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MODELS FOR PREDICTING *AEDES AEGYPTI* LARVAL INDICES BASED ON SATELLITE IMAGES AND CLIMATIC VARIABLES

ELIZABET L. ESTALLO,[1] MARIO A. LAMFRI,[2] CARLOS M. SCAVUZZO,[2] FRANCISCO F. LUDUEÑA ALMEIDA,[1] MARÍA V. INTROINI,[3] MARIO ZAIDENBERG[3] AND WALTER R. ALMIRÓN[1]

ABSTRACT. Forecasting models were developed for predicting *Aedes aegypti* larval indices in an endemic area for dengue (cities of Tartagal and Orán, northwestern Argentina), based on the Breteau and House indices and environmental variables considered with and without time lags. Descriptive models were first developed for each city and each index by multiple linear regressions, followed by a regional model including both cities together. Finally, two forecasting regional models (FRM) were developed and evaluated. FRM_2 for the Breteau index and House index fit the data significantly better than FRM_1. An evaluation of these models showed a higher correlation FRM_1 than for FRM_2 for the Breteau index ($r = 0.83$ and 0.62 for 3 months; $r = 0.86$ and 0.67 for 45 days) and the House index ($r = 0.85$ and 0.79 for 3 months; $r = 0.79$ and 0.74 for 45 days). Early warning based on these forecasting models can assist health authorities to improve vector control.

KEY WORDS Forecasting models, *Aedes aegypti*, larval indices, remote sensing, climatic variables

INTRODUCTION

In the Americas, dengue fever and dengue hemorrhagic fever are the major public health problem and the most important vectorborne viral diseases, primarily in tropical and subtropical areas. The four dengue serotypes are maintained in cycles involving humans and the *Aedes aegypti* (L.) vector (Rigau-Peréz et al. 1998; WHO 2000, 2007), a day-biting urban mosquito that mainly feeds on humans (Gubler and Kuno 1997, Rodhain and Rosen 1997, Stein et al. 2002).

Environmental conditions strongly control the distribution and abundance of *Ae. aegypti* (Chistophers 1960; Rueda et al. 1990; Focks et al. 1993a, 1993b) and, thus, the transmission of dengue viruses (Gubler 1988, Patz et al. 1996). In urban areas, any type of water-holding container, such as discarded bottles, tires, and water cisterns, with clean water is a good larval habitat. These man-made habitats are abundant in urban settlements where the food supply (blood) for gravid female mosquitoes is abundant. In these environments, climatic variables such as temperature, humidity, and rainfall significantly influence mosquito development and survivorship (Chistophers 1960; Focks et al. 1993a, 1993b; Hopp and Foley 2001, 2003).

While a vaccine is under development, the only currently available method of prevention and control of dengue and dengue hemorrhagic fever involves combating the vector mosquitoes at both larval and adult stages (Lloyd et al. 1992, WHO 2002, Reiter et al. 2003, Guzmán et al. 2006). Although only *Ae. aegypti* females are directly involved in dengue transmission, entomological surveillance has been based on larval indices, which have been used for over 60 years to estimate mosquito population densities and determine the risk of dengue transmission (PAHO 1994, WHO 1997). The most widely used indices are the House index (percentage of houses positive for *Ae. aegypti* larvae), and the Breteau index (number of containers positive for *Ae. aegypti* larvae per 100 houses) (Ibañez Bernal and Gómez Dantés 1995, Tun-Lin et al. 1996, Focks 2003, Mercado Hernández et al. 2003).

The objective of this work was to develop forecasting models of larval indices in an area endemic for dengue disease in Argentina. Assuming *Ae. aegypti* larval indices are directly related to adult densities, it would be extremely advantageous to develop a vector abundance early forecasting system based on indices used to predict larval abundance. Our models were derived from analyses of House and Breteau indices estimated in the study area and climatic and environmental variables obtained from terrestrial and satellite observations.

MATERIAL AND METHODS

Breteau and House indices

Entomological surveillance data were recorded by the National Coordination for Vector Control

[1] Centro de Investigaciones Entomológicas de Córdoba, Facultad de Ciencias Exactas, Físicas y Naturales, Universidad Nacional de Córdoba (U.N.C.), Avenida Vélez Sarsfield 1611, CP 5016, Córdoba, Argentina.

[2] Instituto de Altos Estudios Espaciales Mario Gulich, Comisión Nacional de Actividades Espaciales (CONAE), Centro Espacial Teofilo Tabanera, Ruta C45 Km. 8, Falda del Carmen, CP 5187, Córdoba, Argentina.

[3] Coordinación Nacional de Control de Vectores, Misterio de Salud de la Nación, 9 de Julio 356, CP 5000, Córdoba, Argentina.

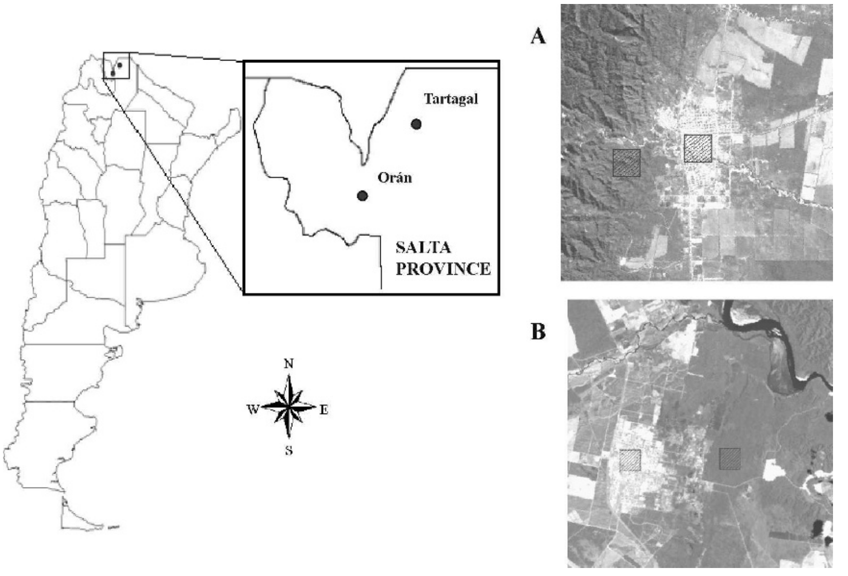

Fig. 1. Map of Argentina showing Salta Province and Orán and Tartagal cities, a 144-km^2 subset of Landsat satellite image path/row 230/76 (April 27, 1997) for Tartagal City and surrounding areas (A), and a 225-km^2 subset of Landsat image path/row 230/76 (November 6, 2003) for Orán City and surrounding areas; Bermejo river to the right side (B). Environmental information was taken from the areas under the black squares.

of the National Ministry of Health in two subtropical, northwestern Argentinean cities: San Ramón de la Nueva Orán City, hereafter Orán City, (23°08′S, 64°20′W, elevation 337 m) and Tartagal City (22°32′S, 63°49′W, elevation 463 m) (Fig. 1). Orán City is 140 km away from Tartagal City. Orán and Tartagal cities are located 270 km and 350 km northeast of Salta City, the main city of Salta Province. The National Coordination for Vector Control recorded monthly entomological data from Orán City, and bimonthly data from Tartagal City. The Breteau index and House index recorded between January 2001 and May 2005 were used to develop our models.

Data obtained from remote sensors

The satellite-derived variables were extracted from Landsat 5 (L5 TM) and Landsat 7 (L7 ETM+) path/row 230/76 satellite images (Fig. 1). A set of 52 images for Tartagal City and a set of 48 images for Orán City, both spanning January 2001 to May 2005, were selected from the National Commission of Spatial Activities (CONAE) catalog. Images were georeferenced and coregistered and then subdivided into areas of interest of 144 km^2 for Tartagal City and 225 km^2 for Orán City (Fig. 1).

Since our time-series data cover about 4.5 years with images from two different sensors (Landsat 5TM and 7ETM+) and a range of acquisition dates, each subset was calibrated using different coefficients on ENVI 4.2 software (ENVI RS 2004). The dynamic range of Chandler and Markham (2003) was used to calibrate L5 TM images, whereas the header coefficient of each image was used to calibrate those from L7 ETM+.

Two 1.44 km^2 areas were defined in each subset, one including the city and the other encompassing the native forest surrounding the city. Using ENVI, we extracted the mean and variance of brightness temperature and the Normalized Difference Vegetation Index (NDVI) from these focal areas, resulting in 8 environmental variables: mean brightness temperature and NDVI, and variance for the brightness temperature and NDVI for each city and forest area. These variables are widely used to characterize the environment. NDVI is calculated with the near-infrared band (band 4) and the red band (band 3) of the Landsat satellite images, and it is an important estimator because vegetation depends on temperature, precipitation, and soil properties. Therefore, the NDVI, which measures vegetation greenness, is a proxy for soil moisture and land-surface wetness where areas with vegetation usually have NDVI > 0. On the other hand, brightness temperature is also a good estimator (Landsat images band 6) that gives an approximation of environmental temperature.

To produce a complete time-series data set, a biweekly raster grid was developed from the first 15 days of January 2001 to the first 2 weeks of May 2005. Images were located in the raster according to acquisition date, and then a spline cubic interpolation was performed for the vari-

Table 1. List of independent variables (X_1 to X_{13}) used to develop the models.

Independent variable	Definition
X_1	Mean NDVI[1] of the forest
X_2	Variance of the NDVI of the forest
X_3	Mean forest brightness temperature
X_4	Variance of the forest brightness temperature
X_5	Mean city NDVI
X_6	Variance of the city NDVI
X_7	Mean city brightness temperature
X_8	Variance of the city brightness temperature
X_9	Precipitation
X_{10}	Maximum temperature
X_{11}	Minimum temperature
X_{12}	Maximum humidity
X_{13}	Minimum humidity

[1] NDVI, Normalized Difference Vegetation Index.

Table 2. Variables with the best time lag (lag 1 to 12) considered in the development of the local and regional models for Tartagal and Orán cities (northwestern Argentina).

Variables	Breteau index (local)		House index (local)		Regional model lags
	Tartagal	Orán	Tartagal	Orán	
X_1	1	4	1	1	1
X_2	1	1	12	1	1
X_3	4	3	4	3	3
X_4	8	2	8	2	2
X_5	1	9	2	7	1
X_6	1	1	8	1	9
X_7	4	3	3	3	3
X_8	3	3	3	3	3
X_9	2	2	1	2	2
X_{10}	6	4	5	5	5
X_{11}	2	1	2	2	11
X_{12}	1	1	9	8	8
X_{13}	9	9	9	1	9

ables NDVI and brightness temperature using ENVI. Larval indices were also added to the raster grids and interpolated.

Daily meteorological data for both cities were obtained from the National Meteorological Service: precipitation (mm), maximum and minimum temperature (°C), and maximum and minimum humidity (%). From each 15-day period, we used the accumulated precipitation and the maximum and minimum values of temperature and humidity. We found that mean temperature and humidity correlated with minimum and maximum temperature and humidity; therefore we only used the latter in developing the models.

Development of models and data analysis

Local models were first developed for each city and each index as descriptive models to understand how the system works at different scales. Assuming that both studied cities are relatively close, with similar environmental conditions, vegetation, and elevation, a regional model was developed considering both cities together. The regional model would thus provide a regional perspective for the northwestern Argentina endemic dengue area. A forecasting regional model (FRM) was then developed and evaluated to predict the larval indices. The predicted larval indices could then be used to manage possible dengue outbreaks by predicting peaks of abundance of adult *Ae. aegypti* for the whole study.

The general model was based on the following equation:

$$y = a_0 + a_1 X_1 + \dots a_n X_n ,$$

where y is the estimated index value (Breteau index or House index), a_0 is a constant, and a_1 to a_n are coefficients of environmental variables X_1 to X_n (Table 1). Once the model was developed, the correlation coefficient (r) was calculated between modeled and observed data.

Because *Ae. aegypti* development is mainly affected by weather conditions (Service 1993, Ludueña Almeida and Gorla 1995, Domínguez et al. 2000), we strove to add realism to the models by considering all environmental variables with and without lags of 15 days (lags 1–12, covering 6 months). Correlations between the 12 lags and each observed index for each city were carried out to select the best time lag for each variable, which was then used to develop the local models. For the regional models, the mean correlation value for each time lag, considering both cities together, was calculated, including the best mean correlation value in the models (Table 2).

Based on the set of descriptive regional models with the best fit, we also developed two FRMs using variables with time lag. In the first FRM, the same variables selected for the descriptive regional model with time lag were included, while a second FRM was developed that took into account the stepwise variable selection.

Multiple linear regression analyses were performed using INFOSTAT software (2002). Due to the nature of the dependent variables, Breteau and House indices were log-transformed to normalize the residuals before use in developing selected models.

The 8 satellite-derived environmental variables (X_1–X_8) and the 5 meteorological variables (X_9–X_{13}) were included in each regression analysis to develop the model. The variables were selected to a better statistical fit, so the ones that least contributed to explain the model ($P > 0.05$) were removed stepwise according to the tolerance and Mallow's Cp values for each variable. The complete data set, i.e., from January 2001 to May 2005, was used for the descriptive models.

However, for the forecasting models, the data set was divided into two subsets: the subset from the period January 2001 to April 2003 was used to develop the model, and the subset from the period May 2003 to May 2005 was used to evaluate the model (i.e., the training and evaluation data sets, respectively; Brzeziecki et al. 1993; Guisan et al. 1998, 1999; Guisan and Zimmermann 2000; Zimmermann and Kienast 1999). To evaluate the forecasting models, we measured the correlation between the field data and the indices calculated by each model.

RESULTS

Descriptive local models

The models without time lag for Orán and Tartagal cities showed the same fit for Breteau and House indices ($R^2 = 0.79$ and 0.83, respectively; $P < 0.0001$). Ten and nine variables were included for the Breteau index models for Tartagal and Orán cities, respectively. The House index models included 6 variables for Tartagal City and 7 for Orán City. The models for the Breteau and House indices for both Tartagal and Orán cities included brightness temperature, NDVI, and temperature variables (Table 3). The eliminated common variable in all local models was the minimum humidity.

All local models developed with time lag showed a good fit, although, in several cases, they had low R^2 values. The Breteau index model for Orán City with time lag ($R^2 = 0.89$; $P < 0.0001$) fit better than the same model without time lag ($R^2 = 0.79$). However, the fit for the Breteau index model for Tartagal City was lower with time lag ($R^2 = 0.74$; $P < 0.0001$). The fit also decreased for the House index models from 0.83 without time lag to 0.73 and 0.8 with time lag for Orán and Tartagal cities, respectively ($P < 0.001$). However, high correlations ($0.87 \leq r \leq 0.95$; $P < 0.05$) were obtained between the observed data and values estimated by the models.

The Breteau index models with time lag included 7 and 12 variables for Tartagal and Orán cities, respectively (Table 3). The Breteau index model for Orán City included almost all variables. However, the common variables for both models corresponded to NDVI, brightness temperature, precipitation, temperature, and humidity. Eight variables were included in the House index local models with time lag for both cities (Table 3) corresponding to NDVI and brightness temperature. The variances of the forest and city brightness temperature were the only two variables included in all local models with and without time lag. Therefore, these variables were present in all descriptive local models.

Table 3. Local models (LM) obtained for Orán and Tartagal cities, and for the Breteau (BI) and House (HI) indices, according to the regression analysis performed considering variables with and without time lag. The Breteau index and House index were log-transformed to normalize the residuals (*LnBI*, *LnHI*).

Model	Model expressions
Oran LM without time lag	$LnBI = -35.58 - 414.31X_2 + 0.45X_3 + 9.85X_4 + 8.97X_5 + 35.52X_6 - 0.34X_7 + 0.83X_8 - 0.04X_{10} + 0.03X_{11}$ $LnHI = -19.59 + 0.43X_3 + 6.89X_4 + 8.95X_5 + 34.55X_6 - 0.38X_7 + 0.94X_8 + 0.03X_{11}$
Oran LM with time lag	$LnBI = -39.30 + 4.87X_1 - 532.44X_2 + 0.48X_3 + 11.97X_4 + 5.30X_5 - 56.27X_6 - 0.36X_7 + 1.34X_8 + 0.004X_9 + 0.07X_{10} - 0.02X_{12} - 0.01X_{13}$ $HI = -1.01 + 0.22X_1 + 0.74X_4 + 0.95X_5 - 2.21X_6 + 0.004X_7 + 0.08X_8 + 0.0005X_9 - 0.004X_{12}$
Tartagal LM without time lag	$BI = -0.16 - 0.63X_1 - 0.02X_3 - 0.26X_4 + 1.66X_5 + 4.39X_6 + 0.02X_7 + 0.08X_8 + 0.0006X_9 + 0.007X_{11} - 0.003X_{12}$ $HI = -0.6990 - 0.0996X_4 + 0.5672X_5 + 0.0023X_7 + 0.0462X_8 + 0.0003X_9 + 0.0057X_{11}$
Tartagal LM with time lag	$BI = 0.022 - 4.73X_2 + 0.06X_4 + 0.052X_8 + 0.0005X_9 + 0.006X_{10} + 0.007X_{11} - 0.004X_{13}$ $HI = -0.39 + 0.19X_1 + 0.002X_3 + 0.06X_4 - 0.45X_5 - 1.95X_6 + 0.04X_8 + 0.005X_{11} - 0.002X_{13}$

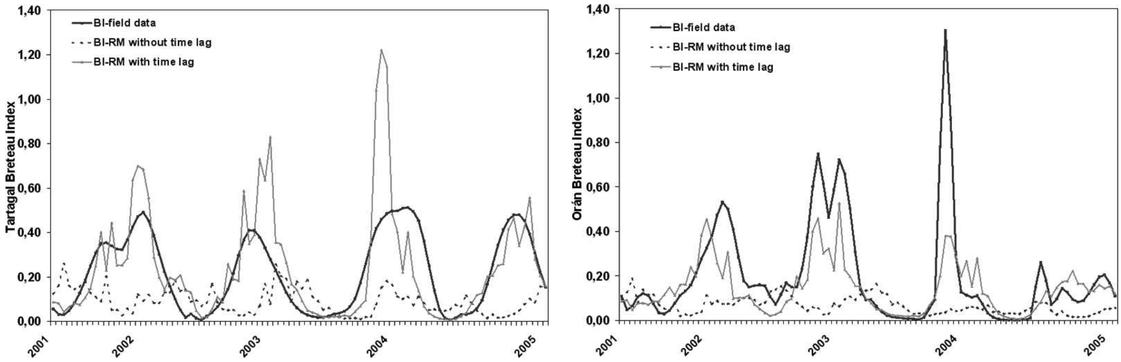

Fig. 2. Breteau index regional model (BI-RM) for Tartagal and Orán cities with (R^2 = 0.67, F = 37.28, $P <$ 0.0001) and without (R^2 = 0.63, F = 28.22, $P <$ 0.0001) lag.

Descriptive Regional Models

Both cities were considered together to develop regional models, and these were analyzed with and without time lag. The Breteau index model fit better with time lag (R^2 = 0.67 and 0.63 with and without time lag, respectively; $P <$ 0.0001). Additionally, the Breteau index model developed using time lag variables fit well with observed field data (Fig. 2), as did the curve in the House index model with time lag (Fig. 3), although the fit was higher in the House index model without time lag (R^2 = 0.63 and 0.66 with and without time lag, respectively; $P <$ 0.0001). The Breteau index model without time lag included all variables, but only 10 variables when time lags were applied (Table 4). Twelve variables were included in the House index models without time lag, and 9 variables were included in the House index models with time lag. The mean forest NDVI, mean forest brightness temperature, mean and variance of city NDVI, variance of city brightness temperature, precipitation, maximum temperature, maximum humidity, and minimum humidity were common for both House and Breteau regional models (Table 4).

Forecasting Regional models

Taking into account the good fit obtained for the descriptive regional models with time lag (Figs. 2 and 3), the same variables were included to develop FRM_1 (Table 5). The FRM_2 was developed by considering the complete set of 13 variables and removing variables stepwise, which provided a set of variables with better statistical fit.

For the Breteau index, FRM_2 fit significantly better than FRM_1 (R^2 = 0.66 and 0.60, respectively; Fig. 4), including 9 and 10 variables, respectively. The common variables were NDVI, brightness temperature, precipitation, temperature, and humidity (Table 5).

Again, FRM_2 for the House index fit significantly better than FRM_1 (R^2 = 0.59 and 0.54, respectively; Fig. 5). The common variables were the NDVI, precipitation, temperature, and humidity. Considering all the FRMs, only 3 variables were included in all models: precipitation, maximum temperature, and minimum humidity (Table 5).

The potential forecast power for $FRMl_1$ and FRM_2 was evaluated by estimating larval indices

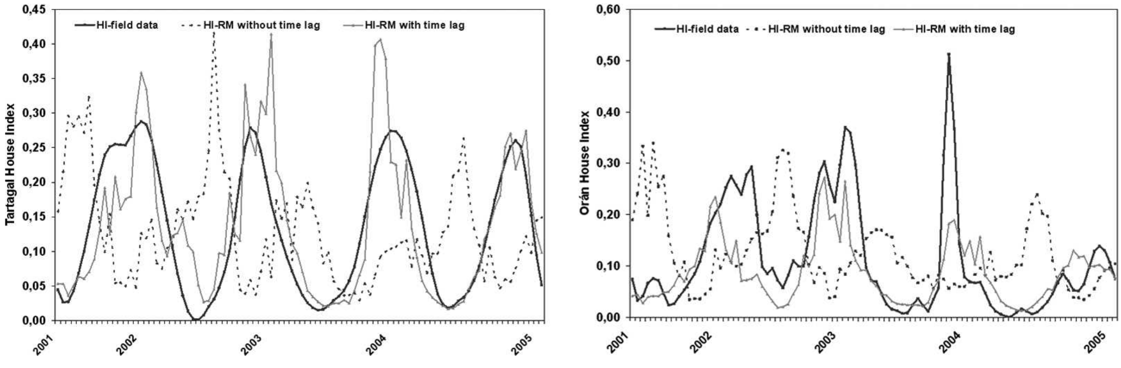

Fig. 3. House index regional model (HI-RM) for Tartagal and Orán cities with (R^2 = 0.63, F = 37.28, $P <$ 0.0001) and without (R^2 = 0.66, F = 31.31, $P <$ 0.0001) lag.

Table 4. Regional models (RM) obtained for Orán and Tartagal cities, and for the Breteau (BI) and House (HI) indices, according to the regression analysis performed considering variables with and without time lag. The Breteau index and House index were log-transformed to normalize the residuals (*LnBI*, *LnHI*).

Model	Model expressions
RM without time lag	$LnBI = -24.16 - 2.93X_1 - 105.83X_2 + 0.08X_3 - 0.28X_4 + 8.45X_5 + 27.47X_6 - 0.01X_7 + 0.56X_8 + 0.002X_9 - 0.05X_{10} + 0.06X_{11} + 0.02X_{12} + 0.002X_{13}$
	$LnHI = -16.43 - 1.94X_1 - 67.73X_2 + 0.07X_3 - 0.24X_5 + 17.24X_6 - 0.03X_7 + 0.63X_8 + 0.002X_9 - 0.02X_{10} + 0.05X_{11} + 0.03X_{12} + 0.007X_{13}$
RM with time lag	$BI = -20.99 - 4.59X_1 - 104.68X_2 + 0.07X_3 + 9.57X_5 - 28.53X_6 + 0.37X_8 + 0.003X_9 + 0.05X_{10} - 0.02X_{12} - 0.008X_{13}$
	$LnHI = -11.55 - 1.94X_1 + 0.03X_3 + 5.46X_5 - 28.72X_6 + 0.50X_8 + 0.002X_9 + 0.04X_{10} - 0.01X_{12} - 0.01X_{13}$

Table 5. Forecasting regional models (FRM) obtained for Orán and Tartagal cities, and for the Breteau (BI) and House (HI) indices, according to the regression analysis performed considering variables with time lag. The Breteau index was log-transformed to normalize the residuals (*LnBI*, *LnHI*).

Model	Model expressions
FRM_1	$LnBI = -13.53 - 0.84X_1 - 199.69X_2 + 0.04X_3 - 1.69X_5 - 2.26X_6 + 0.65X_8 + 0.003X_9 + 0.05X_{10} - 0.004X_{12} - 0.015X_{13}$
	$HI = -0.21 - 0.28X_1 + 0.0007X_3 - 0.64X_5 - 1.39X_6 + 0.05X_8 + 0.0004X_9 + 0.003X_{10} + 0.0002X_{12} - 0.002X_{13}$
FRM_2	$BI = -1.87 - 409.39X_2 - 0.15X_3 + 2.26X_4 + 12.14X_6 + 0.14X_7 + 0.004X_9 + 0.04X_{10} + 0.02X_{11} - 0.009X_{13}$
	$HI = 0.08 - 24.96X_2 + 0.10X_4 - 0.27X_5 + 0.04X_7 + 0.0005X_9 + 0.004X_{10} + 0.002X_{11} - 0.003X_{13}$

with these models and correlating the observed data with data estimated by the respective models. The indices recorded from May 2003 to May 2005 were correlated with predicted values over two short periods, 3 months and 45 days. For the Breteau index, a better correlation was observed for FRM_1 than FRM_2 in both periods ($r = 0.83$ and 0.62 for 3 months; $r = 0.86$ and 0.67 for 45 days; $P < 0.05$). For the House index, again a higher correlation was also observed for FRM_1 than FRM_2 in both periods ($r = 0.85$ and 0.79 for 3 months; $r = 0.79$ and 0.74 for 45 days; $P < 0.05$). Although FRM_2 showed a better fit, the potential power for predicting the larval indices was higher for FRM_1, which could be an excellent tool as a predictive model of larval index. This model included the same variables as the descriptive regional model with the time lags considered according to *Ae. aegypti* biological characteristics, thus providing a better biological understanding of these mosquitoes.

DISCUSSION

Sixteen models were developed in this work, and the variance of the city brightness temperature was present in all but FRM_2. Other important variables in decreasing frequency of appearance in the models were: the variance of the city NDVI in 14 models, the mean city NDVI and precipitation in 13 models, the mean forest brightness temperature and the variance of the forest brightness temperature in 12 models, and maximum temperature and minimum humidity in 11 models. Undoubtedly, climatic variables, particularly the variance of city brightness temperature, the variance of forest brightness temperature, precipitation, maximum temperature, and minimum humidity, have a significant role in the development of *Ae. aegypti* and, thus, an effect on larval indices.

Domínguez et al. (2000) studied the fluctuation of *Ae. aegypti* populations in Córdoba City, located in central Argentina, which is characterized by a temperate climate. Their study correlated mosquito density with mean temperature and precipitation. They found a high correlation ($r = 0.81$; $P < 0.05$) for both variables when analyzed with a time lag of a month. We found a similar relationship in the present work when we used a 1 month time lag for precipitation and temperature in the forest brightness temperature to develop the models. However, we found that the most suitable lag for the variance of city brightness temperature obtained here was 1.5 months.

Precipitation is important in the transmission of mosquitoborne diseases because mosquitoes require water for the aquatic larval and pupal breeding stages. However, both precipitation and temperature should be used to model mosquito

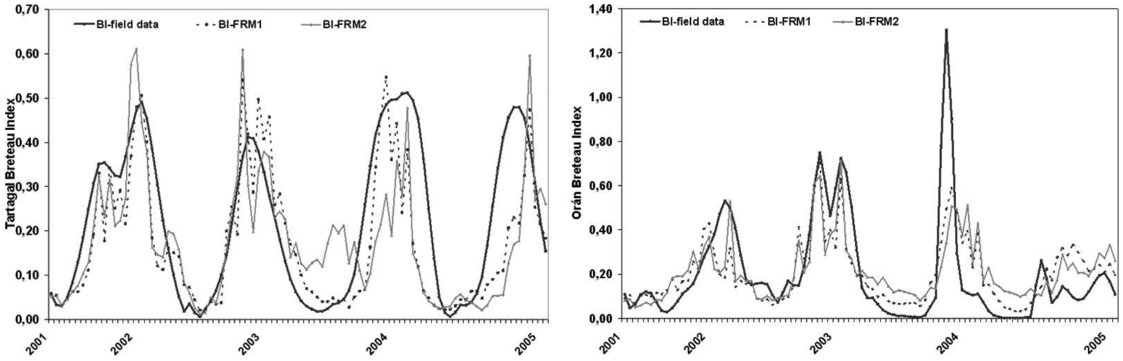

Fig. 4. Breteau index forecasting regional models (BI- FRM) for Tartagal and Orán cities. Forecasting regional model 2 (FRM_2) fit significantly better than forecasting regional model 1 (FRM_1) ($R^2 = 0.66$, F = 21.07, $P < 0.0001$ and $R^2 = 0.60$, F = 15.12, $P < 0.0001$, respectively). FRM_1 is the predictive model of larval index.

vector populations. Quantity, timing, and pattern of precipitation will affect mosquito larval habitats (Lindsay and Mackenzie 1996), but temperature also affects mosquito population growth and pathogen replication rates (Rose et al. 2000).

A complete monitoring program for a mosquitoborne disease should include predictions of vector population size (Eldridge 1987), which may be estimated from the models developed here. Assuming that the entomological data, satellite images, and meteorological data can be currently obtained from the National Coordination for Vector Control of the National Ministry of Health, CONAE, and the National Meteorological Service, respectively, implementation of the predictive model of larval index is quite possible. The extra requirement for our Ministry of Health would be a good computer system, and the appropriate software to process the images, and also a technician to process the images and generate the model. Early warning based on the predictive model of larval index is a realistic tool that may assist health authorities to improve vector control and diminish the risk of a dengue outbreak in northwestern Argentina.

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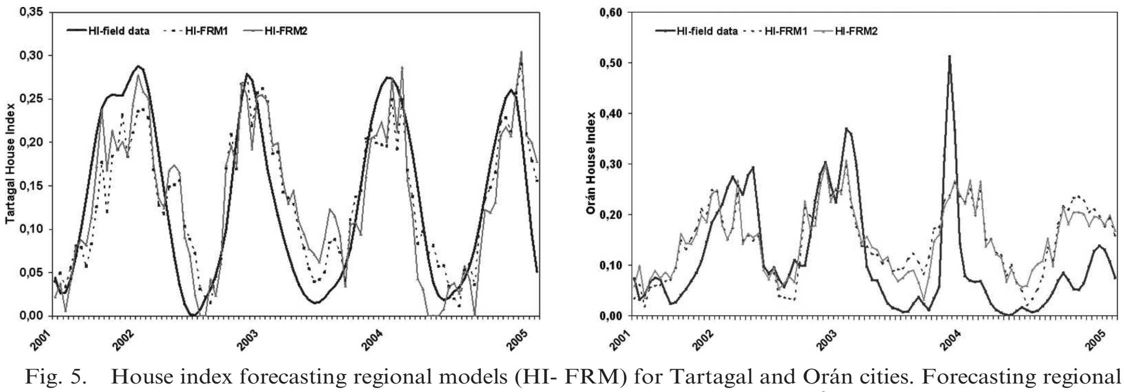

Fig. 5. House index forecasting regional models (HI- FRM) for Tartagal and Orán cities. Forecasting regional model 2 (FRM_2) fit significantly better than forecasting regional model 1 (FRM_1) ($R^2 = 0.59$, F =17.70, $P < 0.0001$ and $R^2 = 0.54$, F = 13.36, $P < 0.0001$, respectively). FRM_1 is the predictive model of larval index.

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