Population Dynamics of Mosquitoes (Diptera: Culicidae) in their Larval Stage: Relationship with Some Climatic Variables through Mathematical Modeling in Villa Clara, Cuba

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Abstract

Emerging and re-emerging diseases are the health problems have aroused interest world. This work to determine the influence some meteorological variables exert in the larval populations of culicids, by means of the mathematical modeling in the province Villa Clara, Cuba. Regressive Objective Regression (ROR) the following variables as responses: general and specific larval densities, and as explanatory variables: relative humidity, temperature, precipitation, cloudiness, mean wind speed and atmospheric pressure. The real and predicted value was plotted for the province. The analysis of variance corresponding time series for the General Larval Density (GLD) and the Specific Larval Density (SLD) the province of Villa Clara and in three municipalities (Ranchuelo, Sagua la Grande and Santa Clara), the correlations were designed between the predicted and real value of meteorological variables. General and specific larval densities showed a cyclical and seasonal behavior, with the high values from May to October, coinciding with the rainy period in Cuba. Temperature, relative humidity, mean wind speed and atmospheric pressure proved to be excellent predictors of population dynamics of mosquitoes with entomoepidemiological importance and; therefore, for surveillance mosquito borne diseases in both human and animal populations. Predictive models for general and specific larval densities based on meteorological variables allowed the population dynamics of mosquitoes, in both urban and rural ecosystems, and their impact on the risk of disease transmission, thus allowing better predictive scenarios to be developed and supporting the implementation of better control strategies.

Keywords: General Larval Density (GLD); Specific Larval Density (SLD); Mathematical Modeling; Mosquitoes; Climate Variables; Villa Clara

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Int J Zoo Animal Biol

Abbreviations: GLD: General Larval Density; SLD: Specific Larval Density; UPLVA: Provincial Unit for Surveillance and Vector Control; MT: Maximum Temperature; AT: Average Temperature; MRH: Maximum Relative Humidity; ARH: Average Relative Humidity; AP: Atmospheric Pressure; AWS: Average Wind Speed; ROR: Regressive Objective Modeling.

Introduction

Emerging and reemerging diseases are health problems which have significantly increased worldwide during last year's [1-3]; many of them are considered catastrophes resulted from their high morbidity and/or lethality as well as their negative economic impact on the health sector, tourism, industry and trading [4-6]. The changing epidemiology and predisposing factors for the responsible for the dramatic resurgence of such diseases are complex since a large proportion are zoonosis [7-10]. Furthermore, global and/or local demographic, social and environmental changes have led to the spread of infection to humans [11-13].

Global warming and the intensification of extreme meteorological disturbances, have brought spatiotemporal changes on the behavior of vectors and the diseases they transmit [14-17]. Meteorological conditions are considered one of the most important factors related to the spread of vector borne diseases, the clematis variables with the most significant influence are temperature, humidity and rainfall [18-20]. Nevertheless, other determining factors contribute to the appearance of major epidemic outbreaks caused by local levels of socioeconomic development, the increase in human mobility and trading, urbanization and deforestation [8,16,21].

Alongside tropical and subtropical regions, vector borne emerging and reemerging diseases affect millions of people yearly [22-25]. Among vectors, culicids are the ones of biggest hygienic-sanitary importance because are responsible for the maintenance and transmission of pathogens causing Malaria, Dengue, Chikungunya, Zika, Yellow Fever, West Nile Fever, and Lymphatic Filariosis [26-31].

Malaria is the main parasitic disease worldwide [31,32], it caused 429,000 deaths in 2015. About 90% of malaria-related global deaths occur in Africa, 70% of them in children under five years old [31,32]. Dengue has spread during last decades and still the worst arboviral disease [3,33,34], Chikungunya and Zika have emerged recently [35-39]. In the Americas, Yellow Fever remains a persistent heath threat 4,066 cases and 58% lethality between 1985 and 2012 [30,31]. An outbreak affected 295 people (72% lethality) in Brazil from December to February 2017 [28,40]. In Africa, 150 Yellow Fever outbreaks were reported between 1980 and 2012, and 200,000 cases occurred globally [27,28,30,41].

Climate is a key factor determining temporal and geographical distribution of arthropods and their life cycles, and therefore evolution of associated arboviruses, as well as the efficiency they are transmitted by culicids to vertebrate hosts [8,10,11,20,33]. As vector reservoirs are susceptible to seasonal changes and climatic conditions and the transmission dynamics of arboviral diseases are interlinked [42-44]. The impact of climate on vector borne diseases might be mitigated by surveillance systems with early warning for epidemic outbreaks, thus reducing disease impact [17,20,34,43].

In Cuba, the emergence and reemergence of arboviral infections are a health problem as there is a tendency to increase the number of cases as well as the populations of vector organisms [9,10,45-47]. Although meteorological variables are determinant in the transmission of arboviral diseases, in Cuba there are few studies on the effect of these variables on larval density of culicids with entomoepidemiological importance.

Therefore, this research was undertaken to determine the influence of meteorological variables on population dynamics of mosquito larval stages through mathematical modeling in Villa Clara province, Cuba.

Materials and Methods

Study Area

The investigation was carried out in all 13 municipalities of Villa Clara province, Cuba, The province, limits to the East with Sancti Spíritus province, to the West with Matanzas province, to the South with Cienfuegos province and to the North with the Atlantic Ocean; its capital and most populated city is Santa Clara (Figure 1).
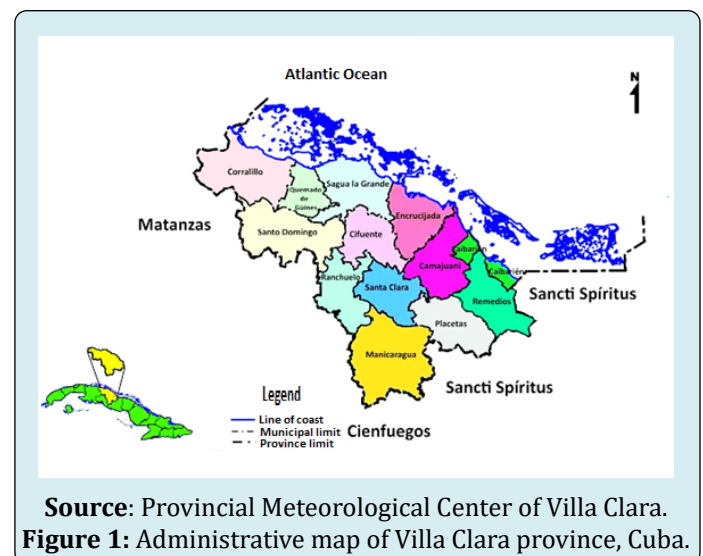
Source: Provincial Meteorological Center of Villa Clara.
Figure 1: Administrative map of Villa Clara province, Cuba.

The Provincial Unit for Surveillance and Vector Control (UPVLA) registered 316,370 houses and/or establishments in the general universe, where 236,391 (74.7%) belong to the urban area. These places cumulate approximately 1,581,850 tanks intended for water storage that provide favorable conditions for the breeding, proliferation and dissemination of culicids. In the province were identified, 304 permanent and 218 temporal culicid.

Survey Design

This retrospective study based on documentary review of statistical records and archives existing from 2007 to 2017 at UPVLA, at the Provincial Department of Health Statistics and the Provincial Meteorological Center of Villa Clara. This step revealed the entire entomological history of the monthly reports of all permanent (n=304) and temporal (n=218) conceived in the urban area of the 13 municipalities, and reached all permanent (n=304) and temporal (n=218) hatcheries spread in the urban area of 13 municipalities. The meteorological variables data (i.e. Maximum Temperature (MT), Average Temperature (AT), Minimum Temperature (MT), Maximum Relative Humidity (MRH), Average Relative Humidity (ARH), Minimum Relative Humidity (MRH), Provincial Precipitation (Prec.), Atmospheric Pressure (AP), Average Wind Speed (AWS) and Cloud cover (Cloud) comprised five meteorological stations located in Santa Clara, Manicaragua, Caibarién, Santo Domingo and Sagua La Grande.

The mosquito larvae collection was performed by the bucket method [48], later larvae were identified under a MSB-9 stereo microscope following specialized keys [49-52] taking into account all later variations in the systematics and taxonomy of culicids [53-55].

Calculation of Larval Density (LD)

The calculation of General Larval Density (GLD) and Specific Larval Density (SLD) of *Anopheles* mosquitoes followed the formula:

$$LD = \frac{L}{N \, X \, F}$$

Where;

LD = Larval Density,
L = Total of collected larvae,
N = Number of buckets,
and F = Fraction, a constant which is equal to 0.01 in 10 cm diameter buckets, as the constant is the bucket diameter square expressed in square meters.

Information Analysis

The surveillance data was organized in Windows Excel by the variables: years, months the reported general and specific larval densities. Then, were calculated time series and tendencies for each of the variables at the municipal and provincial levels.

Mathematical Modeling

The prediction model was fitted using a Regressive Objective Modeling (ROR) [52,56], where the focality of *Ae. aegypti* was the Response Variable and the meteorological variables were the Explanatory Variables. The data was processed using Pearson and t Student correlations as statistical significance tests in the statistical package SPSS ver. 13.

As a first step for the ROR prediction were created the dichotomous variables DS, DI and NoC, where:

NoC: Number of cases,
DS = 1, if NoC is odd,
DI = 0, if NoC is even,
When, DI = 1, DS = 0 and vice versa.

Subsequently, was executed the corresponding Regression analysis module on the statistical package SPSS version 19.0 (IBM, 2010), specifically the ENTER method where the predicted variable and the ERROR were obtained.

Then the ERROR variable auto correlograms were obtained, with special attention on the maximums of the significant partial autocorrelations (PACF). The new variables were then calculated according to the PACF significant Lag. Finally, these regressed variables were included in the new regression in a process of successive approximations until obtaining a white noise in the regression errors, delays of one year in advance were used for atmospheric pressure as recommended by other authors for climate indexes [52,56].

Results

The Provincial ROR Model

The combination of delays 1, 2 and 6, showed a perfect model for each of the municipalities. The 100% variance was explained, with a practically imperceptible standard error; the Durbin Watson statistic indicates there is no information on the residuals, since a perfect model was fitted (Table 1).

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Model	R	R^2	Corrected R^2	Estimation typical error	Durbin-Watson
1	1.000[a]	1	.	.	1.268

Table 1: Summary of the ROR model for Villa Clara province.
a. Prediction Variables: LAG6Foci, DI, LAG1 Foci, LAG2 Foci.
b. For regression through the origin (the model with no intersection term), R2 measures the proportion of the variability of the dependent variable explained by the regression through the origin. The comparison with R2 is not possible in models that include an intersection.
c. Dependent Variable: Province; d. Linear regression through origin.

The model visualized in Table 2 shows the coefficient for the different model parameters. This depends on the number of outbreaks 1, 2 and 6 years ago, where the tendency (NoC) was extracted from the model, so there is stability in collecting the provincial data.

Model		Non-standardized coefficients		Typified coefficients	t	Sig.
B		Typical error	Beta			
1	DS	14114.7	0	1.4	.	.
	DI	12952.32	0	1.049	.	.
	LAG2Foci	-0.546	0	-0.574	.	.
	LAG1Foci	-0.886	0	-0.917	.	.
	LAG6Foci	0.875	0	0.685	.	.

Table 2: Coefficients obtained according to ROR methodology for the province.
a. Dependent Variable: Province; b. Linear regression through origin.

	Minimum	Maximum	Mean	Typical deviation	N
Predicted value	4497	9749	7601	1999.6683	5
Residual	0	0	0	0	5
Typical predicted value	-1.552	1.074	0	1	5
Typical residue	.	.	.	.	0

Table 3: shows the residuals statistics for predicted value and residual.
a. Dependent Variable: Province; b. Linear regression through origin.

In the provincial model the predicted value showed an excellent coincidence with the real value from 2013 to 2017, then the forecast for 2018 remain similar to the previous year (Figure 2).
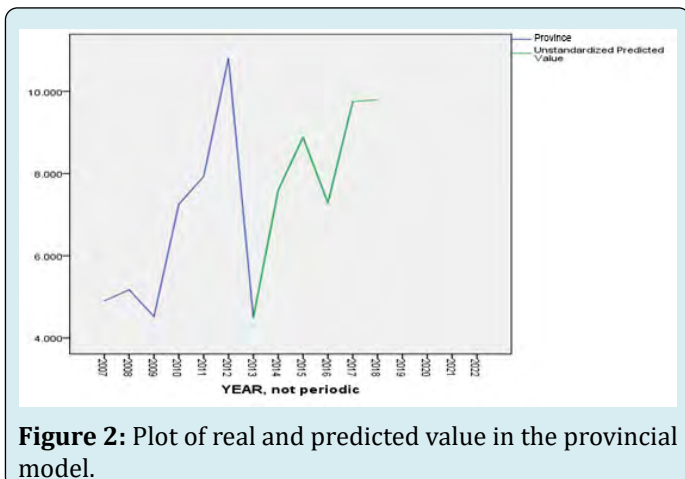

Figure 2: Plot of real and predicted value in the provincial model.

Analysis of Variance

Since the residuals are zero, the analysis of variance for the General Larval Density (GDL) indicates that the Fisher's F cannot be determined (Table 4).

Model		Sum of squares	gl	Mean square	F	Sig.
1	Residual regression	3.05E+08	5	60,971,099,200	.	.[a]
		0	0	.		
	Total	3.05E+08	5			

Table 4: Analysis of variance for the General Larval Density (GLD) in Placetas municipality.
a. Prediction Variables: LAG6Foci, DI, LAG1 Foci, LAG2 Foci, DS
b. The total squares sum was not corrected for the constant because the constant zero in the regression through origin.
c. Dependent Variable: Province
d. Linear regression through origin

A summary of the obtained models express that most of explained variance occurreds equally in all municipalities and it is 100%; most of tendencies did not appear, except in Cifuentes municipality were it was prone to increase and in Caibarién and Ranchuelo to decrease. The most significant delays were 2, 1 and 6 (Table 5).

Municipalities	Durbin Watson	DS	DI	NoC	Lag2	Lag1	Lag6
Corralillo	1.459	16.99	2.709		-1.09	1.936	-2.198
Quemado	1.889	22.85	3		0.148	-3.89	18.41
Sagua	0.892	2400	3919		-2.36	-1.36	6.348
Encrucijada	2.184	5.968	6.437		-0.48	0.378	-0.194
Camajuaní	1.655	141.7	65.98		-2	0.802	0.534
Caibarién	2.044		-14.88	**-4.604**	3.378	-1.38	5.901
Remedios	1.328	160.4	300.25		-2.89	-0.6	6.846
Placetas	1.808	126.9	-14.28		-2.78	-1.45	12.97
Santa Clara	1.397	13432	12753		-0.43	-0.76	0.008
Cifuentes	1.567	143.4	-136.4	19.708	0.807		-0.986
Santo Domingo	1.57	356.3	399.82		-0.75	-2	15.04
Ranchuelo	1.63	-78.03	-130.3	**-33.25**		0.253	10.69
Manicaragua	2.415	418.5	467.47		-1.3	-0.15	0.482
Province	1.268	14114	12952		-0.55	-0.89	0.875

Table 5: Results of the GLD modeling per municipalities.

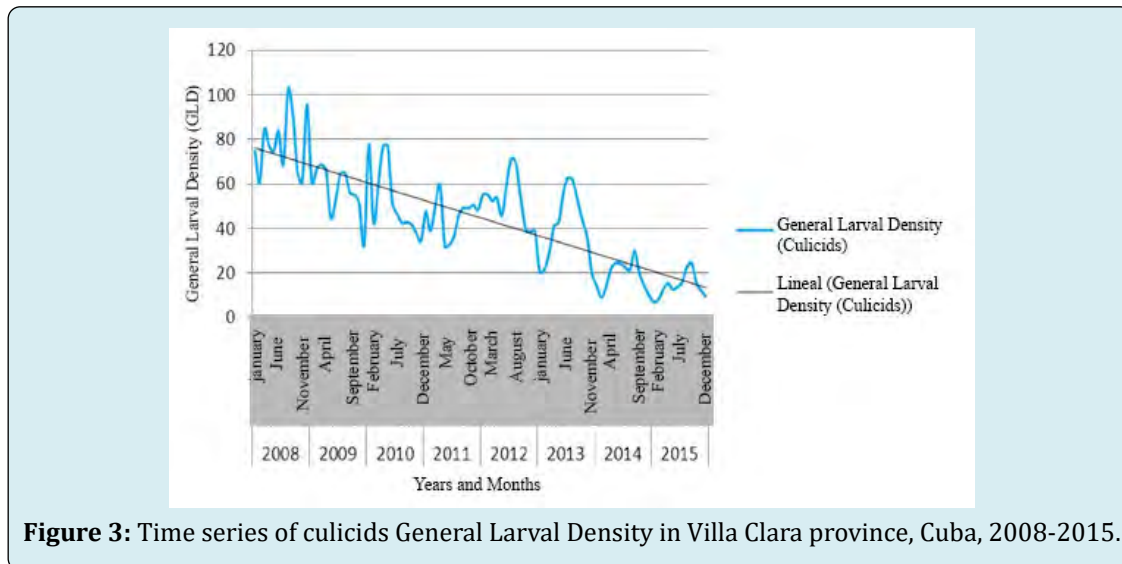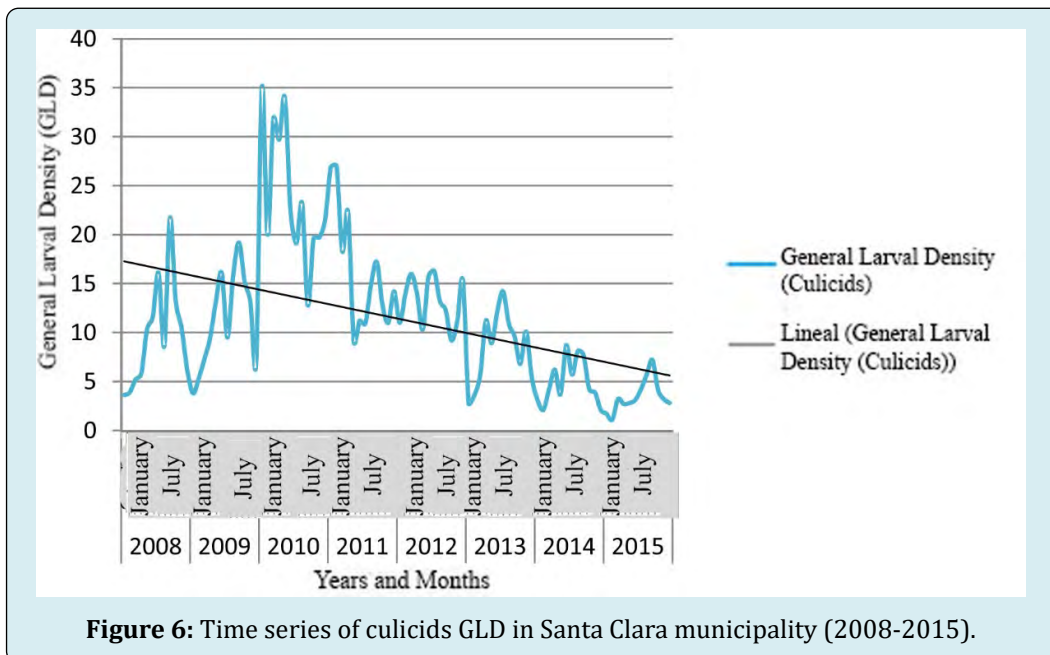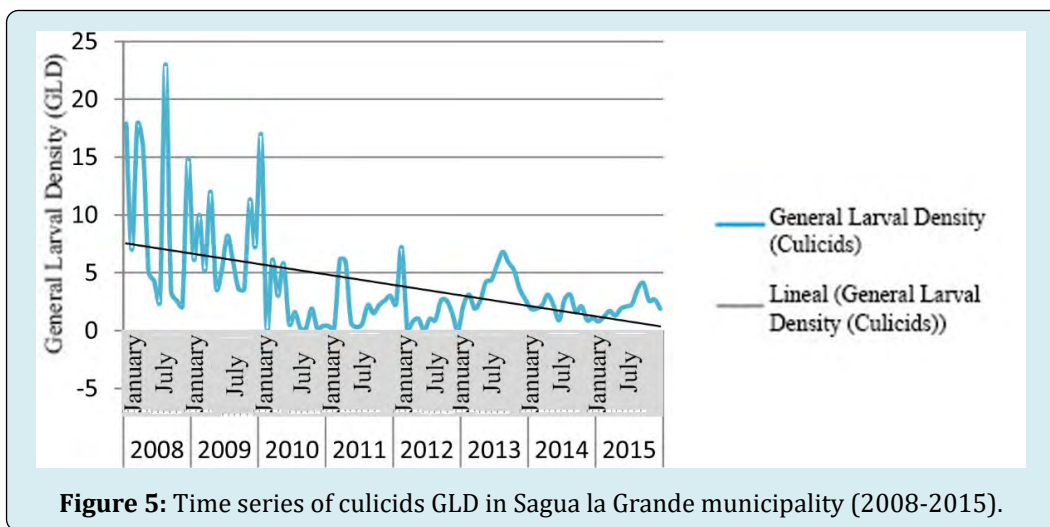Figure 3 shows the time series of culicids GLD in Villa Clara province, from 2008 to 2015.
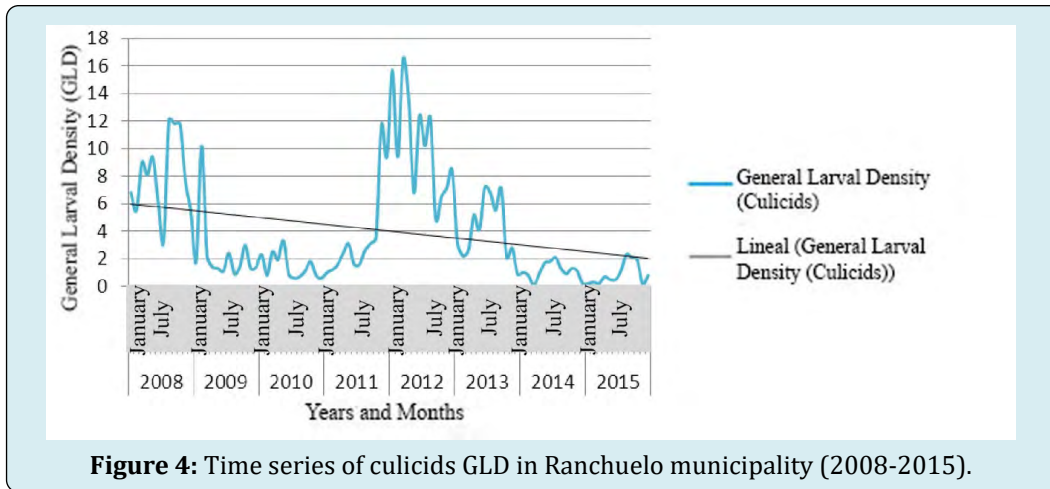

Figure 3: Time series of culicids General Larval Density in Villa Clara province, Cuba, 2008-2015.
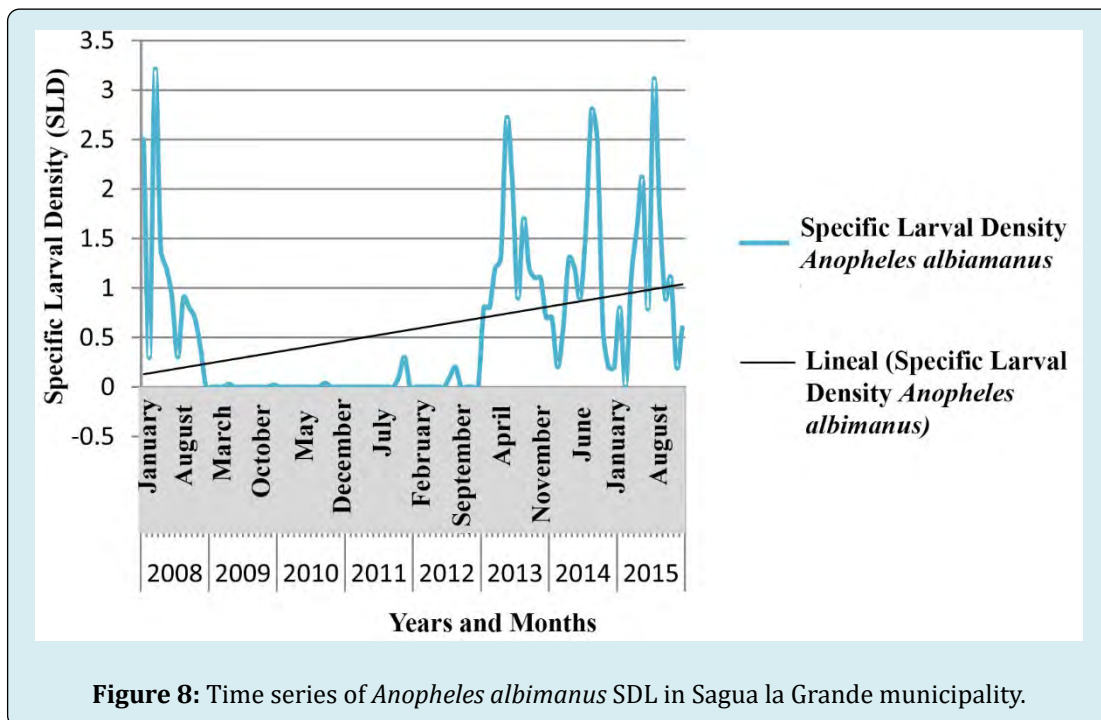
Figures 4-6 show the time series for GLD in three municipalities of Villa Clara province; these results confirm the seasonal cyclical behavior of culicids, and the downward tendency of this variable.

Figure 4: Time series of culicids GLD in Ranchuelo municipality (2008-2015).

Figure 5: Time series of culicids GLD in Sagua la Grande municipality (2008-2015).

Figure 6: Time series of culicids GLD in Santa Clara municipality (2008-2015).

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The tendency of the Specific Larval Density (SLD) was to increase, displaying a full correspondence between meteorological variables and the ecology of vectors belonging to *Anopheles* genus.

Figures 7-9 show the seasonal cyclical behavior of *Anopheles albimanus* larval density, the highest indexes coincided with the rainy season.

Figure 7: Time series of *Anopheles albimanus* SDL in Ranchuelo municipality (2008-2015).

Figure 8: Time series of *Anopheles albimanus* SDL in Sagua la Grande municipality.

Figure 9: Time series of *Anopheles albimanus* SDL in Santa Clara municipality.
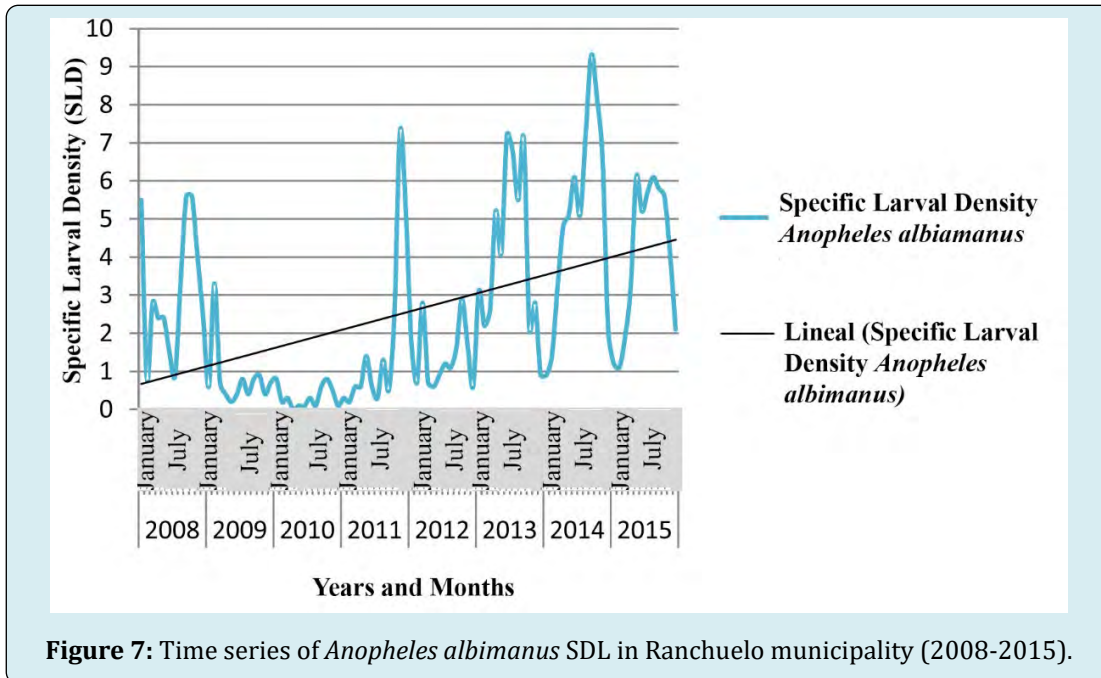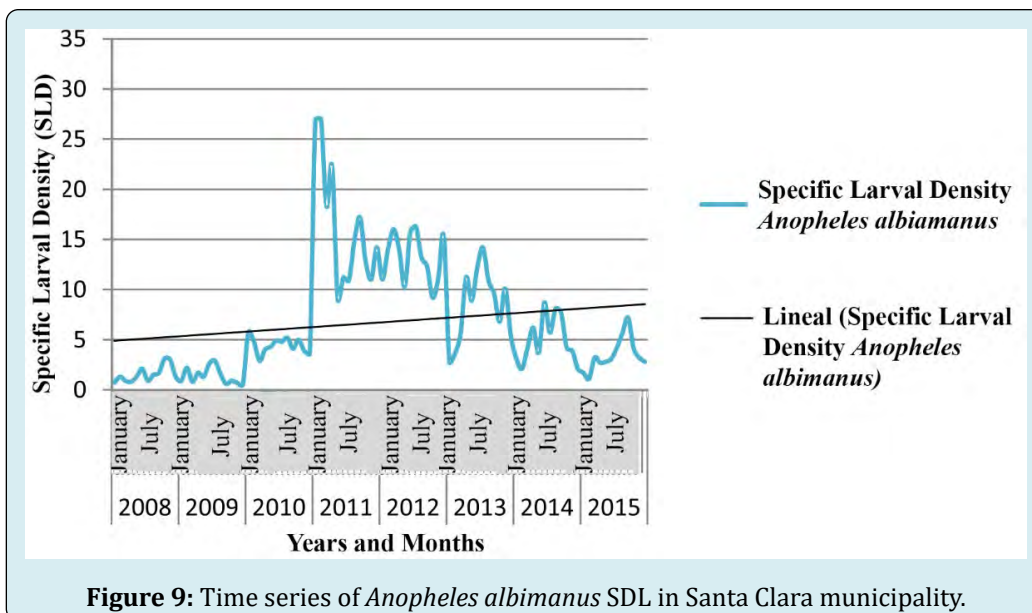
Prediction with Statistical and Climatic Variables

The prediction with statistical variables first, and then with climatic variables, showed the later had the highest correlation with the errors of the pure statistical models, influencing the proximity of the meteorological station. The correlations between the real value and those predicted by both models were calculated, observing that 9 models with climatic variables exceed the pure statistics and 4 models remain the same, since the influence of climatic variables was not significant. Table 6 resume the climatic variables that entered as significant in the models, for example, in Santa Clara the Atmospheric Pressure and the Average Relative Humidity recorded in the Meteorological Station Yabú. Santa Clara was the best modeled municipality with climatic variables (52.14% SKILL).

Municipalities	Pure statistic model	Model with climate variables	SKILL (%)	Climate variables
Corralillo	0.287	0.515**	44	Average Temperature Sagua
Quemado	0.486*	0.486**	-	-
Sagua	0.505**	0.505**	-	-
Encrucijada	0.726**	0.726**	-	-
Camajuaní	0.475**	0.626**	24.12	Average Humidity Sagua
Caibarién	0.741**	0.882**	15.99	Precipitation Sagua
Remedios	0.538**	0.538**	-	-
Placetas	0.657**	0.658**	0.15	Atmospheric Pressure Yabú
Santa Clara	0.246	0.514**	52.14	Atmospheric Pressure, Average Relative Humidity Yabú
Cifuentes	0.617**	0.681**	9.4	Cloud cover Yabú
Santo Domingo	0.370*	0.593**	37.61	Minimum Relative Humidity Sto. Domingo
Ranchuelo	0.382**	0.482**	20.75	Average Wind Velocity Yabú
Manicaragua	0.686**	0.751**	8.66	Atmospheric Pressure Average Relative Humidity Yabú

Table 6: Correlation between predicted and real values of climate variables per municipalities.
SKILL = (1 – (Pure Model / Model with Climate Variables)) *100.

As an example, Santa Clara municipality was selected for show the results of the model with climatic variables (Table 7). The model explained 91% of variance (standard deviation of 270 foci), the Durbin Watson statistic advice more variables might be including and that more information from the residuals might be add to the model.

Model	R	R^2	Corrected R^2	Estimation typical error	Durbin-Watson
1	.910[a]	0.829	0.805	270.242	1.239
a. Prediction Variables: xy13_mean, DS, Lag25Foci, Lag13Foci, Lag73Foci, NoC, xy10_mean					
b. For regression through the origin (the model with no intersection term), R^2 measures the proportion of the variability of the dependent variable explained by the regression through the origin. The comparison with R^2 is not possible in models that include an intersection.					
c. Dependent Variable: Santa Clara					
d. Linear regression through origin					

Table 7: Abstracted model with climate variables for Santa Clara.

The analysis of variance was significant, with a 35.2 Fisher's F (Table 8).

Model		Sum of squares	gl	Mean square	F	Sig.
	Regresión	18001018.2	7	2571574.03	35.21	.000[a]
1	Residual	3724565.804	51	73030.702		
	Total	21725584.000[b]	58			

Table 8: Analysis of variance with climate variables for Santa Clara.
a. Prediction Variables: xy13_mean, DS, Lag25Foci, Lag13Foci, Lag73Foci, NoC, xy10_mean
b. The total squares sum was not corrected for the constant because the constant was zero in the regression through origin.
c. Dependent Variable: Santa Clara
d. Linear regression through origin

The model depends of the foci data one year and a month ago (Lag13Foci), two years and a month ago (Lag25Foci) and six years and a month ago (Lag73Foci), although they were non-significant variables they provided variance to the model. The tendency was negative and non-significant (Table 9).

Model B	Non-standardized coefficients		Typified coefficients	t	Sig.
	Typical error	Beta			
DS	60.47	72.938	0.069	0.829	0.41
Tendency	-0.377	2.467	-0.064	-0.15	0.88
Lag25Foci	-0.151	0.098	-0.16	-1.54	0.13
Lag13Foci	-0.197	0.121	-0.183	-1.62	0.11
Lag73Foci	0.075	0.114	0.083	0.656	0.52
Mean Relative Humidity	35.55	9.426	4.773	3.771	0
Atmospheric Pressure	-2.237	0.736	-3.664	-3.04	0
a. Dependent Variable: Santa Clara					
b. Linear regression through origin					

(Note: the leftmost column shows "1" spanning the data rows.)

Table 9: Foci model with climate variables for Santa Clara.

Discussion

The combination of delays 1, 2 and 6 allowed fitting a perfect model for each of the municipalities. Since the influencing parameters could not be measured because were displayed divisions by zero, it was necessary to apply mathematical definitions recommended by other authors [56,57].

The standardized residuals showed a mean value of zero and a standard deviation of 1, as corresponds to a perfect model, coinciding with previous researches [52,56,57]. The models exposed in Table 5 indicate that the highest explained variance occurred equally in all municipalities and was 100%; the most significant delays were 2, 1 and 6. These good fitting results by ROR models were also reported by others [56-59].

The GLD showed a seasonal cyclical behavior (Figures 2-6), with a tendency to decrease. Peak values of GLD appeared between May and October, coinciding with the highest temperature and rainfall in Cuba. This climate favor mosquito proliferation, catalyzing the hatching/emergence of eggs, increasing the female's sub-population and shortening their life cycle; therefore, increase the morbidity due to mosquito borne diseases in humans and animals [60-63]. Results of this research partially agree with those reported by García, et al. [64], who found the highest larval density in river ecosystems occurred in October 2009 and 2010 in a health area of Santa Clara municipality. Nevertheless, both researches differs regarding the extension of the study area and period, the present work covered 522 temporal and/or permanent *Culicidae* hatcheries throughout Villa Clara province during eight years, which allowed displaying confident chronological series since they need three to four years data at least. Additionally, García, et al. [64] carried out their work under a different design, including only a health area of Santa Clara, which is the most densely populated municipality in the province showing the highest rates of culicids Larval Density, the highest urbanization and the largest number of deposits for water storing.

The time series for GLD in three municipalities of Villa Clara province (Figures 4-6) displayed a tendency to decrease coinciding with the intensification of control actions against culicids since the emergence of two arboviral diseases in Cuba: Chikungunya and Zika in 2013 and 2015 respectively.

The SLD tendency of *Anopheles* genus was to increase following seasonal cyclical behavior (Figures 7-9), and showing a full correspondence with meteorological and biological/ecological variables, similar results to those achieved by different authors [9,65,66]. The *An. albimanus* larval density displayed the highest indexes during the rainy season, which constitutes a potential risk for the local transmission of imported Malaria in Cuba [44,57]. The fitted model depended on the foci data one year and a month ago (Lag13Foci), two years and a month ago (Lag25Foci) and six years and a month ago (Lag73Foci), despite being non-significant variables they provide variance to the model. Climate variables highly influenced larval density, as the Average Relative Humidity increases by 1%, the number of foci increases by 35.5, while increasing Atmospheric Pressure in one Hectopascal influence the focis to decrease by 2.2, results according to those achieved for mosquitoes and other organisms [9,25,44,45,59].

The wide geographical distribution and increasing proportion among culicids of *St. aegypti* and *St. albopictus* in Villa Clara province, represents a high entomoepidemiological risk as they transmit various viruses such as: Dengue, Yellow Fever, West Nile Fever, Chikungunya and Zika [67-69]. These species are present throughout all Cuban territory, colonizing under the influence of climate variables a significant number of breeding sites generated by the human activity [4,34,35,40], thus showing their high ecological plasticity and adaptability to diverse ecological niches [9,70].

Conclusion

The meteorological variables significantly influence the modeling of culicids population dynamics. In Santa Clara municipality, the fitted model significantly depended on climate variables recorded in Yabú Meteorological Station; so that as the Average Relative Humidity increases by 1%, the foci quantity increases by 35.5; while one Hectopascal increase of the Atmospheric Pressure, provokes a decrease of 2.2 on the foci amount.

Conflict of Interest Statement

The authors declare that they have no conflict of interest.

Contribution

All the authors contributed substantially to the concrescence of the manuscript, with the largest being concentrated in the first five authors.

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