weather. Mosquito abundance is a key determinant of outbreaks of mosquito-borne diseases, such as West Nile virus (WNV). In this work, the short-term impact of weather conditions (temperature and precipitation) on *Culex pipiens* L.–*Culex restuans* Theobald mosquito abundance in Peel Region, Ontario, Canada, was investigated using the 2002–2009 mosquito data collected from the WNV surveillance program managed by Ontario Ministry of Health and Long-Term Care and a gamma-generalized linear model. There was a clear association between weather conditions (temperature and precipitation) and mosquito abundance, which allowed the definition of threshold criteria for temperature and precipitation conditions for mosquito population growth. A predictive statistical model for mosquito population based on weather conditions was calibrated using real weather and mosquito surveillance data, and validated using a subset of surveillance data. Results showed that WNV vector abundance on any one day could be predicted with reasonable accuracy from relationships with mean degree-days >9°C over the 11 preceding days, and precipitation 35 d previously. This finding provides optimism for the development of weather-generated forecasting for WNV risk that could be used in decision support systems for interventions such as mosquito control.

KEY WORDS mosquito abundance, temperature, precipitation, climate, generalized linear model

Global warming is an unequivocal fact (IPCC 2007a) even at the regional scale in southern Ontario, as evidenced by increases of both the daily minimum and maximum temperature (Zhang et al. 2000). Global warming is already thought to be affecting human health (IPCC 2007b), via effects that include those on vector-borne diseases, such as West-Nile virus (WNV) and Lyme disease (Epstein 2000, Paz 2006, Reisen et al. 2008, Ogden et al. 2010).

West Nile virus (WNV), first detected in North America in 1999 (Nash et al. 2001), is transmitted primarily through the bite of infected mosquitoes. The activity of WNV in the Region of Peel, Ontario, Canada, was first reported in birds and mosquitoes in 2001 (Peel Public Health 2002). The following year, 2002, marked the year with the greatest number of confirmed human cases in this region, including two deaths (Peel Public Health 2002). Mosquito vector species are sensitive to temperature change and variation (Kunkel et al. 2006, Shone et al. 2006, Paz and Albersheim 2008, Walsh et al. 2008). It is helpful to understand the responses of WNV transmission to a changing climate for public health policies, and the public health also needs adaption to the effects of climate change on WNV risk. One such adaptation would be enhanced warning of high-risk periods for WNV by forecasting methods that have been used with some success elsewhere in the world for vector-borne diseases (Thomson et al. 2005, 2006; Ceccato et al. 2007). Recent efforts regarding forecasting arbovirus risk in North America include those of DeGaetano (2005), who used a multiple linear regression model to build a biometeorological model for *Culex* populations on a monthly time scale, and Trawinski and MacKay (2008) who used time series analysis techniques to forecast *Culex pipiens -restuans* populations on a weekly time scale. A weekly forecast model was also built by multiple linear regression techniques for *Culex tarsalis* Coquillett, a vector for western equine encephalitis virus, developed by Raddatz (1986). These early studies showed that it is helpful for forecasting the mosquito abundance by understanding how weather conditions affect the count of vector mosquitoes.

Culex pipiens L. and *Culex restuans* Theobald mosquitoes are two primary WNV vectors in southern Ontario (Peel Public Health 2002). They live in temperate regions, and immature life stages prefer water habitats with a high organic content (Turell and Dohm

The views expressed in this report are the views of the requester and do not necessarily reflect those of the Ministry of Health and Long-Term Care of Ontario, Canada.

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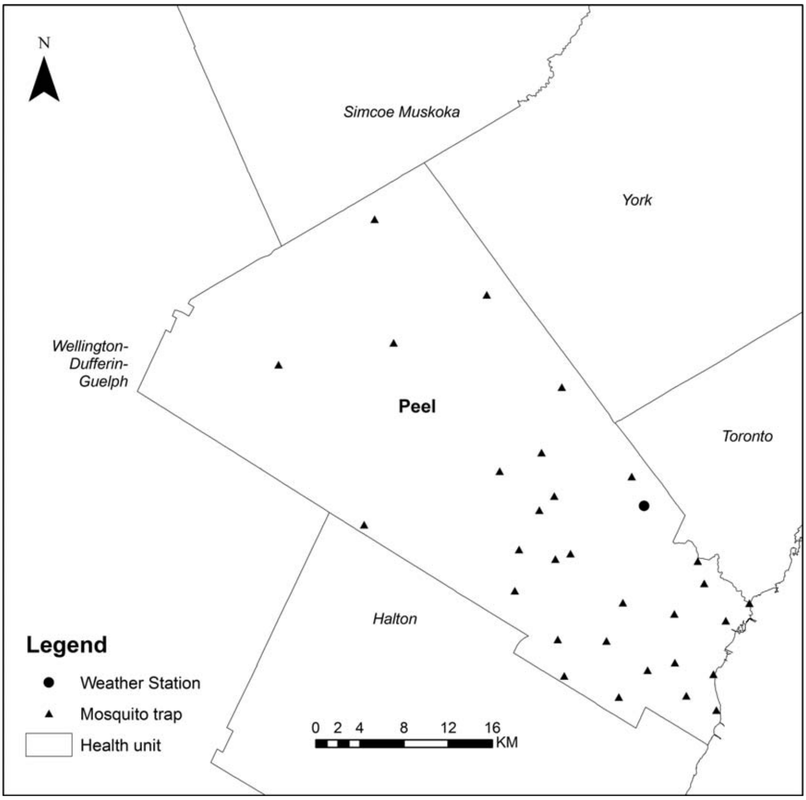

Fig. 1. Peel Region mosquito traps and weather station map. Triangles indicate mosquito trap locations, and solid circle indicates weather station at Pearson International Airport.

2005). It is difficult to distinguish the two species morphologically (DeGaetano 2005, Diuk-Wasser et al. 2006). For these two species collected in southern Ontario, some could be identified as *Cx. pipiens* or *Cx. restuans*, and some could not be identified. The undistinguished *Cx. pipiens* and *Cx. restuans* were put together in the mosquito surveillance dataset from Peel Region and therefore were grouped in our study as had been done previously (DeGaetano 2005, Kilpatrick et al. 2005, White et al. 2006, Trawinski and MacKay 2008).

Using the mosquito surveillance data and temperature and precipitation records, we developed a predictive statistical model for the vectors of WNV in the Peel Region using a generalized linear regression method.

Materials and Methods

The Region of Study. Peel Region is a municipality in southern Ontario on the north shore of Lake Ontario, between the City of Toronto and York Region extending from latitude 43.35°N to 43.52°N and from longitude 79.37°W to 80.00°W. The region comprises the cities of Mississauga and Brampton and the town of Caledon. It also contains portions of the Oak Ridges Moraine and the Niagara Escarpment (a United Nations Educational, Scientific and Cultural Organization World Biosphere Reserve), 3,270 ha of wetland (≈2.6% of land area), and 41,329 ha of farmland (≈33% of land area). There are four clear seasons in the region, as follows: a rainy cool (mean 10°C) spring from late March to mid-June, a hot (sometimes >32°C) summer from mid-June to late September, and a short fall season before a cold (average temperature between −3 and −6°C) and snowy winter that begins in late November.

Mosquito surveillance in Ontario was started in 2001 by the Ministry of Health and Long-Term Care (MOHLTC). The Peel Region Health Unit used the Centers for Disease Control miniature light trap (Service 1993) with both CO_2 and light to attract host-seeking adult female mosquitoes. Adult mosquitoes were trapped weekly from mid-June to early October (usually weeks 24–39), and the continuous observation for each trap started in 2004. The locations of the 30 mosquito traps were mapped by global positioning system in Fig. 1. Trapped mosquitoes were identified to species (except for some *pipiens* and *restuans*), counted, and tested for WNV by Brock University (year 2002–03), Entomogen (year 2004), GDG Environment Group (year 2005–08), and Cosray Laboratories (year 2009), respectively.

Except for year 2002, mosquito abundance in 2003–2009 was measured during a period of active larval

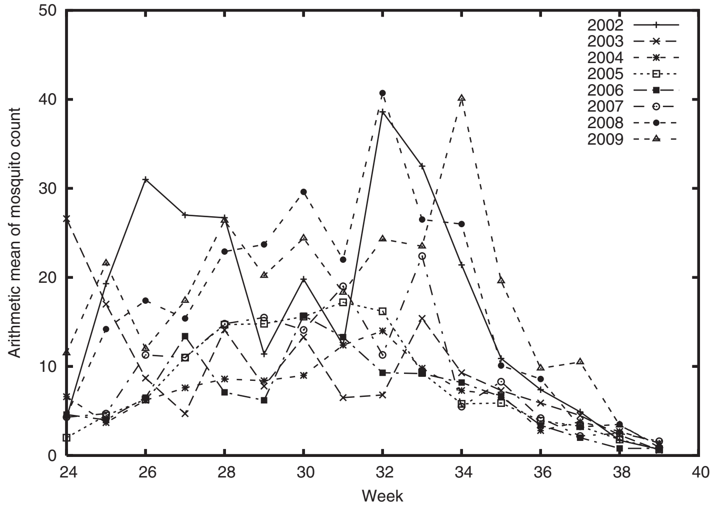

Fig. 2. The smoothed arithmetic mean of the *Cx. pipiens* and *Cx. restuans* mosquito count per trap night each week in Peel Region from 2002 to 2009. The horizontal axis is weeks during mosquito surveillance. Week 24 corresponds to around 10 June–16 June, and week 39 corresponds to around September 23–September 29.

control in catch basins and surface water sites (dominant by ditches and culverts or woodland pool). During each mosquito season, there were four rounds of larval mosquito control in catch basins by using either methoprene pellets/briquets or *Bacillus sphaericus*, and the schedule was almost the same for every year, not surveillance based. The larviciding in surface water sites was surveillance based and conducted by applying *B. sphaericus* and *Bacillus thuringiensis* variety *israelensis* (Peel Public Health 2009). Larviciding was not done, however, in 2002.

We used the average mosquito counts from 30 trap locations to represent the mosquito population at regional level. For each trap, the original count was smoothed over preceding and succeeding weeks: $W_j = (w_{j-1} + w_j + w_{j+1})/3$, where w_j is the original mosquito count in week j, and W_j is its smoothed value for the week that reduces random effects, such as moonlight, on capture probabilities (Service 1993). The weekly arithmetic means of mosquito counts, which were used to reduce the effect of outlier values, are presented in Fig. 2.

Preprocessing of the Mosquito Surveillance Data. The arithmetic mean of mosquito counts had a skewed distribution (Fig. 3), and examination of the relationships between the annual means and standard deviations (SD) indicated that the coefficient of variation (CV = SD/mean) can be treated as a constant (Fig. 4). Therefore, mosquito counts in Peel Region could be modeled by a gamma distribution (Hogg and Craig 1978, Hwang and Hu 1999). Furthermore, the distributions of the data were not significantly different from a gamma distribution, when applying the Kolmogorov-Smirnov test in *R*

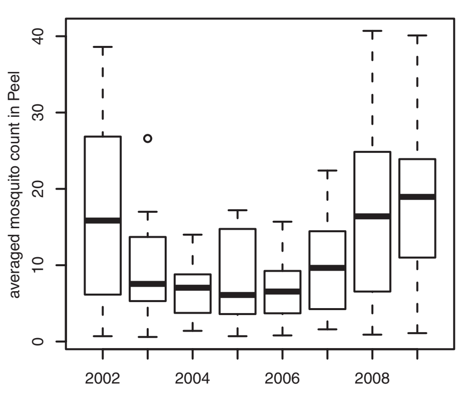

Fig. 3. A box and whisker plot (showing minimum, lower quartile, median, upper quartile, and maximum) of the arithmetic mean of mosquito counts per trap night per year in Peel Region in 2002–2009.

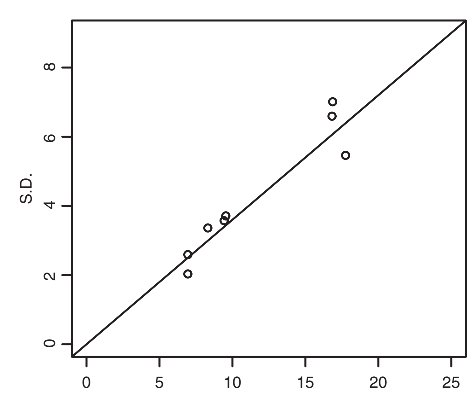

Fig. 4. The mean plotted against the SD of the arithmetic means of mosquito counts per trap night for each year from 2002 to 2009 in Peel Region.

(R Development Core Team 2005) ($P > 0.05$ for all years).

The gamma distribution is described by the formula:

$$\Gamma(\rho;\ \alpha,\ \beta) = \frac{(\rho/\beta)^{(\alpha-1)}e^{-\rho/\beta}}{\beta\Gamma(\alpha)},\ \rho,\ \alpha,\ \beta > 0, \qquad [2.1]$$

where ρ is the arithmetic mean of mosquito count per tarp night for Peel Region, α and β are shape and scale parameter, respectively. $\Gamma(\rho;\ \alpha,\ \beta)$ denotes the frequency (or probability) of the mosquito counts, which equals to ρ.

Assessing Effects of Weather on Mosquito Abundance. Although weather and environmental factors all likely contribute to variation in mosquito abundance, in this study we focus on the impact of temperature and precipitation, because the former affects rates of immature mosquito development and activity of adults, and precipitation determines, in part, the amount of larval habitat.

The surface temperature of the water, which is experienced by the immature mosquitoes, can be represented by the ambient air temperature, because the air and surface water temperature are often highly correlated on both short and long timescales, and the closest agreement is seen in summer (Livingstone and Dokulil 2001). Kothandaraman (1972) analyzed daily mean air and water temperature records and found that the air-water temperature relationship appears to be a stationary linear process and it is possible to predict water temperatures at a location from the ambient temperature records.

The data for daily maximum, minimum, and mean temperature and precipitation of Peel Region were obtained from Canada's National Climate Archive (www.climate.weatheroffice.gc.ca). There are three weather stations in Peel Region having both temperature and precipitation records available (Pearson Airport, Georgetown, and Orangeville). Although their locations were widely separated, temperature and precipitation data among these stations were highly correlated (data not shown). Therefore, we used the data from Pearson Airport station, which had no missing data, to represent the weather conditions for the Peel Region.

We used degree-days above 9°C (dd), below which immature *Culex* mosquito development is effectively arrested (Madder et al. 1983, Tachiiri et al. 2006), calculated as follows:

$$dd = \begin{cases} 0^0C & T_m \leq 9^0C, \\ T_m - 9^0C & T_m > 9^0C. \end{cases} \qquad [2.2]$$

The arithmetic means of daily dd (ddm) from 1 to 60 d before each collection was explored as explanatory variables for mosquito abundance at the time of collection. The arithmetic means of daily precipitation (ppm) from 1 to 60 d before surveillance also was explored as explanatory variables for mosquito abundance at the time of collection.

Modeling the Impact of Temperature and Precipitation on Mosquito Abundance. The regional average mosquito counts for 16 wk each year over 7 yr (2002–2008) were used for model calibration and validation ($n = 16 \times 7 = 112$ data points). The data for 2009 were used for validating model predictions. Because the mosquito count frequency had a gamma distribution, we used a generalized linear model, gamma-GLM, that accounted for this distribution (McCullagh and Nelder 1989) to analyze the mosquito abundance data. Because the coefficient of variation (CV = SD/mean) is constant (see Fig. 4), the shape parameter of the gamma distribution $\alpha = 1/CV^2$ is taken as constant. The GLM of mosquito count with weather conditions of temperature (ddm) and precipitation (ppm), as explanatory variables, is given by the following:

$$\log(E(\rho)) = \log(\mu) = g(ddm,\ ppm),\ \rho \sim Gamma(\alpha,\ \beta), \qquad [2.3]$$

where ρ is the average mosquito count per trap night on the regional level, which is assumed to satisfy a gamma distribution, α and β are the shape and scale parameters, respectively; $\mu = E(\rho) = \alpha\beta$ is the expectation of ρ. Considering the nonlinear impacts of temperature and precipitation conditions on mosquito abundance, g(ddm, ppm) is taken as a quadratic function of ddm and ppm:

$$g(ddm,\ ppm) = a_T ddm^2 + b_T ddm + a_p ppm^2 + b_p ppm + c, \qquad [2.4]$$

where a_T and b_T are coefficients related to temperature, a_p and b_p are coefficients related to precipitation, and the constant c is the baseline parameter when the impact of temperature and precipitation is ignored. For simplicity, interactions between ddm and ppm are not included because there is only minor change in the Akaike information criterion with or without this term.

The likelihood of a particular mosquito count value under given weather conditions is defined as folows:

$$L = \Pi_{k=1}^{n}\Gamma(\rho_k;\ \alpha,\ \beta_k), \qquad [2.5]$$

where n is the sample size, ρ_k is the observed mosquito count, α is the shape parameter that we take as a constant, and β_k is the scale parameter. The Simplex method (O'Neil 1971) was applied to estimate the parameters maximizing the likelihood function L.

The likelihood ratio test was used to detect the impact of the covariates. The test statistic is asymptotically χ_q^2 distributed under null hypothesis, with q being the difference in the number of free parameters in the two hypotheses (Cox and Hinkley 1974). The significance level is set as 0.5%, and the covariate that maximizes the test statistic is called the most significant covariate in this study.

Model Validation. Temperature and precipitation were used as predictor variables to build a predictive statistical model of mosquito counts in Peel Region, using the gamma-GLM model (2.3). The model was verified by "leave-one-out" cross-validation: a single observation from the original sample is taken as the validation data, and the remaining observations are

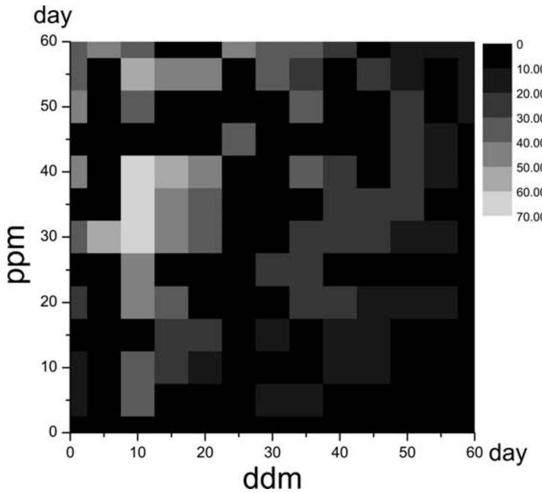

Fig. 5. The likelihood ratio test statistic using temperature (*ddm*) and precipitation (*ppm*) as covariates. The horizontal axis is the number of days preceding mosquito capture for *ddm*; the vertical axis is the number of days preceding mosquito capture for *ppm*. The scale in the contour map is listed to the right of the map.

used as the training data. This is repeated such that each observation in the sample is used once as the validation data. Then we used this model to predict 2009 mosquito abundance.

Results

Predictive Weather Conditions. For the temperature and precipitation, we used ddm_i and ppm_i for $i = 1,2,–60$ to run the simulations.

GLMs were constructed with ddm_i values for $i = 1, 2,$ to 60 d before surveillance and ppm_j values for $j = 1, 2,$ to 60 d before trapping. The likelihood ratio test statistic results using combinations of these values (i.e., $60 \times 60 = 3{,}600$ computations) are displayed as a contour map in Fig. 5, and individually for ddm_i and ppm_j in Fig. 6.

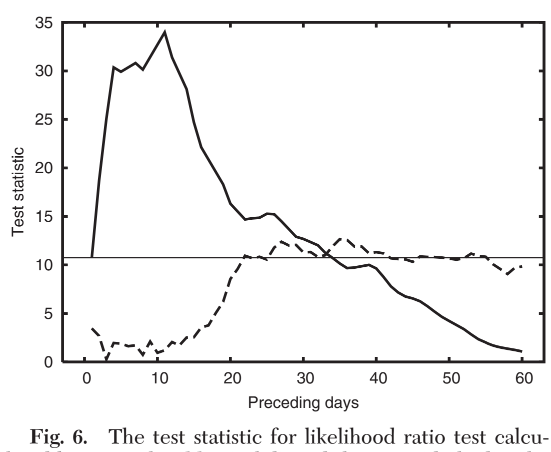

Fig. 6. The test statistic for likelihood ratio test calculated by using the *ddm* (solid) and the *ppm* (dashed). The straight gray line is the threshold level for significance (0.5%).

From these figures the temperature in the time window from 1 to 34 d before mosquito capture was a significant predictor of mosquito abundance, with the highest test statistic being achieved when the number of preceding days is 11, i.e., *ddm11.* A significant effect of precipitation is not seen until the time window is longer than 24 d. At *ppm35,* the test statistic reached its highest value, suggesting that the daily mean precipitation during the continuous 35 d before the mosquito capture had the most significant impact on the mosquito count.

Model Validation and Prediction Simulations. Using the most significant temperature (*ddm11*) and precipitation (*ppm35*) conditions as predictors, the gamma-GLM was trained using the data from 2002 to 2008, and its performance was verified by using leave-one-out cross-validation. The mosquito population in 2009 was predicted using temperature and precipitation conditions in 2009, and compared with observed trap counts. The result is shown in Fig. 7.

For the validation period (2002–2008), the simulated mosquito count closely approximated the surveillance data, except for 2002, before mosquito control was implemented. The time phases match each other, and a good agreement was seen for the peak times. The magnitude of the peak values in simulations was also close to the observations, although it was under- or overestimated. Mosquito count typically peaked in the middle of the season (end of July and beginning of August), a pattern that was consistent across most of the years.

Mosquito abundance in 2009 was predicted by the trained model using the preceding weather conditions (*ddm11* and *ppm35*). The timing and magnitude of the peaks of mosquito counts were well reproduced by the model simulation, although the population in the early half of the season was repeatedly underestimated.

The model was more accurate at predicting high values of mosquito counts than lower values (Fig. 8). Analysis of peak values for each year (Fig. 9) suggested that unusually high peak mosquito values could be the result of either unusually wet and normally warm weather (2008 and 2009), or unusually hot and dry weather (2002 and 2007). The mean values for *ddm11* and *ppm35* during 8 yr were 11.6°C and 2.2 mm, respectively. Temperatures of *ddm11* preceding the mosquito count peaks in 2008 (11.8°C) and 2009 (12.6°C) were close to normal, whereas rainfall (*ppm35*) was extremely high (7.1 mm in 2008 and 5.8 mm in 2009). For 2002 and 2007, the *ddm11* before the peak mosquito count was 3.5°C above the mean, whereas the rainfall was lower than normal: *ppm35* was 1.7 mm in 2002, and 1.2 mm in 2007. In years with low peak mosquito abundance (2003–2006), temperature was lower than 2002 and 2007, and the rainfall was close to normal. These observations suggested that very high mosquito abundance may occur when threshold values for the most significant temperature condition (*ddm11*) or precipitation condition (*ppm35*) are exceeded.

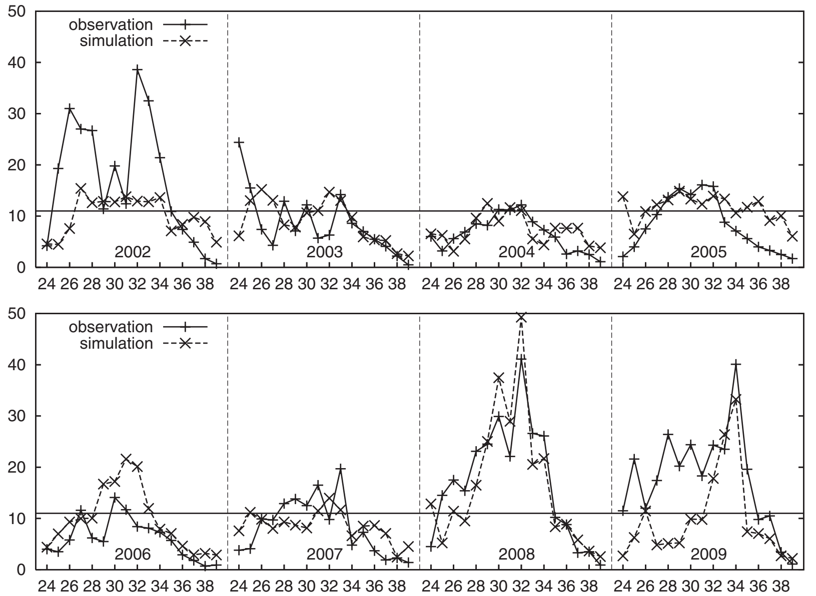

Fig. 7. The validation of the predictive statistical model for mosquito count in Peel Region in 2002–2008 and the prediction simulation in 2009. The solid line is the observed, and the dashed line the simulated counts per trap night. The horizontal line is the overall mean mosquito count per trap night in Peel Region.

Discussion

Using mosquito surveillance data for Peel Region, the linkage between mosquito abundance and preceding weather conditions (temperature and precipitation) was demonstrated using a gamma-GLM. This raises optimism for forecasting mosquito abundance using weather data. We also raise the hypothesis that particularly high mosquito abundance may be signaled when conditions exceed threshold weather conditions.

The distribution of mosquito count frequency in Peel Region was characterized by a gamma distribution, which has also been used in theoretical and experimental studies of other insect populations (Costantino and Desharnais 1981, Benton et al. 2002). Because a linear regression cannot be used on this skewed distribution, a GLM was applied to link the mosquito count and weather conditions, with weather explanatory variables approximated by quadratic polynomials. Through likelihood ratio analysis, we found the most significant temperature and precipitation predictors of mosquito abundance: the effect of precipitation was much lower than that of tempera-

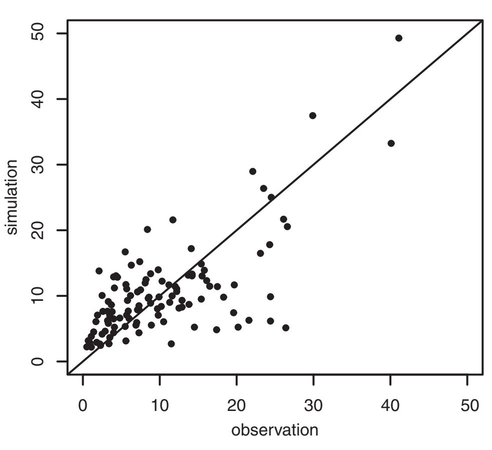

Fig. 8. The scatter plot of the observed and simulated mosquito counts per trap night in Peel Region in 2003–2009, with correlation 0.71. The horizontal axis is observed mosquito count, and the vertical axis is the simulated value using covariates ddm_{11} and ppm_{35}.

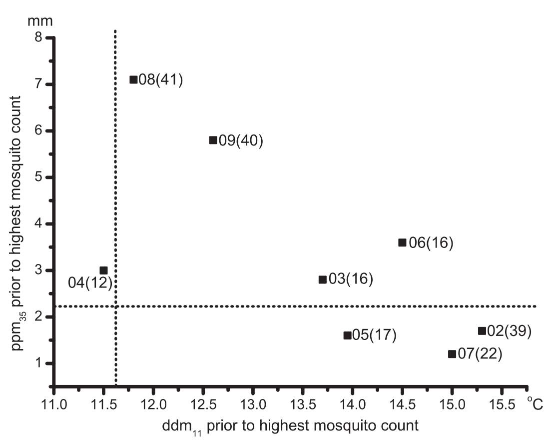

Fig. 9. The highest mosquito count (the number in the parenthesis) in each year and the corresponding weather conditions (temperature: *ddm11* and precipitation: *ppm35*) in observation. The vertical and horizontal dotted lines are the mean state of *ddm11* and *ppm35* during 2002–2009 surveillance seasons, respectively.

ture, the impact of temperature was seen in the period immediately before mosquito capture, and precipitation over a longer time period had the greatest effect. The gamma-GLM model using these two covariates in a simple form reproduced well both the phase and magnitude of the mosquito count, especially the peak values, in Peel Region.

Combining the mosquito count and the related weather conditions, we find that the hot and dry conditions just before sampling were positively related to increased counts of *Cx. pipiens-restuans*, which is consistent with other studies (Paz and Albersheim 2008). Also, high rainfall several weeks before sampling was positively related to *Cx. pipiens-restuans* counts under normal temperature conditions, because rainfall provided surface water for gravid females to lay eggs and larvae to develop (Jacob et al. 2009). These two types of extraordinary weather conditions can be used as indicators for taking action on mosquito control to prevent a disease outbreak by reducing the vector abundance.

The limitation of our study is the short length of the data record. A longer time data series would improve the parameter estimation, and more predictor variables and parameters could be included in the models. In the current study, only temperature and precipitation are involved (these are the two key elements in weather); other meteorological elements, such as humidity and evaporation, and some environmental factors, such as land cover and elevation, also affect mosquito abundance (Norris 2004, DeGroote et al. 2007). The time from egg to adult emergence also should be modeled, because this is nonlinearly associated with temperature: the developmental time from egg to adult mosquito can vary from 7 to 30 d at various temperatures and densities under field conditions (Madder et al. 1983). The fixed preceding time window (such as *ddm11*) used in the model is just a mean of the delayed response of the mosquito population to temperature. To improve the prediction, a variable time delay related to temperature should be modeled. The variation of the delay time can be studied by varying the time-window length of preceding weather conditions in the same framework as presented in this study.

Lastly, our study showed the importance of using different models in which larviciding is used, because comparing 2002 data with the other years, larviciding had a marked effect on mosquito abundance. Nevertheless, the data also show that even in the face of larviciding, mosquito abundance can be high if threshold temperature or rainfall conditions are exceeded, which can be expected in a future changing climate.

In conclusion, our study shows optimism for weather-based forecasting of *Cx. pipiens-restuans* mosquito abundance. Further studies are needed to explore whether other predictor variables, such as land cover index, can improve the prediction, especially for the early half summer in 2009, and whether the mechanism of the weather condition impacts on mosquito populations should be investigated by dynamical equations.

Acknowledgments

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