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Incidence of climate on the population dynamics of *Aedes aegypti* (Diptera: Culicidae) in the Ignacio Agramonte health area of Camagüey, Cuba

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Abstract

The *Aedes aegypti* mosquito transmits three of the most serious viruses (DENV), ZIKV, and CHIKV), causing significant morbidity and mortality in humans worldwide. The objective of this research was to determine the impact of certain climatic variables on the population dynamics of the *Ae. aegypti* mosquito in the "Ignacio Agramonte" health area of Camagüey, Cuba. A correlation was established between the total number of positive mosquito deposits and three temperature ranges; in addition, the total number of positive deposits was correlated with three humidity levels, as well as with precipitation, wind direction, wind speed and force, and atmospheric pressure. All analyses were performed using Pearson's correlation coefficient.

Finally, a linear regression analysis was performed using the Durbin-Watson statistic and the ANOVA test (Fisher's F-test), which allowed for an analysis of variance. The results showed no significant correlation with any of the temperatures; however, the correlation between the total number of positive deposits and those outside the enclosures was highly significant. In the regression analysis, the model was also highly significant, with a Fisher's F-test significant at the 100% confidence level. Regarding variances, they were significant at the 95% confidence level, except for LAG12VM, where the model trend was significant and increased depending on the mean wind speed and direction frequency, both of which were regressed over 7 months. It is concluded that climate does influence the population dynamics of the *Ae. aegypti* mosquito.

Keywords: *Aedes aegypti*; Health Area; Camagüey; Population Dynamics; Climatic Variables

1. Introduction

Throughout history, humanity has suffered from the scourge of potentially fatal viral and parasitic diseases, including Yellow Fever, Dengue, Zika, Chikungunya, Malaria, Chagas disease, Leishmaniosis, Onchocerciasis, Angiostrongylosis, and Fasciolosis, among many others. In most of these diseases, a vector organism is often a common factor [1-3]. These diseases are widespread in the tropics, with local variations in risk, and are therefore highly dependent on factors such as rainfall, temperature, and rapid, unplanned urbanization [4-6].

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To these problems are now added global warming and the intensification of extreme weather events, which have brought about changes in disease behavior and transmission, with the establishment of vector species in previously unrecorded locations [7-9]. Climate change is considered one of the main environmental problems, and its effects undoubtedly have a negative impact on human health [7,10-12]. Several studies link climatic variables to the increase in infectious diseases, with arboviruses being among the most studied, and a positive relationship has been demonstrated between climate variation and the incidence of these infectious entities [13-17].

The relationship between Dengue incidence and climatological variables is primarily due to the characteristics of the vector, its life cycle, and the conditions that favor its proliferation [18-21]. Among the most influential climatic variables are elevated temperature, humidity, and rainfall [22-25].

All vector-borne diseases worldwide have very high incidence rates; for example, it is estimated that Dengue alone accounts for 50-100 million cases annually [5,26,27]. This viral disease has been considered a global public health problem for many years, especially in tropical countries where environmental variables contribute to the increasing number of cases each year [5,12,27].

However, malaria remains the main vector-borne health problem [28-32]; this disease causes the death of one person every 60 seconds [29-32]. Due to its geographical location and climatic characteristics, Cuba has a wide fauna of mosquitoes with proven vector capacity, making them of great interest to human health and other animals [19,32,33].

It is possible to make high-quality, precise, and accurate forecasts using various methodologies, among which the Objective Regression Method (ORM) stands out. Its simplicity and accuracy allow it to provide valuable insights into the future of climatic variables or daily data, years in advance [14,16,23]. This cycle can be extended to the 11-year solar cycle, or to longer cycles known in nature. The population dynamics of mollusks and insects, such as mosquitoes and their interactions with specific environmental variables, can also be modeled to establish timely and prophylactic control measures within epidemiological surveillance programs [34-36]. Consequently, there is a growing need to develop and implement other strategies for controlling infectious diseases and their vectors that can complement existing methods more effectively and efficiently.

The objective of the research was to determine the incidence of some climatic variables on the population dynamics of the *Aedes aegypti* mosquito species in the "Ignacio Agramonte" health area of the Camagüey province, Cuba.

2. Materials and Methods

2.1. Study Area

The study was conducted in the capital municipality of the province of Camagüey (central region of Cuba), which is located between approximately 20° 31' 01" (Cabeza del Este Lighthouse) and 22° 29' 00" (Paredon Grande Lighthouse) north latitude and 76° 57' 00" west longitude of the Greenwich Meridian. It is bordered to the north by the Old Bahamas Channel, to the south by the Caribbean Sea, to the east by the province of Las Tunas, and to the west by Ciego de Ávila. In terms of area, it is the largest and flattest province in Cuba, with a total surface area of 15,990.1 km^2, of which 14,158.06 km^2 are mainland and 1,832 km^2 are adjacent keys, occupying 13.2% of the national territory.

2.2. Characterization of the selected Health Area

The Ignacio Agramonte Health Area (AS-IA) has a land area of 4.5 km2 and an estimated population of 19 452 inhabitants. The suburban area occupies approximately 15% of the total surface area and belongs to the main municipality of the same name (Figure 1).

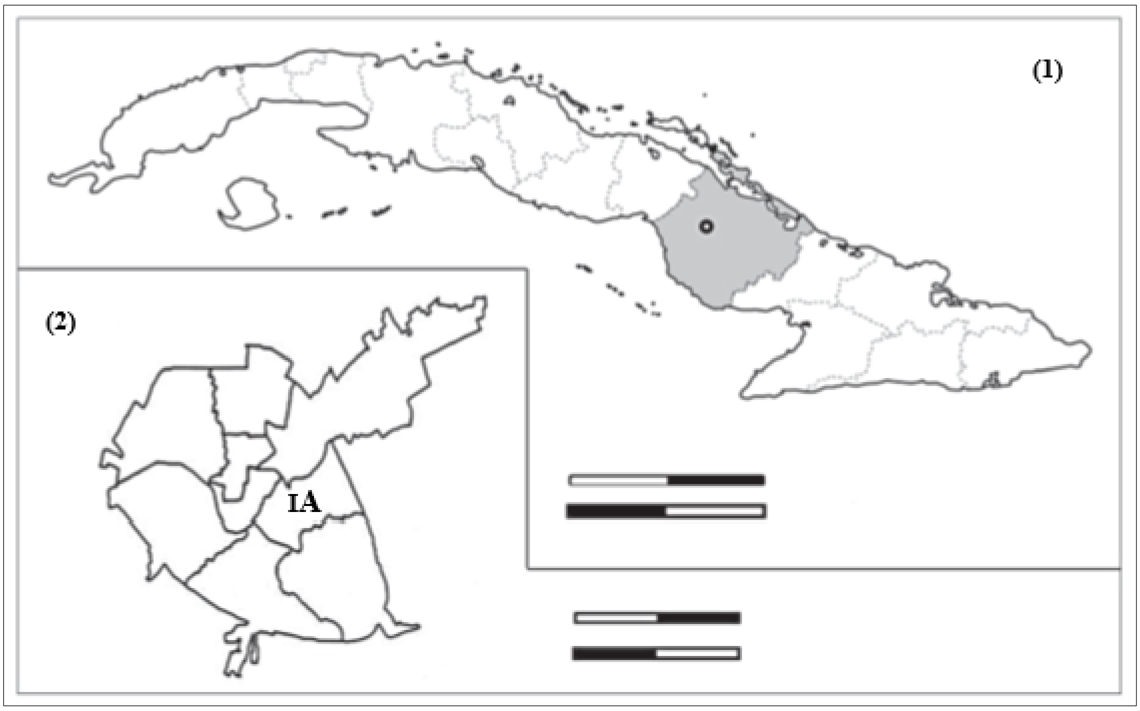

Figure 1 Map of Cuba showing the province of Camagüey (1), and its namesake municipal capital (Camagüey) (●). In detail the urban center evaluated (2) in which the geographical location of the Ignacio Agramonte Health Area (IA) is highlighted

2.2.1. Study period

The two climatic periods reported for Cuba were considered: rainy (May-October) and dry (November-April) [37].

2.2.2. Data used

The database (models 91-11) of the Municipal Laboratory of Medical Entomology, Municipal Unit of Hygiene and Epidemiology (LMEM-UMHE) of Camagüey was used, with the entomological results from the Vector Control Department of the Ignacio Agramonte Health Area (AS-IA).

2.3. Regarding the Objective Regression Methodology (ROR)

To work with the Objective Regression Method (ROR) [38], a database is required. This database is organized by arranging the data in ascending chronological order. Then, in the first step, dichotomous variables DS, DI, and NoC are created, where:

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

DS represents a sawtooth function, and DI represents the same function but inverted, such that the variable to be modeled is trapped between these parameters, thus explaining a large amount of variance.

Next, the curves are modeled, and finally, the regressed variables with the greatest impact are added. Subsequently, the Regression analysis module of the SPSS statistical package version 19.0 (IBM Company, 2010) will be executed, specifically the ENTER method where the predicted variable and the ERROR are obtained.

Next, the autocorrelograms of the ERROR variable were obtained, paying attention to the peaks of the significant partial autocorrelations (PACF). The new variables were then calculated considering the significant lag of the PACF. Finally, these regressed variables were included in the new regression in a process of successive approximations until white noise was obtained in the regression errors. For atmospheric pressure, lags of one year in advance can be used.

3. Results and Discussion

3.1. Correlations

The correlations of the total positive deposits in the Ignacio Agramonte (IA) health area with climatic variables were analyzed, and it could be seen that there is no significant correlation with any of the temperatures; however, between the total positive deposits and the exterior ones, the correlation turned out to be highly significant, with a value of 0.987, significant at 99% (Table 1); results that correspond with those obtained by other authors in this regard, both in Cuba and in other geographical latitudes, when they analyze the increase in the focality in the months of increase of high temperatures, precipitation and variations of climatological variables [11,24,38-41].

Table 1 Results of the correlation between the total number of positive deposits and the three temperatures

Correlations		**Tmax (°C)**	**Tmed (°C)**	**Tmin (°C)**	**Total Positives**
Tmáx (°C)	Pearson correlation	1	0.923**	0.777**	0.166
	Sig. (bilateral)		0.000	0.000	0.169
	N	70	70	70	70
Tmed (°C)	Pearson correlation	0.923**	1	0.951**	0.155
	Sig. (bilateral)	0.000		0.000	0.199
	N	70	70	70	70
Tmín (°C)	Pearson correlation	0.777**	0.951**	1	0,131
	Sig. (bilateral)	0.000	0.000		0.280
	N	70	70	70	70
Total Positives IA	Pearson correlation	0.166	0.155	0.131	1
	Sig. (bilateral)	0.169	0.199	0.280	
	N	70	70	70	72
Abroad IA	Pearson correlation	0.189	0.172	0.146	**0.987****
	Sig. (bilateral)	0.116	0.155	0.229	0.000
	N	70	70	70	72

** Correlation is significant at the 0.01 level (2-tailed).

Table 2 shows that none of the three humidity levels were significant, and even the deposits on the exteriors of the houses were not, which contrasts with results obtained in previous years in other provinces of the country, when analyzing the population dynamics of *Ae. aegypti* [20,40,42,43].

Table 2 Correlation between the total number of positive deposits and the three humidity levels

Correlations		**Total Positives**	**Abroad**	**Hmax (%)**	**Hmed (%)**	**Hmin (%)**
Total Positives IA	Pearson correlation	1	0.987**	-0.219	0.002	0.054
	Sig. (bilateral)		0.000	0.069	0.990	0.654
	N	72	72	70	70	70
Abroad IA	Pearson correlation	0.**987****	1	-0.207	0.000	0.043
	Sig. (bilateral)	0.000		0.085	0.998	0.721
	N	72	72	70	70	70
Hmax (%)	Pearson correlation	-0.219	-0.207	1	**0.787****	**0.678****
	Sig. (bilateral)	0.069	0.085		0.000	0.000
	N	70	70	70	70	70
Hmed (%)	Pearson correlation	0.002	0.000	**0.787****	1	**0.966****
	Sig. (bilateral)	0.990	0.998	0.000		0.000
	N	70	70	70	70	70
Hmin (%)	Pearson correlation	0.054	0.043	**0.678****	**0.966****	1
	Sig. (bilateral)	0.654	0.721	0.000	0.000	
	N	70	70	70	70	70

** Correlation is significant at the 0.01 level (2-tailed).

Correlation between positive deposits with precipitation, direction frequency, wind speed and force, and atmospheric pressure

Tables 3, 4, and 5 show that outdoor cases were highly significant (95%) with precipitation, while total outdoor cases were also highly significant with direction frequency (this variable indicates the frequency of the direction; that is, as the direction increases, total outdoor cases decrease). As the direction increases from NE to E, passing through ENE, total and outdoor cases decrease, while when the direction is NNE, a greater number of total outdoor cases should be present. These results agree to some extent with those obtained by other authors on this subject [8, 21, 40, 44]. The other climatic variables were not significant [3, 43, 45].

Table 3 Correlation between positive cases outdoors according to the precipitation variable

		Total Positives	Abroad	Prec. (mm)
Total Positives IA	Pearson correlation	1	**0.987****	0.214
	Sig. (bilateral)		0.000	0.075
	N	72	72	70
Abroad IA	Pearson correlation	**0.987****	1	**0.247***
	Sig. (bilateral)	0.000		0.039
	N	72	72	70
Prec. (mm)	Pearson correlation	0.214	**0.247***	1
	Sig. (bilateral)	0.075	0.039	
	N	70	70	70
V. med (km/h)	Pearson correlation	-0.224	-0.234	**-0.485****
	Sig. (bilateral)	0.063	0.051	0.000
	N	70	70	70
Heading Frequency	Pearson correlation	**-0.316****	**-0.311****	**0.276***
	Sig. (bilateral)	0.008	0.009	0.021
	N	70	70	70
FP.med (h)	Pearson correlation	0.110	0.125	**0.587****
	Sig. (bilateral)	0.363	0.301	0.000
	N	70	70	70
Pm.med (hPa)	Pearson correlation	-0.130	-0.161	**-0.345****
	Sig. (bilateral)	0.284	0.183	0.003
	N	70	70	70

Table 4 Correlation between positive cases outdoors with the frequency of wind direction and speed

		V.med (km/h)	Heading Frequency	FP.med (h)
Total Positives IA	Pearson correlation	-0.224	**-0.316****	0.110
	Sig. (bilateral)	0.063	0.008	0.363
	N	70	70	70
Abroad IA	Pearson correlation	-0.234	**-0.311****	0.125
	Sig. (bilateral)	0.051	0.009	0.301
	N	70	70	70
Prec. (mm)	Pearson correlation	**-0.485****	0.276*	**0.587****
	Sig. (bilateral)	0.000	0.021	0.000
	N	70	70	70
V.med (km/h)	Pearson correlation	1	-0.077	**-0.339****
	Sig. (bilateral)		0.525	0.004

	N	70	70	70
Heading Frequency	Pearson Correlation	-0.077	1	**0.449****
	Sig. (bilateral)	0.525		0.000
	N	70	70	70
FP.med (h)	Pearson correlation	**-0.339****	**0.449****	1
	Sig. (bilateral)	0.004	0.000	
	N	70	70	70
Pm.med (hPa)	Pearson correlation	**0.337****	0.040	-0.123
	Sig. (bilateral)	0.004	0.745	0.311
	N	70	70	70

Table 5 Correlation between positive outdoor totals and atmospheric pressure

		Pm.med (hPa)
Total Positives IA	Pearson correlation	-0.130
	Sig. (bilateral)	0.284
	N	70
Abroad IA	Pearson correlation	-0.161
	Sig. (bilateral)	0.183
	N	70
Prec. (mm)	Pearson correlation	**-0.345****
	Sig. (bilateral)	0.003
	N	70
V.med (km/h)	Pearson correlation	**0.337****
	Sig. (bilateral)	0.004
	N	70
Heading Frequency	Pearson correlation	0.040
	Sig. (bilateral)	0.745
	N	70
FP.med (h)	Pearson correlation	-0.123
	Sig. (bilateral)	0.311
	N	70
Pm.med (hPa)	Pearson correlation	1
	Sig. (bilateral)	
	N	70

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

3.2. Regression

Table 6 shows the model that explains 95.8% of the variance with an error of only 32 cases; the Durbin-Watson statistic is small, so it could be considered in the future to include new variables; however, this model is highly significant with a Fisher's F (Table 7) of 100.760, significant at 100%.

Table 6 Model that explains the variance according to the Durbin Watson statistic

Model summary[c, d]					
Model	**R**	**R squared[b]**	**Adjusted R-squared**	**Standard error of the estimation**	**Durbin-Watson**
1	0.958[a]	0.918	0.909	32.001	1.391

a. Predictors: Lag7RUMBO, STEP65, STEP55, NoC, Lag7VM, Lag12VM
b. For regression through the origin (the model without an intercept), R-squared measures the proportion of the variability in the dependent variable about the origin explained by the regression. This CANNOT be compared to the R-squared for models that include an intercept.
c. Dependent variable: Total Positive IA
d. Linear regression through the origin

Table 7 Model that explains the variance according to Fisher's F

ANOVA[a, b]						
Model		**Sum of squares**	**gl**	**Mean squares**	**F**	**Sig.**
1	Regression	619110.537	6	103185.090	100.760	0.000[c]
	Residue	55299.463	54	1024.064		
	Total	674410.000[d]	60			

a. Dependent variable: Total Positive IA
b. Linear regression through the origin
c. Predictors: Lag7RUMBO, STEP65, STEP55, NoC, Lag7VM, Lag12VM
d. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

In table 8, the model depends on the trend, which is significant towards an increase. STEP 65 and STEP 55 are two cases in the sample that have specific importance, with an increase of 142 and 109 cases respectively. The model depends on the mean wind speed returned over 7 months (Lag7VM) and Lag7Rumbo, that is, the frequency of the course returned over 7 months [17,21,43]. All variances were significant at the 95% confidence level except for LAG12VM, but this contributes variance to the model, and we prefer to leave it in the model. The residual statistics are also shown, with a mean of 0.026 and a standard deviation of almost 1 (0.956).

Table 8 Model representation according to trend

Coefficients[a, b]						
Model		**Non-Standardized coefficients**		**Standardized coefficients**	**T**	**Sig.**
		B	**Standard error**	**Beta**		
1	Trend	2.136	0.228	0.925	9.364	0.000
	STEP65	142.437	33.122	0.173	4.300	0.000
	STEP55	109.565	32.830	0.133	3.337	0.002
	Lag7VM	2.889	1.272	.318	2.271	0.027
	Lag12VM	-1.689	1.389	-0.189	-1.216	0.229
	Lag7COURSE	-0.723	0.308	-0.231	-2.348	0.023

a. Dependent variable: Total Positive IA
b. Linear regression through the origin

The Histogram of the errors shows that for the totals the results obtained do not differ from a normal distribution with mean zero and variance almost 1 (Figure 2).

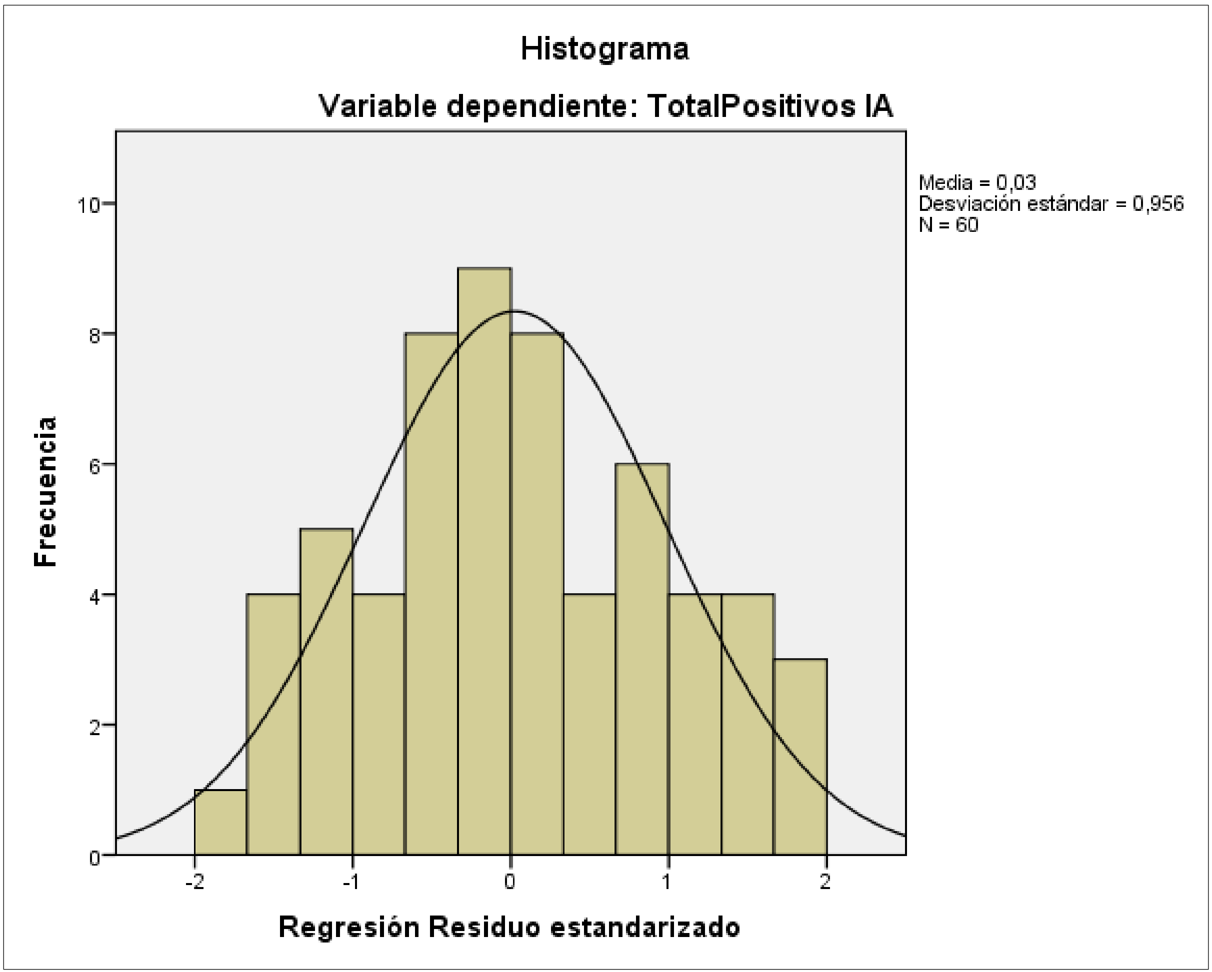

Figure 2 Histogram of the residuals for the total values

Figure 3 shows how the expected probability and the observed probability are on a straight line, so the model can be considered good.

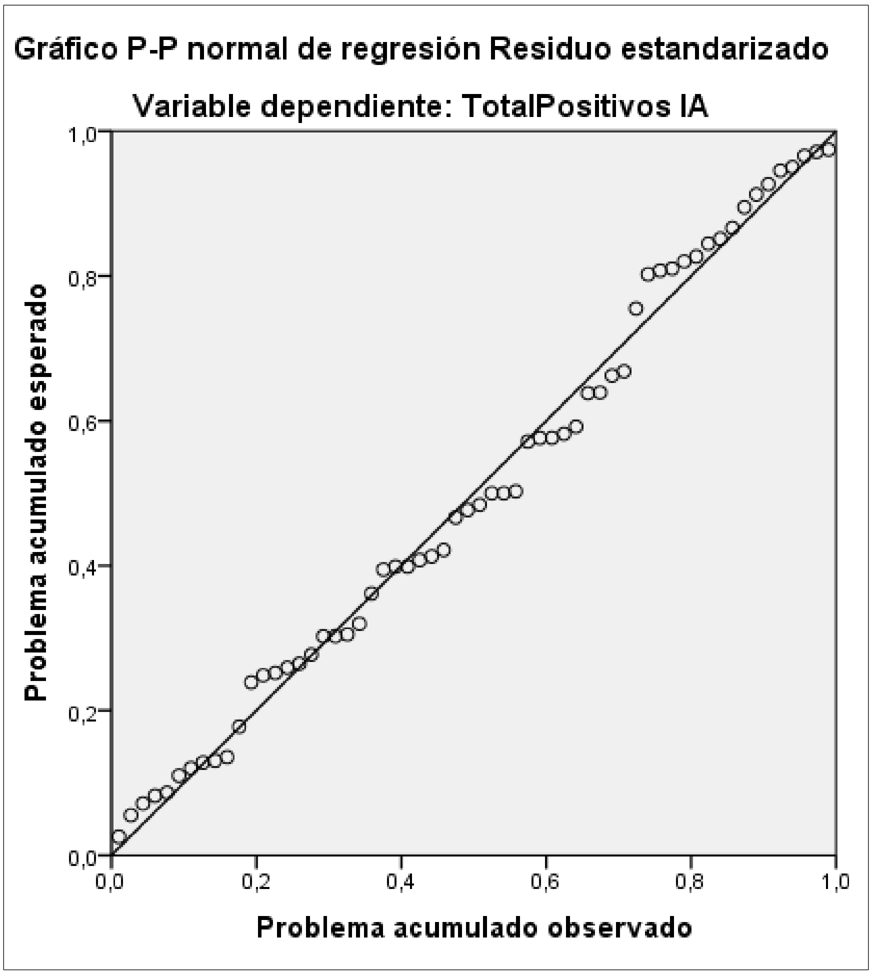

Figure 3 Expected probability of standardized residuals vs. observed probability

For the outdoor model, 95% of the variability is explained with an error of 29 cases (Table 9).

Table 9 Variability results for the outdoor model

Model Summary[c]					
Model	**R**	**R squared[b]**	**Adjusted R-squared**	**Standard error of the estimation**	**Durbin-Watson**
1	0.950[a]	0.902	0.891	29.035	1.409

a. Predictors: Lag7RUMBO, STEP65, STEP55, NoC, Lag7VM, Lag12VM
b. For regression through the origin (the model without an intercept), R-squared measures the proportion of the variability in the dependent variable about the origin explained by the regression. This CANNOT be compared to the R-squared for models that include an intercept.
c. Dependent variable: Exterior IA
d. Linear regression through the origin

The analysis of variance was significant with a Fisher's F of 82.9, significant at 100% (Table 10).

Table 10 Results of the analysis of variance

ANOVA[a, b]						
Model		**Sum of squares**	**gl**	**mean squares**	**F**	**Sig.**
1	Regression	419703.363	6	69950.560	82.973	0.000[c]
	Residue	45524.637	54	843.049		
	Total	465228.000[d]	60			

a. Dependent variable: External IA
b. Linear regression through the origin
c. Predictors: Lag7RUMBO, STEP65, STEP55, NoC, Lag7VM, Lag12VM
d. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

The model depends on the same variables as for the total, but with different coefficients. Due to the high correlation between the totals and the external factors, we were able to apply the same model, which yielded good results (Table 11). Regarding the residual statistics, we obtained a mean of zero and a standard residual of almost 1, very similar to that obtained in other studies carried [24,25,42,43].

Table 11 Model results according to correlation between totals and exteriors

Coefficients[a, b]						
Model		**Non-Standardized coefficients**		**Standardized coefficients**	**T**	**Sig.**
		B	**standard error**	**Beta**		
1	NoC	1.750	0.207	0.912	8.452	0.000
	STEP65	124.105	30.052	0.182	4.130	0.000
	STEP55	83.409	29.787	0.122	2.800	0.007
	Lag7VM	2.904	1.154	0.385	2.516	0.015
	Lag12VM	-1.678	1.260	-0.226	-1.332	0.188
	Lag7COURSE	-0.696	0.279	-0.268	-2.491	0.016

a. Dependent variable: External IA
b. Linear regression through the origin

Figure 4 shows the good agreement between the actual and predicted values, according to the model results for the totals.

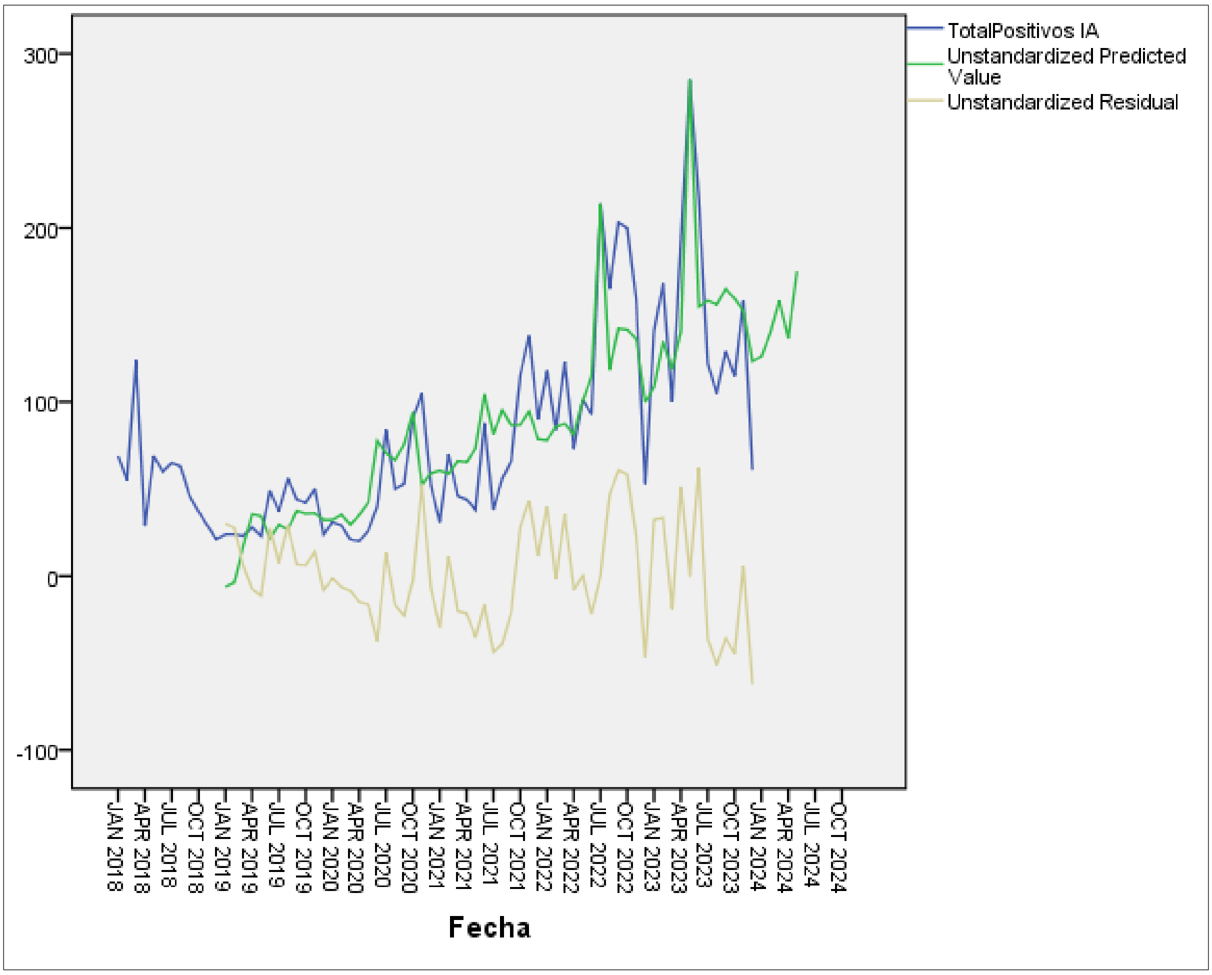

Figure 4 Model results for total positives

In Figure 5 and Table 12, the outdoor model graph also shows the forecast results and model errors, very similar to what was obtained in another research on the subject [25,43-46].

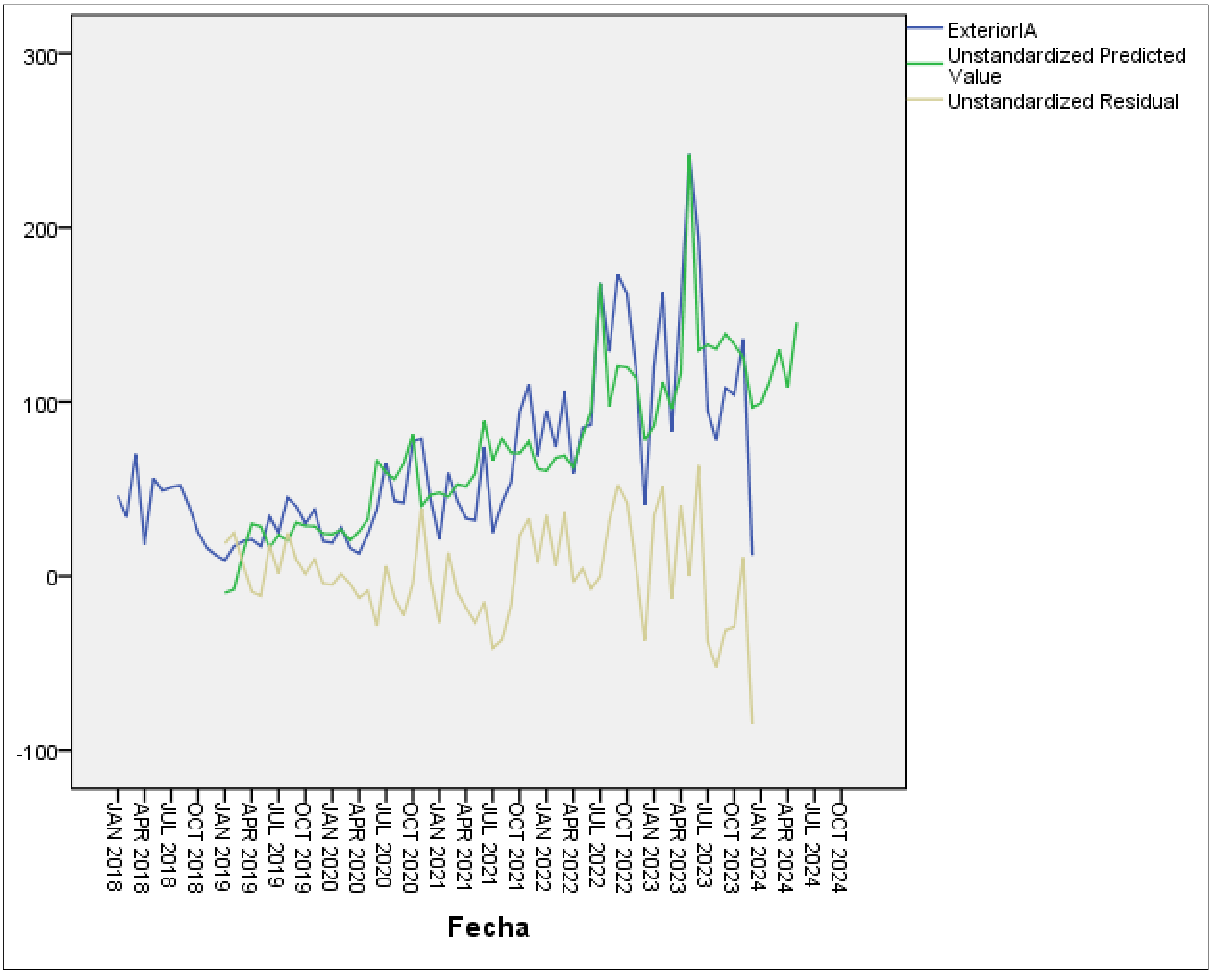

Figure 5 Model results for the total number of outdoor areas according to the years covered by the study

Table 12 Summary of cases according to predicted value and model errors

Case summaries[a]				
	Date. Format: "MMM YYYY"	**Abroad IA**	**Unstandardized Predicted Value**	**Unstandardized Residual**
1	JAN 2018	46	.	.
2	FEB 2018	34	.	.
3	MAR 2018	70	.	.
4	APR 2018	18	.	.
5	MAY 2018	56	.	.
6	JUN 2018	49	.	.
7	JUL 2018	51	.	.
8	AUG 2018	52	.	.
9	SEP 2018	40	.	.
10	OCT 2018	25	.	.
11	NOV 2018	16	.	.
12	DEC 2018	12	.	.

13	JAN 2019	9	-9.73541	18.73541
14	FEB 2019	17	-7.73549	24.73549
15	MAR 2019	20	12.49111	7.50889
16	APR 2019	21	29.96402	-8.96402
17	MAY 2019	17	28.42895	-11.42895
18	JUN 2019	34	16.21340	17.78660
19	JUL 2019	25	23.62110	1.37890
20	AUG 2019	45	20.41304	24.58696
21	SEP 2019	40	30.71381	9.28619
22	OCT 2019	30	28.74721	1.25279
23	NOV 2019	38	28.58672	9.41328
24	DEC 2019	20	24.35306	-4.35306
25	JAN 2020	19	24.02475	-5.02475
26	FEB 2020	28	26.74127	1.5873
27	MAR 2020	16	20.47777	-4.47777
28	APR 2020	13	25.55723	-12.55723
29	MAY 2020	24	32.50144	-8.50144
30	JUN 2020	38	66.52522	-28.52522
31	JUL 2020	65	59.29738	5.70262
32	AUG 2020	43	55.60640	-12.60640
33	SEP 2020	42	64.43397	-22.43397
34	OCT 2020	77	81.29145	-4.29145
35	NOV 2020	79	40.17760	38.82240
36	DEC 2020	44	46.55440	-2.55440
37	JAN 2021	21	47.76047	-26.76047
38	FEB 2021	59	45.51409	13.48591
39	MAR 2021	43	52.58083	-9.58083
40	APR 2021	33	51.30161	-18.30161
41	MAY 2021	32	58.79988	-26.79988
42	JUN 2021	74	88.93165	-14.93165
43	JUL 2021	25	66.46000	-41.46000
44	AUG 2021	42	78.78877	-36.78877
45	SEP 2021	54	70.68373	-16.68373
46	OCT 2021	94	70.56051	23.43949
47	NOV 2021	110	77.10592	32.89408
48	DEC 2021	69	61.48852	7.51148
49	JAN 2022	95	60.31047	34.68953
50	FEB 2022	74	67.96324	6.03676

51	MAR 2022	106	69.24126	36.75874
52	APR 2022	59	62.42369	-3.42369
53	MAY 2022	85	80.88221	4.11779
54	JUN 2022	87	94.29441	-7.29441
55	JUL 2022	168	168.00000	.00000
56	AUG 2022	129	97.35924	31.64076
57	SEP 2022	173	120.81720	52.18280
58	OCT 2022	162	119.79894	42.20106
59	NOV 2022	119	113.72720	5.27280
60	DEC 2022	41	78.04504	-37.04504
61	JAN 2023	121	86.29462	34.70538
62	FEB 2023	163	111.44748	51.55252
63	MAR 2023	83	96.01123	-13.01123
64	APR 2023	157	116.41441	40.58559
65	MAY 2023	242	242.00000	.00000
66	JUN 2023	193	129.63954	63.36046
67	JUL 2023	95	132.80456	-37.80456
68	AUG 2023	78	130.30947	-52.30947
69	SEP 2023	108	138.99595	-30.99595
70	OCT 2023	104	133.06811	-29.06811
71	NOV 2023	136	125.45924	10.54076
72	DEC 2023	12	96.85785	-84.85785
73	JAN 2024	.	99.31067	.
74	FEB 2024	.	112.46710	.
75	MAR 2024	.	130.08921	.
76	APR 2024	.	108.38742	.
77	MAY 2024	.	145.50240	.
78	JUN 2024	.	.	.
79	JUL 2024	.	.	.
80	AUG 2024	.	.	.
81	SEP 2024	.	.	.
82	OCT 2024	.	.	.
83	NOV 2024	.	.	.
84	DEC 2024	.	.	.
Total N	84	72	65	60

a. Limited to the first 100 cases.

4. Conclusion

Undoubtedly, climate has a direct impact on the population dynamics of the mosquito species *Ae. aegypti*, with some climatic variables having a much more marked effect on others, as can be seen in this study.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors have no area of conflict of interest.

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

References

[1] Guzmán MG, Kourí G. Dengue: an update. Lancet Inf Dis. 2002; 2: 33-42.

[2] World Health Organization (WHO). Zoonoses and Veterinary Public Health. Emerging Zoonoses. 2016. URL: http://www.who.int/zoonoses/emerging_zoonoses/en/

[3] Campos SCM, Guillen LL, del Valle LD, Acosta EI, Rodríguez HD, Osés RR, et al. Modeling and prediction of dengue cases in the short and long term in Villa Clara, Cuba using climatic variables and objective regressive regression. GSC Biological and Pharmaceutical Sciences. 2022; 18(03): 035-045.

[4] Troyo A, Calderón AO, Fuller DO, Solano ME, Avedaño A, Arheart KL. Seasonal profiles of *Aedes aegypti* (Diptera: Culicidae) larval habitats in an urban area of Costa Rica with a history of mosquito control. J Vector Ecol. 2008; 33(1): 76-88.

[5] Gould E, Pettersson J, Higgs S, Charrel R, de Lamballerie X. Emerging arboviruses: why today? One Health. 2017; 4: 1-13.

[6] Benavides MJA, Montenegro CMC, Rojas CJV, Lucero CNJ. Sociodemographic and clinical characterization of patients diagnosed with Dengue and Chikungunya in Nariño, Colombia. Cuban Journal of Tropical Medicine. 2021; 73(1): e451

[7] Gore A. An inconvenient truth [videocinta] E.U.A: Paramount Classic and Participant Productions; 2007.

[8] Fajardo R, Valdelamar J, Arrieta D. Prediction of the potential establishment of the *Aedes aegypti* mosquito in urban non-housing spaces in Colombia, using ecourban and landscape variables. Environmental Management. 2016; 20(1): 10-19.

[9] Benítez PMO. Role of Aedes mosquitoes in pathogen transmission. AMC. 2018; 22 (5): 634-639.

[10] Ehelepola N, Ariyaratne K, Buddhadasa W, Ratnayake S, Wickramasinghe M. A study of the correlation between dengue and weather in Kandy City, Sri Lanka (2003-2012) and lessons learned. Infectious Diseases of Poverty. 2015; 4: 2-8.

[11] Sharmin S, Glass K, Harley D. Interaction of Mean Temperature and Daily Fluctuation Influences Dengue Incidence in Dhaka, Bangladesh. PLoS Negl Trop Dis. 2015; 9(7): e0003901.

[12] Márquez MK, Martínez E, Peña V, Monroy Á. Influence of environmental temperature on the Aedes spp mosquito and Dengue virus transmission. CES Medicine. 2019; Enero- Abril; XXXIII (1): 18-23.

[13] García GS, Pérez BA, Fimia DR, Osés RR, Garín LG, González GR. Influence of some climatological variables on larval densities in culicid breeding grounds. Pol Cap. Roberto Fleites 2009-2010. REDVET. 2012; 13(05B). URL: http://www.veterinaria.org/revistas/redvet/n050512B.html

[14] Osés RR, Fimia DR, Iannacone OJ, Saura GG, Gómez CL, Ruiz CN. 2016. Modeling of the equivalent effective temperature for the Yabu station and for the total larval density of mosquitoes in Caibarién, Villa Clara province, Cuba. Peruvian Journal of Entomology. 2016; 51(1): 1-7.

[15] Sánchez ÁML, Osés RR, Fimia DR, Gascón RBC, Iannacone J, Zaita FY, et al. Objective Regressive Regression beyond white noise for the viruses circulating in Villa Clara province, Cuba. The Biologist (Lima). 2017;15 (Special Supplement 1): 127 pp.

[16] Osés RR, Fimia DR, Marinice P, Castillo CJC, Pedraza MA, Cepero RO, et al. Modeling of total larval and Anopheles mosquito density in Villa Clara, Cuba. Impact of atmospheric pressure. REDVET. 2018a; 19 (6). URL: Uhttp://www.veterinaria.org/revistas/redvetUU

[17] Fimia DR. Mathematical modeling of population dynamics of the *Aedes aegypti* (Diptera: Culicidae) mosquito with some climatic variables in Villa Clara, Cuba. International Journal of Zoology and Animal Biology. 2020a; 3(3): 1-3.

[18] Brenda TB, James AA, Bruce MC. Genetics of Mosquito Vector Competence. Microbiol Mol Biol Rev. 2000; 64(1): 115-137.

[19] Marquetti FM. Bioecological aspects of importance for the control of *Aedes aegypti* and other culicids in the urban ecosystem [doctoral thesis]. Havana City. “Pedro Kourí” Institute of Tropical Medicine (IPK). 2006. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2554876/

[20] Fimia DR, Marquetti FM, Iannacone J, Hernández CN, González MG, Poso del Sol M, Cruz RG. Anthropogenic and environmental factors on culicid fauna (Diptera: Culicidae) of Sancti Spiritus province, Cuba. The Biologist (Lima). 2015; 13(1): 53-74.

[21] Wilke ABB, Medeiros-Sousa AR, Ceretti-Junior W, Marrelli MT. Mosquito populations dynamics associated with climate variations. Acta Tropica. 2016; 166: 343-350. Available at: http://dx.doi.org/10.1016/j.actatropica.2016.10.025

[22] Osés RR, Fimia DR, Otero MM, Osés LC, Iannacone J, Burgos AI, et al. Incidence of the annual rhythm on some climatic variables in larval populations of culicid mosquitoes: forecast for the 2018 cyclone season in Villa Clara, Cuba. The Biologist (Lima). 2018b; 16, jul-dic, Special Supplement 2. Available at: Uhttp://sisbib.unmsm.edu.pe/BVRevistas/biologist/biologist.htm

[23] Osés RR, Aldaz CJW, Fimia DR, Segura OJJ, Aldaz CNG, Segura JJ, et al. The ROR's methodology and its possibility to find information in a white noise. Int J Curr Res. 2018c; 9(03): 47378-82.

[24] Machado VI. Mathematical modeling of the population dynamics of the *Aedes aegypti* mosquito (Diptera: Culicidae) with some meteorological variables in Villa Clara province. 2007-2017 [master thesis]. ResearchGate. 2019.

[25] Fimia DR, Zambrano GFE, Aldaz CJW, Osés RR, Machado VI, de la Paz GE, Aldaz SRB, et al. Mathematical modeling of population dynamics of the *Aedes aegypti* (Diptera: Culicidae) mosquito with some climatic variables in Villa Clara province, Cuba. Academia Journal of Biotechnology. 2020; 8(12): 264-272.

[26] Bezerra JMT, Araújo RGP, Melo FF, Gonçalves CM, Chaves BA, Silva BM, et al. Aedes (Stegomyia) albopictus dynamics influenced by spatio temporal characteristics in a Brazilian dengue-endemic risk city. Acta Tropica. 2016; 164: 431-437. URL: http://dx.doi.org/10.1016/j.actatropica.2016.10.010

[27] Guzmán MG, Álvarez M, Halstead SB. Secondary infection as a risk factor for dengue haemorrhagic fever/dengue shock syndrome: an historical perspective and role of antibody-dependent enhancement of infection. Arch Virol. 2013; 158: 1445-1459.

[28] Rydzanicz K, Czulowska A, Dyczko D, Kiewra D. Assessment of mosquito larvae (Diptera: Culicidae) productivity in urban cemeteries in Wroclaw (SW Poland). International Journal of Tropical Insect Science. 2021: 1-7. URL: Uhttps://doi.org/10.1007/s42690-020-00415-1

[29] Zhou G, Minakawa N, Githeko A, Yan G. 2004. Association between climate variability and malaria epidemics in the East African highlands. Proc Natl Academ Sci USA. 2004; 101: 2375-2380.

[30] Zhang Y, Bi P, Hiller JE. 2010. Meteorological variables and malaria in a Chinese temperate city: A twenty-year time-series data analysis. Environment International. 2010 ; 36: 439-445.

[31] Beck-Johnson LM, Nelson WA, Paaijmans KP, Read AF, Thomas MB, Bjornstad ON. The effect of temperature on Anopheles mosquito population dynamics and the potential for Malaria transmission. PLOS ONE. 2013; 8 (11): e79276. URL: http://dx.doi.org/10.1371/journal.pone.0079276

[32] Fimia DR, Aldaz CJ, Aldaz CN, Segura OJ, Segura OJ, Cepero RO, Osés RR, Cruz CL. Mosquitoes (Diptera: Culicidae) and their control by means of biological agents in Villa Clara province, Cuba. International Journal of Current Research. 2017a; 8 (12): 43114-43120.

[33] Diéguez FL, García JA, San Martín MJL, Fimia DR, Iannacone OJ, Alarcón-Elbal PM. Seasonal behavior and relevance of permanent and useful reservoirs for the presence of Aedes (Stegomyia) aegypti in Camagüey, Cuba. Neotropical Helminthology. 2015; 9(1): 103-111.

[34] Fimia DR, Iannacone J, Osés RR, González GR, Armiñana GR, Gómez CL, García CB, Zaita FY. Association of some climatic variables with fasciolosis, angiostrongylosis and the river malacofauna of the Villa Clara province, Cuba. Neotropical Helminthology (aphia). 2017b; 10 (2): 259-273.

[35] González RIC, Fimia DR, García PM. Evaluación del programa para la vigilancia del mosquito Stegomyia aegypti en el municipio Santa Clara, provincia Villa Clara. Año 2007. REDVET. 2010; 11(03B). Available at: Uhttp://www.veterinaria.org/revistas/redvetU

[36] Machado VI, Hernández CL, Fimia DR, Pérez TBE, Santana RM, Molina PA, Quintero SN. The resident focal point: an alternative in the control of *Aedes aegypti* (Diptera: Culicidae) and the prevention of dengue in a health area of Santa Clara municipality, Villa Clara, Cuba. REDVET. 2018; 19(6): 1-7.

[37] Samek V, Travieso A. Climate regions of Cuba. Agriculture Magazine. 1968; 2: 5-23.

[38] Osés R, Grau R. Regressive modeling (ROR) versus ARIMA modeling, using dichotomous variables in HIV mutations. Central University Marta Abreu of Las Villas, February 25. Feijóo Publishing House. 2011.

[39] Alkhaldy I. 2017. Humidity in Jeddah, Saudi Arabia − a generalized linear model with modelling the association of dengue fever cases with temperature and relative break-point analysis. Acta Tropica. 2017; 168: 9-15.

[40] Cabezas SC, Fiestas DV, García MM, Palomino SM, Mamani CE, Donaires A F. Dengue in Peru: a quarter of a century after its reemergence. Peruvian Journal of Experimental Medicine in Public Health. 2015; 66(2): 219-227.

[41] Aldaz CJW, Osés RR, Fimia DR, Segura OJ, Aldaz CNG, Segura OJJ, Fundora GR. 2017. The climate prediction with a year in advance through the Bultó's index for Havana city, Cuba. International Journal of Current Research. 2017; 9 (01): 45382-45386. Available online: http://www.journalcra.com.

[42] Xu HY, Fu X, Lee LKH, Ma S, Goh KT, Wong J, et al. Statistical Modeling Reveals the Effect of Absolute Humidity on Dengue in Singapore. PLoS Negl Trop Dis. 2014; 8(5): e2805.

[43] Fimia DR, Guerra VY, del Valle LD, Morales GRJ, Castañeda LW, Leiva HJ, et al. Population dynamic of *Aedes aegypti* (Diptera: Culicidae); contributions to the prevention of arbovirosis in Villa Clara, Cuba. GSC Biological and Pharmaceutical Sciences. 2022; 18(02): 173-188.

[44] Real CJ. Factors related to dengue dynamics in Guayaquil, based on historical trends. Faculty of Medicine. 2017; 78(1): 37-41.

[45] Fimia DR, Machado VI, Osés RR, Aldaz CJW, Armiñana GR, Castañeda LW, et al. Mathematical modeling of the population dynamics of the *Aedes aegypti* mosquito (Diptera: Culicidae) with some climatic variables in Villa Clara, Cuba. 2007- 2017. The Biologist (Lima), vol.17, jul-dic, Especial Supplement. 2019; 2.

[46] Rivera GO. *Aedes aegypti*, Dengue, Chikungunya, Zika viruses and climate change. Maximum medical and official alert. REDVET. 2014; 15(10). URL: http://www.veterinaria.org/