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Stochastic Models for Greenhouse Whitefly Flight Behavior based on Wireless Image Monitoring System Measurements

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ABSTRACT

One of the most harmful greenhouse insect pests is the *Trialeurodes vaporariorum* or most commonly known as the greenhouse whitefly. The easiest way to monitor the population of greenhouse whiteflies is by the use of yellow sticky paper traps. The insect count information from the traps can be used for analyzing insect behavior by constructing biological models. In this work, stochastic models describing the effects of temperature and the time of day on the flight behavior of greenhouse whiteflies were developed. Sticky paper images and temperature data were collected from an organic tomato seedling greenhouse by using integrated wireless imaging and environmental sensors. The greenhouse whitefly counts were determined by processing the images using an insect counting algorithm. From the results obtained, differences between the flight rates of the greenhouse whiteflies for different ranges of temperature were observed. The relationship was shown to be best fit using a double Weibull distribution function with an r^2 of 0.988 and mean squared error of prediction (MSEP) of 0.001. Using the model, it was found that the optimal temperature for flight of greenhouse whiteflies was around 20-26^{o}C. From the real-time counting data, different daily peak flight times were discovered. The peak flight rates were modeled using multi-peak probability distribution functions where it shows that the multi-peak Gaussian distribution has the best fit with an r^2 of 0.961 and MSEP of 0.006. The developed models can be used for developing insect pest control methods such as fuzzy temperature control and pesticide application scheduling.

Keywords: Biological model, insect population, insect flight, integrated pest management, yellow sticky paper

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INTRODUCTION

One of the most tackled issues in agriculture is the need for a drastic increase in world food production to meet with rapid population growth. As a result, there is a more urgent need to assist farmers in making decisions for insect pest management in order to protect their crops. The primary method to prevent insect pests is the use of pesticides. However, with careless application of pesticides, insect pests tend to develop immunity and it becomes more difficult to eliminate them. In addition, reduction of pesticide usage is also necessary for environmental protection. The only way to determine the optimal dosage and timing of spraying pesticides is through prior insect population monitoring (Lamichhane et al., 2016; Potamitis et al., 2017). The greenhouse whitefly, *Trialeurodes vaporariorum*, is one of the main transmitters of plant diseases. In general, the weakness of all whitefly species is their attraction to yellow color and light (Bonsignore, 2015). The three basic methods to monitor whitefly population include the use of sticky paper traps, pheromone traps, and light traps. Among the three methods, the use of sticky paper traps is the most efficient trapping method due to its availability and simplicity (Pinto-Zevallos & Vänninen, 2013). The number of whiteflies trapped on the yellow sticky traps can be counted by manual inspection to obtain their population density. However, this is very cumbersome and time-consuming. In order to simplify the process, automatic detection and counting of whiteflies through wireless cameras was achieved in our previous work (Rustia & Lin, 2017). In spite of this, the raw information gathered cannot be simply given to the farmers as they should be interpreted. With the use of mathematical models, the phenomena related to whitefly behavior can be quantified. The models can be used to obtain measures or indices that can guide them in taking actions for whitefly prevention and control (Wang & Song, 2009; Watt, 1961).

Furthermore, whiteflies are ectothermic or cold-blooded insects. This means that their activity and reproduction rate is greatly affected by warm ambient temperature (Nava-Camberos et al., 2001; Bonsignore, 2015). In fact, it was proven by Bonsignore (2015) through a controlled experiment that the best temperature for the reproduction of greenhouse whiteflies on tomatoes was around 25°C. On the other hand, the development rate of whiteflies declines at temperature ranges below 20°C and above 30°C (Nava-Camberos, Riley, & Harri., 2001). However, from recent studies, most mathematical models for whitefly population were derived from controlled environments. Obtaining inconsistent interpretations is highly possible due to the unpredictable climate change (Lamichhane et al., 2016). The only solution is to continuously develop models that are derived from new data.

The goal of this paper is to establish stochastic models based on collected data from wireless image and environmental monitoring system that can describe the flight behavior of greenhouse whiteflies. Using the modeling methods developed herein, combined with the monitoring system, a decision-making system could be designed for the use of farmers in integrated pest management.

MATERIALS AND METHODS

Data Collection

The greenhouse whitefly population count and temperature data were obtained from a wireless imaging and sensor network with 7 nodes installed in a 528.8 m^2 seedling greenhouse in Chiayi County, Taiwan. Each wireless node held a yellow sticky paper trap using an acrylic board installed 8-10 cm above the crops. The greenhouse grew lettuce, cabbage, and tomato seedlings which were some of the most common host plants for whiteflies. Spraying of pesticides, installation of pheromone traps, and other preventive measures were not applied to remove biases and effects to the experimental results.

Throughout this text, the number of whitefly detections is defined as the number of whiteflies trapped on the yellow sticky paper traps. It was automatically counted from yellow sticky paper RGB images processed using an image processing and deep neural network algorithm that has 97% accuracy for whitefly identification (Rustia et al., 2018). The temperature readings were collected using AM2301 temperature and humidity sensors (Aosong Electronics Co. Ltd., China) with resolution of 0.1°C and accuracy of ±0.5°C. The images were collected every 10 minutes from 7am to 7pm while the temperature data were read every 5 minutes all day. The selected image collection time was determined from previous experiments using the wireless imaging and sensor network in which it was observed that virtually no insects are detected during the night and early morning when light is not yet present (Rustia & Lin, 2017). The observations were conducted from July 2017 to March 2018 in which each observation period lasted for 2 weeks to enable replacement of the yellow sticky paper traps and avoid overcrowded sticky papers that would reduce the accuracy of the counting algorithm.

Biological Modeling and Data Analysis

In this work, non-linear stochastic models were proposed that can possibly best describe the effects of temperature and time of day in relation to the flight behavior of whiteflies. All plotting and data analysis were done using R version 3.4.3, coded in RStudio version 1.0.153, with the assistance of Table Curve 2D version 5.01.02 for automated equation fitting. R was used since it is a programming language purposely optimized for fast statistical analysis and scientific plotting, while Table Curve 2D was used to find different available equations that can be used for fitting the data sets.

Flight Rate and Temperature Model

Our previous experimental observations showed that temperature has a significant effect on the number of whiteflies detected on the sticky paper per day (Rustia & Lin, 2017). This proves that temperature can largely affect the reproductive rate and flight behavior of whiteflies. However, collecting more data further proved that the number of whiteflies trapped on the sticky papers followed a certain distribution that could best describe when the reproduction or flight of whiteflies might stop. Using the data obtained, Table Curve 2D was used to search for the best equations that can represent the distribution. Based on model simplicity and goodness of fit parameters, four-parameter log-normal, four-parameter Weibull, and double Weibull functions were selected. Other than that, the first two equations were already used several times for describing insect flight and reproduction behavior (Damos & Savopoulou-Soultani, 2012; Régnière et al., 2012) and have been proven to be suitable for most ectothermic insect species. Both functions can describe why at certain extreme low and high temperatures, insects cannot reproduce effectively. On the other hand, the double Weibull function, the product of a two parameter Weibull function and its complement, is a flexible function that is widely used for modeling biological phenomena (Haefner, 2005). Equations 1, 2 and 3 show the respective functions used for four-parameter log-normal, four-parameter Weibull, and five-parameter double Weibull function and their corresponding parameters.

Four-parameter log-normal function:

$$F = k_1 exp\left[-\frac{\ln(2)}{\ln(k_4)^2}\ln\left(\frac{(T-k_2)(k_4{}^2-1)}{k_3k_4}+1\right)^2\right] \tag{1}$$

Four-parameter Weibull function:

$$F = k_1\left(\frac{k_4-1}{k_4}\right)^{\frac{1-k_4}{k_4}}\left[\frac{T-k_2}{k_3}+\left(\frac{k_4-1}{k_4}\right)^{\frac{1}{k_4}}\right]^{k_4-1} e^{\left[-\left(\frac{T-k_2}{k_3}+\left(\frac{k_4-1}{k_4}\right)^{\frac{1}{k_4}}\right)^{k_4}+\frac{k_4-1}{k_4}\right]} \tag{2}$$

where:
F = flight rate (time^{-1})
T = temperature (°C)
k_1 = amplitude (max. of F)
k_2 = center (T value at max of F)
k_3 = width
k_4 = shape

Five-parameter double Weibull function (Haefner, 2005):

$$F = k_1\left(1-e^{-\left(\frac{T}{k_2}\right)^{k_4}}\right)e^{-\left(\frac{T}{k_3}\right)^{k_5}} \tag{3}$$

where:
F = flight rate (time^{-1})
T = temperature (°C)

k_1 = amplitude (max. of F)
k_2 = center (T value at max of F)
k_3 = width
k_4 = shape (1) (coefficient of variation of Weibull)
k_5 = shape (2) (coefficient of variation of Complemented Weibull)

In this work, the flight rate *F* is defined as the derivative of the whitefly count on the yellow sticky papers determined from the automatic image monitoring system described above. Specifically, it is computed from the difference of whitefly detection count at time *t* and *t-1*. The flight rate can partially describe the reproduction rate and growth rate of the whiteflies (Bonsignore, 2015). Additionally, the flight rate was normalized from 0 to 1 in order to generalize the model. Therefore, the k_1 values for all functions are always equal to 1 and k_2 is the peak temperature level at which there is the highest probability of whitefly flight. The width parameter k_3 and shape parameter k_4 of all the functions affect the area under the curve of the models, which reflects the actual number of flights on the specified temperature level. Moreover, the width parameter is used to control the skewness and kurtosis of the curve while the shape parameter affects the slope of the curve. Differently, the double Weibull function has two shape parameters which are used for its ordinary Weibull function and a complementary Weibull function with parameters named k_4 and k_5, respectively. The Levenberg–Marquardt method for nonlinear least square curve-fitting problems, more commonly known as the LM method, was used as a parameter estimation method to iteratively obtain the most optimal parameters for both functions (Press et al., 1992). However, due to the limitation in the range of the measured temperature data, extrapolated points were added by obtaining the flight rate at selected minimum temperature values as specified for temperatures at 9°C, 10°C, and 11°C. The collected flight rates and mean temperature values per day, fitted with all the functions, are shown in Figure 1.

The model presented in Figure 1 is based on the mean flight rates, with a unit time^{-1}, at each temperature *T*. The mean flight rates represent how fast flight can occur for each temperature point. The observed data shows that there are certain points at which whiteflies begin and stop emerging. After obtaining the median of the flight rate probability points, a threshold line was drawn to specify high and low probability. Specifically, at temperature levels between 15°C and 27°C, the probability of flight was high; outside this range, the probability was low. This observed phenomenon was also found to be true for other whitefly subspecies. As mentioned, Bonsignore (2015) found through a controlled experiment that the ideal temperature for the development of greenhouse whiteflies was around 25°C which is very close to the data collected in this work. Similarly, their work also showed that below 15°C, the developmental rates were close to 0. Additionally, visual inspection showed that the double Weibull function had the best fit compared to the other functions used, as can be seen from the low and high temperature ranges in which the very low probabilities of flight dropped to zero, unlike the two other functions that failed to show the low probabilities when the temperature range was extended to 5°C.

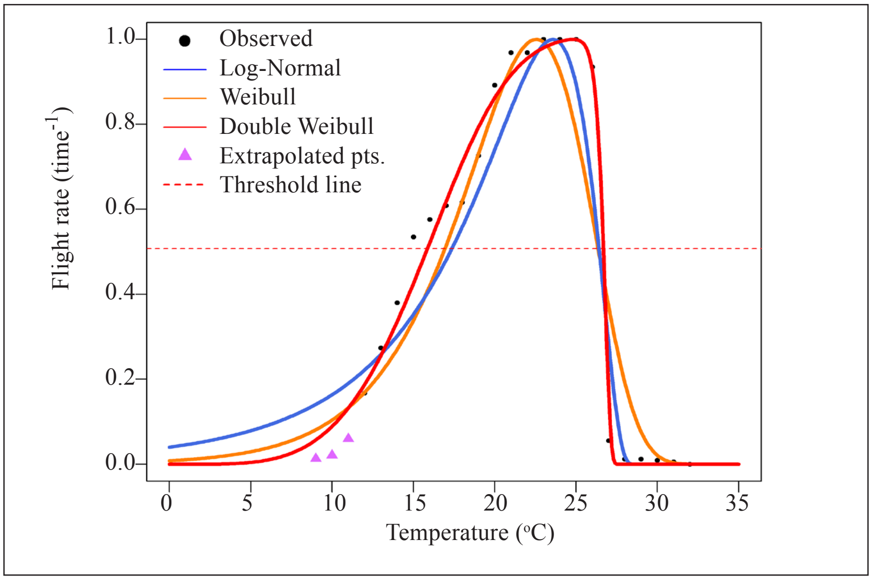

Figure 1. Observed normalized flight rates at each mean temperature level and fitted non-linear function curves. A dotted threshold line indicates the separation between low and high probability of flight based on the median of the flight rate.

Flight Rate and Temperature Model Validation

Furthermore, the models were tested based on several model validation parameters. Model validation was done in order to test the correctness and sensitivity of the models. Statistical validation was done through F-test for variance comparison and Welch two sample t-test for mean comparison with significance confidence level (α) of 0.05 for both tests. For goodness of fit testing, the traditional coefficient of determination, r^2, was used and adjusted r^2. The susceptibility of the models to error was tested using mean square error of predictions (MSEP) and Theil's U (Haefner, 2005), a statistic that measures the accuracy of the model by significantly increasing the errors. Table 1 shows a summary of the validation tests.

The statistical validation results in Table 1 show that the null hypotheses of the model, having different mean and variance from the observed values, are not rejected based on F-tests and T-tests. Therefore, it means that the three models were not significantly different according to the data derived from the experiments. Additionally, the coefficient of determination values show that the models are suitable for showing the trend of the observed values and are robust enough to accept new observations without losing the

Table 1
Evaluation summary of flight rate and temperature relationship models

Parameter	Weibull	Log-Normal	Double Weibull
F-test F value (α>0.05, df=20)	0.018	0.017	0.016
Paired T-test T value (α>0.05, df=20)	-5.162	-4.845	-4.822
Coefficient of determination, r^2	0.891	0.925	0.988
Adjusted r^2	0.777	0.847	0.976
Theil's U	0.102	0.086	0.032
MSEP	0.016	0.011	0.001

trend information. However, the three models differ greatly in terms of adjusted r^2 values, signifying that the double Weibull model can successfully predict the observed values, and better in comparison to the other two; even the number of predictors was decreased. Theil's U and MSEP values of double Weibull show that it is more robust and resistant to error compared to the other two models.

The model validation results prove that the models can also be used as a reference at which temperature levels whitefly flight or reproduction can possibly be prevented. It also proved that integrating environmental sensors into the imaging system can successfully collect data that can accurately describe the whitefly flight behavior as affected by temperature; the results match other controlled experiments.

Flight Pattern Model

Another bit of valuable information that can be obtained from the whitefly count collected is the probability of flight in correspondence to the time of day. From our previous observation results, the change in insect pest count has some possible correlation to the time of day, most especially in relation to light intensity (Rustia & Lin, 2017). It appears that insects, similar to human beings, have a similar daily activity pattern in which they are more active during the day, especially at noon, and before the evening. During these peak times, our data showed that light intensity had its highest change in values during those times. This was similarly observed in a research by Jha et al. (2009) which showed that chilli thrips were most active several times of the day. This was also proven from a research which showed that insects had a tendency to exhibit poikilothermic behavior, which meant they would need light to provide heat and prepare their muscles before flying (Ribak et al., 2016; Liang et al., 2010). Therefore, this work also aims to develop a model that can approximate the time of day when the whiteflies will take flight.

One of the ways to discover the time of day the whiteflies might begin to fly is to investigate the number of whiteflies detected per hour on the yellow sticky paper traps. The derivative of the insect pest counts per hour were computed to obtain the peaks that can indicate the times of day the flight rate of the whiteflies are at its highest. At first glance, the raw data show that the hourly flight rate of the whiteflies can possibly be described by using logistic curves. However, it can also be noticed that during some days there are multiple normalized flight rate peaks. The results obtained match previous researches that discovered multiple peaks during different times of day (Jha et al., 2009). Therefore, it shows that there are instances that the logistic curve function might not be an appropriate model to accurately describe the whitefly flight behavior. To solve this problem, multi-peak distribution models were used in this work.

Two multi-peak distribution model functions were compared: Gaussian probability density function and logistic probability density function. The formula and corresponding parameters of the said functions are shown in Equation 4 and 5:

Multi-peak logistic probability density function:

$$F = \frac{e^{-\frac{(t-\mu_1)}{\sigma_1}}}{\sigma_1(1+e^{\frac{(t-\mu_1)}{\sigma_1}})^2} + \frac{e^{-\frac{(t-\mu_2)}{\sigma_2}}}{\sigma_2(1+e^{\frac{(t-\mu_2)}{\sigma_2}})^2} + \cdots \frac{e^{-\frac{(t-\mu_i)}{\sigma_i}}}{\sigma_i(1+e^{\frac{(t-\mu_i)}{\sigma_i}})^2} \tag{4}$$

where:
F = flight rate (time^{-1})
t = time
μ = mean
σ = standard deviation
i = logistic function number

Multi-peak Gaussian probability density function:

$$F = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t-\mu_1)^2}{2\sigma_1{}^2}} + \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t-\mu_2)^2}{2\sigma_2{}^2}} + \cdots \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t-\mu_{i1})^2}{2\sigma_i{}^2}} \tag{5}$$

where:
F = flight rate (time^{-1})
t = time
μ = mean
σ = standard deviation
i = Gaussian function number

Equation 4 and 5 expresses the sum of multiple logistic and Gaussian probability density functions, respectively. The number of functions for each model may be tuned depending on how the system should be described and it corresponds to the number of peaks in the model. The mean of both model functions are used for determining the location of the peaks and the standard deviation controls the amplitude of each peak. The multiple logistic function model is very useful for analyzing systems that have more than one phase of logistic growth, which is also appropriate to describe the data gathered, rather than a single logistic growth curve (Meyer, 1994). On the other hand, the multiple Gaussian function model or often called as Gaussian Mixture Model (GMM) is one of the best general models notably used for biometric systems, speech recognition, and applications that make use of multiple peak detection (Reynolds, 2015). To generalize both models, the mean observed hourly flight rates of all the experiments were computed. The averaged data were fitted using Equations 4 and 5 and parameters were optimized using the LM method. Model fits comparing the two multi-peak models are shown in Figure 2.

A visual inspection of Figures 2a and 2b shows that the fitted three-peak Gaussian model can better describe the hourly flight rate pattern of the whiteflies compared to the fitted three-peak logistic model. It can also be seen in Figure 2a that the sources of fitting error in using three-peak logistic model is that the troughs at around 10:00 and 15:00 were exaggerated and some under-fitting occurred during the afternoon and evening periods. While on the other hand, the three-peak Gaussian model was able to define the troughs properly and there were less prediction errors on the troughs. Using the two multi-peak fitting methods, the most possible times of day, specifically at around 8:00, 12:00, and 16:00, were predicted and proves that the whiteflies do follow a certain optimal flight schedule. One possible reason for the three-peak activity phenomenon is that the changes in environmental conditions may possibly be highest at the peaks. This is because the change in environmental condition causes the whiteflies to fly and search for a more ideal place to stay (Nava-Camberos et al., 2001). The model can be used as a reference to further understand the flight behavior of the whiteflies. This also proves that the imaging system

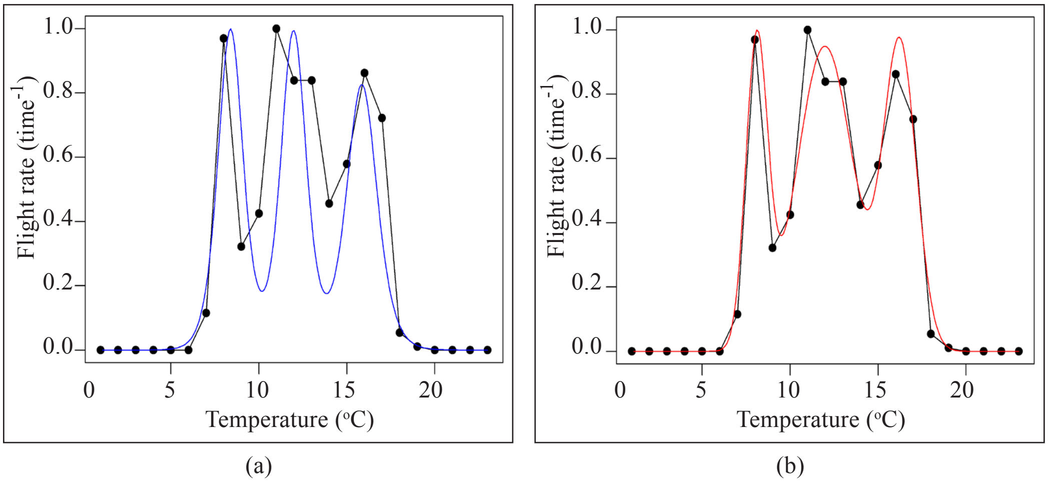

Figure 2. Mean hourly flight rates for all experiments and the corresponding fitted models using (a) summed logistic functions and (b) Gaussian Mixture Model

can be used to discover more about the flight behavior not only of whiteflies, but also of other insects, in a more systematic way. However, it is highly recommended to correlate the flight rate pattern to the environmental conditions to know the exact reasons for the phenomena observed.

Flight Pattern Model Validation

The flight pattern models were validated using similar validation methods to those applied in Table 1. The validation methods were done individually for each model as shown in Table 2.

Table 2 shows that the three-peak Gaussian model has better model predictions compared to the three-peak logistic model based on F-test. The T-test T value results show that the prediction results of the three-peak Gaussian model are more significant. From the statistical tests, high correlation and low prediction errors, it clearly shows that the three-peak Gaussian function model outperformed the three-peak logistic model. The validation results obtained showed that the three-peak probability density function models are proven to be generalized models that can be used for understanding the flight behavior of the whiteflies in relation to the time of day. As future work, multivariate analysis can be done to make the prediction method more holistic by including the effects of the environmental conditions.

Table 2
Evaluation summary of hourly flight rate models using the three-peak logistic function model and the three-peak Gaussian Mixture Model

Parameter	Three-peak logistic	Three-peak Gaussian
F-test F value (α>0.05, df=20)	1.356	1.035
Paired T-test T value (α>0.05, df=20)	0.537	-0.124
Coefficient of determination, r^2	0.719	0.961
Adjusted r^2	0.424	0.919
Theil's U	0.221	0.076
MSEP	0.039	0.006

RESULTS AND DISCUSSION

Model Testing and Application

Using the model in Figure 1, a threshold line can be used as a reference to simply determine the temperature ranges at which there is a high or low probability of whitefly flight. From the raw observations, it can be seen that there were least detections for temperature levels higher than 27°C and below 17°C, as shown in Figure 3.

Figure 3 is based on the total daily whitefly detections per experimental period (every 2 weeks) and the mean temperature on the specified period. The red marked experimental periods indicate that the mean temperature in that period is higher than 27^{o}C. On the other hand, experiments with mean temperatures of 15°C to 26°C are marked with blue. It can be proven in Figure 3 that the model developed in Figure 1 can be used to determine thresholds in which whitefly flight is low or high at specific mean temperature points. Additionally, it can be seen in Figure 3 that for a 15-day experiment, the increase in whitefly counts are quite constant, depending on the mean temperature in that period. Otherwise, if the mean temperature is inside the optimal flight temperature range, sudden increases in whitefly counts were observed. This shows that temperature changes also have a lot of potential effect on the whitefly flight; however, this effect should be analyzed deeper by developing more models that can describe the effects of temperature change to the whitefly flight, and can be used for future improvement of this work.

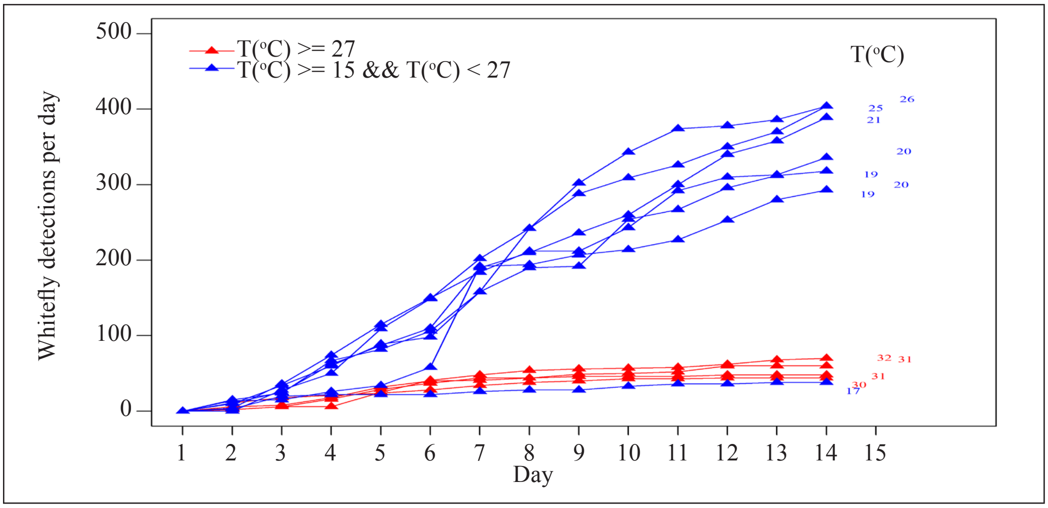

Figure 3. Number of whitefly detections detected per day in each experiment in relation to mean ambient temperature. The mean temperature for each experimental period are shown at the end of each line

CONCLUSION

In this work, different models were developed to further understand the flight behavior of greenhouse whiteflies using information obtained from a wireless image monitoring system. Two models were presented based on: flight rate in relation to temperature and hourly flight rate. The flight rate vs. temperature model was able to describe the phenomenon with an r^2 of 0.976. Using the model, it was found that the optimal flight temperature range for the whiteflies is around 20-26°C. The hourly flight rate model, using a multi-peak Gaussian model, was able to accurately show the possible peak rates for flight of the whiteflies with an r^2 of 0.961. However, it is recommended to include the effects of other environmental parameters, such as light intensity and humidity, to the models to further understand whitefly flight behavior. The models developed herein may be used as references for possible pesticide application scheduling and environmental control. In conclusion, this work can be used for real-time entomological behavior analysis and integrated insect pest management.

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