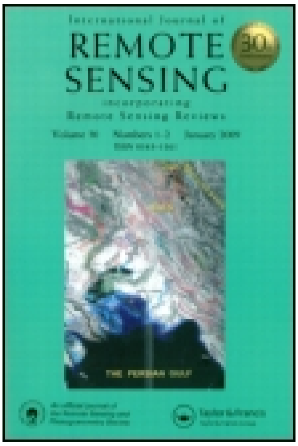

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Effectiveness of normalized difference water index in modelling *Aedes aegypti* house index

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The application of remotely sensed data to public health has increased in Argentina in the past few years, especially to study vector-borne viral diseases such as dengue. The normalized difference vegetation index (NDVI) has been widely used for remote sensing of vegetation as well as the brightness temperature (BT) for many years. Another environmental variable obtained from satellites is the normalized difference water index (NDWI) for remote sensing of the status of the vegetation liquid water from space. The aim of the present article was to test the effectiveness of NDWI together with other satellite and meteorological data to develop two forecasting models, namely the SATMET (satellite and meteorological variables) model and the SAT (satellite environmental variables) model. The models were developed and validated by dividing the data file into two sets: the data between January 2001 and April 2004 were used to construct the models and the data between May 2004 and May 2005 were used to validate them. The regression analysis for the SATMET and SAT models showed an adjusted R^2 of 0.82 and 0.79, respectively. To validate the models, a correlation between the estimates and the observations was obtained for both the SATMET model ($r = 0.57$) and the SAT model ($r = 0.64$). Both models showed the same root mean square error (RMSE) of 0.04 and, therefore, the same forecasting power. For this reason, these models may have applications as decision support tools in assisting public health authorities in the control of *Aedes aegypti* and risk management planning programmes.

1. Introduction

Dengue is one of the most widespread vector-borne diseases in the world (WHO 2009a) caused by any one of four antigenically distinct serotypes of the dengue virus (DEN-1, DEN-2, DEN-3 and DEN-4) transmitted by the *Aedes aegypti* mosquitoes. These mosquitoes mainly feed on humans, biting during the daytime, and live in urban areas (Gubler and Kuno 1997, Rodhain and Rosen 1997). Their breeding habitats consist of any type of water-holding container, from tree holes or leaves to discarded

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bottles (Hopp and Foley 2001, 2003, WHO 2009a). About 2500 million people live in areas with potential risk of dengue transmission (Gubler 2004). The global incidence of dengue has grown dramatically in recent decades; furthermore, there has been an increasing trend in dengue outbreaks in South America during the past years (WHO 2009b). In 2009, Argentina experienced the worst dengue outbreak of the last few decades, with 26 923 confirmed autochthonous cases (locally transmitted by mosquitoes) and 5 deaths. Cases were distributed in 14 locations, 10 of which (Buenos Aires, Ciudad Autónoma de Buenos Aires, Catamarca, Chaco, Córdoba, Entre Ríos, La Rioja, Santa Fe, Santiago del Estero and Tucumán) registered autochthonous dengue cases for the first time. On that occasion, all the reported cases were caused by the DEN-1 serotype, 92% of which were concentrated in the provinces of Chaco (46%), Catamarca (36%) and Salta (10%), warm areas with ideal environmental conditions for vector mosquitoes to breed (Ministerio de Salud de la Nación 2009).

While a vaccine is under development, the only currently available method of prevention and control of dengue is combating the vector mosquitoes at both the larval and adult stages (WHO 2009b). Although only *A. aegypti* females are directly involved in dengue transmission, entomologic surveillance has been based on different larval indices (container index, house index (HI) and Breteau index) where HI (percentage of larvae-positive houses) is one of the most widely used (Focks 2003, Sanchez *et al*. 2006, Estallo *et al.* 2008). These indices have been used for many years to estimate and monitor *A. aegypti* populations and to determine the potential risk of dengue transmission (PAHO 1995, Tun-Lin *et al*. 1996, WHO 1996). Although some authors have questioned the use of indices to identify dengue outbreak risk (Gomez-Dantes *et al*. 1995, Sulaiman *et al*. 1996), larval indices are still the main tool for monitoring *A. aegypti* because of their easy implementation. For that reason, it is important to generate predictive models that allow for estimating larval indices considering the environmental conditions of the vector breeding sites.

The *A. aegypti* distribution and abundance is strongly dependent on environmental conditions (Focks *et al*. 1993a,b, Hopp and Foley 2001, 2003). Temperature, humidity and precipitation have proven to significantly influence mosquito development and survival (Hopp and Foley 2001, 2003). Several authors have hypothesized that the spatial and temporal patterns of mosquito population dynamics are controlled by environmental factors that can be remotely observed (Hay *et al*. 1997). Two vegetation indices, potentially indicative of the mosquito habitat existence, may be derived from the satellite images: the normalized difference vegetation index (NDVI) and the normalized difference water index (NDWI). The NDVI has been widely used for remote sensing of vegetation and has been applied to mosquito studies for many years (Hay *et al*. 1997), as well as in many other applications including health and studies on vector-borne diseases (Linthicum *et al*. 1987, Pope *et al*. 1992, Lacaux *et al*. 2007). The NDWI is an indicator of the liquid water molecules (vegetation water content) in vegetation canopies that interact with the incoming solar radiation (Gao 1996). NDWI increases as the leaf layer increases, indicating that it is sensitive to the total amount of liquid water stacked in the leaves. This index is less susceptible to atmospheric scattering effects than the NDVI (Gao 1996). The vegetation water content is also used to retrieve the soil moisture from microwave remote sensing observations (Jackson *et al*. 2004). This index has been used to explore the remote sensing potential to map and monitor the vegetation water content for corn and soybean canopies (Jackson *et al*. 2004), to monitor the water stress in semi-arid environments (Fensholt and Sandholt 2003) and to characterize the land cover and the vegetation type (Xiao *et al*. 2002, Boles *et al*. 2004). In this project, it was used to generate models that included NDWI as an environmental predictor to forecast HI, considering that NDWI could better forecast environmental variables to characterize mosquito habitat environments. Therefore, the objective of this study was to test the effectiveness of NDWI and other satellite and meteorological data and to develop two forecasting models for *A. aegypti* HI in the city of San Ramón de la Nueva Orán.

2. Methods

2.1 *Study site*

The city of San Ramón de la Nueva Orán, hereafter Orán, is located in the province of Salta (23° 08′ S, 64° 20′ W, elevation 337 m) in northwestern Argentina (figure 1). With a population of 72 712 (INDEC 2001), Orán is the second largest city in the province. Orán is surrounded by subtropical native forest. Despite its dry season, the climate is subtropical, with an annual accumulated rainfall of 1000 mm, 78% mean annual humidity and 21°C mean annual temperature. Summers are hot with absolute maximum and minimum temperatures of 45°C and 11.5°C, respectively. Winters are temperate with one or two frosts in July, with absolute maximum and minimum temperatures of 38°C and –3°C, respectively (Servicio Meteorológico Nacional).

2.2 *Data collection*

2.2.1 Entomological data. An entomological survey to assess *A. aegypti* infestation levels in Orán was carried out between 2001 and 2005 by personnel of the National Coordination for Vector Control (NCVC) of the National Ministry of Health. Technicians of the NCVC exhaustively inspected homes in Orán to estimate *A. aegypti* infestation monthly. Our analyses were based on HI (percentage of positive

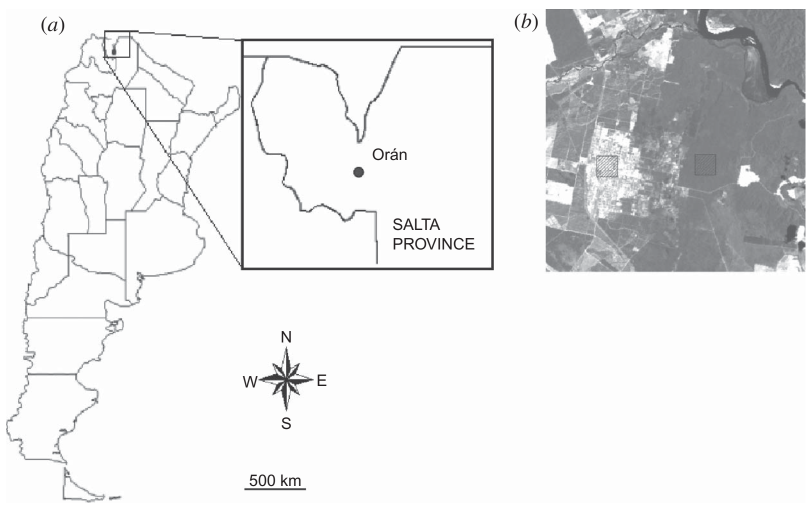

Figure 1. (*a*) Map of Argentina showing San Ramón de la Nueva Orán city (Salta province) and (*b*) a 225 km^2 subset of Landsat image path/row 230/76 (6 November 2003) for Orán and its surrounding areas. Satellite-derived variables (NDVI, NDWI and BT) were extracted from the black square on the subset image.

houses for *A. aegypti* larvae), one of the most widely used and easy to apply larval indexes, where HI is the number of houses with *A. aegypti* larvae multiplied by 100 divided by the total number of inspected houses (Focks 2003, Sanchez *et al*. 2006, Estallo *et al*. 2008). HI was recorded by the NCVC for a 4.5-year period (January 2001 to May 2005).

2.2.2 Remotely sensed data. The satellite-derived variables were obtained from Landsat 5 (L5 TM) and Landsat 7 (L7 ETM+) path/row 230/76 satellite images (16 days temporal resolution). A set of 26 images for Orán spanning January 2001 to May 2005 were selected from the Argentine Space Agency (CONAE) catalogue. ENVI (Environment for Visualizing Images, Research Systems) 4.2 software (2004) was used for image processing. The images were georeferenced using a georeference image from the GLCF (Global Land Cover Facility). Subsequently, a 225 km^2 subset area that included Orán (figure 1) was generated.

Since our time series data cover about 4.5 years and include images from two different sensors (L5 TM and L7 ETM+) and a range of acquisition dates, the images were calibrated to convert L5 TM or L7 ETM+ digital numbers to exoatmospheric reflectance (reflectance above the atmosphere) using their respective coefficients (USGS Landsat 2010). In order to quantify the vegetation coverage and the vegetation water content, we calculated the NDVI and the NDWI. Values of the earth's surface temperature were estimated through the brightness temperature (BT) (Landsat images band 6), which gives an approximation of the environmental temperature (Kalluri *et al*. 2007, Fenoglio *et al*. 2009). As we were looking for a surrogate variable to explain the temporal behaviour of HI, we used the Landsat band 6 BT (referenced as temperature), which includes the actual surface temperature, the surface emissivity and the atmospheric effect on it. In each subset scene that included Orán, two 1.44 km^2 areas were defined (figure 1), for which we calculated the mean and the variance values for NDVI, NDWI and BT. The first area is located within the city and the second one encompasses the native forest surrounding the city. Since Orán city is surrounded by native vegetation and cultivated fields, we hypothesized that the environmental conditions (NDWI, NDVI, BT) surrounding the city could be affecting the larval indices in an indirect way. We randomly selected an area of native vegetation close enough to the city, representing the environmental conditions that could be influencing the city and the larval indices. Besides, the abundant vegetation surrounding the city could be acting as a shelter for many mosquitoes. Since there were no important differences in the characteristics of the area surrounding the city, the forest block used in our work could have been placed in different locations with the same result. The NDVI is defined as

$$\mathrm{NDVI} = (\rho_{\mathrm{NIR}} - \rho_{\mathrm{RED}})/(\rho_{\mathrm{NIR}} + \rho_{\mathrm{RED}}), \tag{1}$$

where ρ_{RED} is the radiance (in reflectance units) of a red channel near 0.66 μm and ρ_{NIR} the radiance (in reflectance units) of a near-infrared channel around 0.86 μm (Gao 1996). For L5 TM/L7 ETM+, ρ_{NIR} and ρ_{RED} correspond to band 4 (0.78–0.90 μm) and band 3 (0.63–0.69 μm), respectively. The NDWI uses two near-infrared channels, one approximately at 0.86 μm and the other at 1.24 μm. It is defined as

$$\mathrm{NDWI} = (\rho_{\mathrm{NIR}} - \rho_{\mathrm{SWIR}})/(\rho_{\mathrm{NIR}} + \rho_{\mathrm{SWIR}}), \tag{2}$$

where ρ_{SWIR} is the reflectance or radiance in a short-wave infrared wavelength channel (1.2–20.5 μm). For L5 TM/L7 ETM+, ρ_{NIR} and ρ_{SWIR} correspond to band 4 (0.78–0.90 μm) and band 5 (1.55–1.75 μm), respectively (Jackson *et al*. 2004).

2.2.3 Meteorological data. Daily maximum and minimum temperatures (°C), humidity (%) and rainfall (mm) were provided by the Orán City National Meteorological Station (Servicio Meteorológico Nacional). The biweekly maximum and minimum temperatures, humidity and the rainfall were calculated to match the satellite temporal data.

2.3 *Development of the models and data analysis*

The degree of correlation between the HI and the satellite and meteorological variables over a 15-day time lag, from 1 to 6 months (lags 1–12), was analysed. The 6-month (lags 1–12) time lag was taken as the base for the analysis since longer time lags would have no major influences over the annual dynamics of *A. aegypti*. Besides, for almost 4 months of the year, the vector activity is diminished (May to September).

The time-lagged independent variables that best correlated with the HIs were selected (table 1). This allowed for an expedited forecast of the magnitude of such indices in the future, by forecasting increases and decreases in vector activity based on an environmental characterization that accounted for lag times in the independent variables considered. Accordingly, vector control measures could be applied anticipating probable vector peaks, thus avoiding potential increases of *A. aegypti*. The NDVI, BT and meteorological variable lags were obtained from the selected lags for Orán by Estallo *et al*. (2008). In order to develop forecasting models, a multiple linear regression analysis (stepwise backward elimination) was performed with the set of variables using the highest correlated time lags, in relation to the HI values. Two forecasting models were developed and evaluated to predict the *A. aegypti* HI for Orán: the SATMET model including both satellite (SAT) and meteorological (MET) data and the SAT model including only the satellite variables. The data set was divided into two subsets, from May 2001 to May 2004 to develop the models ($n = 72$ observations) and from May 2004 to May 2005 to evaluate them ($n = 25$ observations).

The HI was estimated using the equation

$$y = a_0 + a_1 \times X_1 + \cdots + a_n \times X_n + E, \tag{3}$$

where y is the estimated Orán HI value, a_0 is a constant, a_1 to a_n are coefficients of the independent variables X_1 to X_n (see table 1) and E is the residual term.

We used Akaike's information criterion (AIC) to rank candidate models. This technique identifies the most parsimonious model for the data by balancing the overall fit of the model with the number of parameters included in it (Akaike 1974). Therefore, the smallest value of AIC was considered as the standard to identify the best-fit model (Brockwell and Davis 1991). Statistical analyses were conducted using R2.6 software (2007). Because of the nature of the dependent variable, the HI was log-transformed to normalize the residuals before using it to develop the models. Pearson correlation coefficient (r) between the observed HI values and those forecast by the models was used to evaluate the models. In addition, the predictive validity of the models was evaluated by using the root mean square error (RMSE) criterion. The smaller the RMSE,

Table 1. List of independent variables (X_1–X_{17}) used to develop the models and the corresponding time lag (1 time lag = 15 days).

	Independent variables	Number of lags	Correlation coefficient ($p < 0.05$)
X_1	Mean NDVI of the forest	1 (15 days)	0.36
X_2	Variance of the NDVI of the forest	1 (15 days)	−0.15
X_3	Mean BT of the forest	3 (1.5 months)	0.53
X_4	Variance of the BT of the forest	2 (1 month)	−0.28
X_5	Mean NDVI of the city	7 (3.5 months)	0.35
X_6	Variance of the NDVI of the city	1 (15 days)	0.46
X_7	Mean BT of the city	3 (1.5 months)	0.57
X_8	Variance of the BT of the city	3 (1.5 months)	−0.26
X_9	Precipitation	2 (1 month)	0.59
X_{10}	Maximum temperature	5 (2.5 months)	0.49
X_{11}	Minimum temperature	2 (1 month)	0.52
X_{12}	Maximum humidity	8 (4 months)	−0.47
X_{13}	Minimum humidity	1(15 days)	0.49
X_{14}	Mean NDWI of the forest	1 (15 days)	−0.40
X_{15}	Variance of the NDWI of the forest	6 (3 months)	−0.40
X_{16}	Mean NDWI of the city	7 (3.5 months)	−0.41
X_{17}	Variance of the NDWI of the city	1(15 days)	−0.34

Notes: Satellite-derived variables: NDVI, normalized difference vegetation index; BT, brightness temperature; NDWI, normalized difference water index.

the better the model in terms of the ability of the forecast (Hu *et al*. 2004). We used the forecast of the previous year (May 2004 to May 2005) and calculated the RMSE of 25 observations. We also assessed multicollinearity, as measured by the variance inflation factor (VIF), for the variables included in each developed model. All analyses were performed with R2.6 and Statistica software.

3. Results

The RMSE obtained from the georeferencing was about 0.40 pixels. From the 17 variables (table 1) considered to develop the SATMET forecasting model, only 7 were significant and were included in the multiple regression model: 2 meteorological variables (precipitation (X_9) and minimum humidity (X_{13})) and 5 satellite-derived variables (the variance of the BT of the forest and the city (X_4 and X_8, respectively), the variance of the NDWI of the forest and the city (X_{15} and X_{17}, respectively) and the mean NDWI of the city (X_{16})).

For the SAT forecasting model, 12 variables were considered, but only 8 were significant and were therefore included in the model. These variables were the variance of the NDVI of the forest (X_2), the variance of the BT of the forest and the city (X_4 and X_8, respectively), the mean NDVI of the city (X_5), the mean BT of the city (X_7), the mean NDWI of the forest and the city (X_{14} and X_{16}, respectively) and the variance of the NDWI of the forest (X_{15}).

Table 2. House index (HI) forecasts models obtained for Orán city, according to the regression analysis performed considering lag variables.

Forecast model	Model expression	Model error
SATMET	$\ln(\mathrm{HI}) = -2.6396 + 0.4199X_4 + 0.2009X_8 + 0.1684X_9 + 0.1731X_{13} - 0.3066X_{15} - 0.5150X_{16} - 0.1498X_{17}$	0.4186
SAT	$\ln(\mathrm{HI}) = -2.6396 - 0.1641X_2 + 0.5704X_4 - 0.1766X_5 - 0.1690X_7 + 0.1883X_8 + 0.3138X_{14} - 0.6968X_{15} - 0.9178X_{16}$	0.4486

Note: HI was log-transformed to normalize the residuals (ln(HI)).

The best regression coefficients, for both the SATMET and SAT forecast models, correspond to the variance of the BT of the forest (X_4), the variance of the NDWI of the forest (X_{15}) and the mean NDWI of the city (X_{16}) (table 2). Both models fit quite well: the SATMET forecast model with an adjusted coefficient of determination $R^2 = 0.82$ ($p < 0.0001$; $F = 47.10$; AIC = 88.45) and the SAT forecast model with an adjusted $R^2 = 0.79$ ($p < 0.0001$; $F = 34.98$; AIC = 99.26). The SATMET forecast model showed the lowest value of the AIC. Although the Pearson correlation between the predicted and the observed HI for the validation data was higher for the SAT forecast model ($r = 0.64$; $p < 0.0001$) than for the SATMET forecast model ($r = 0.57$; $p < 0.0001$) (figure 2), the RMSE for both models was the same, 0.0411 for the SATMET model and 0.0413 for the SAT model; therefore, both models according to the RMSE have the same predictive power. No multicollinearity was found (<4).

4. Discussion

This study showed the effectiveness of NDWI as well as other satellite and meteorological data to develop forecasting models for the *A. aegypti* HI in a city of Argentina where dengue is endemic. The SATMET and SAT models show a good association between NDWI and BT to model HI, showing that these environmental variables (NDVI and BT) have the highest model regression coefficients using the SATMET and SAT developed models. Besides, it proved the complementarity between the indices (NDVI and NDWI), which is in agreement with the views of Gao (1996) that NDWI is a complementary index, not a substitute for NDVI.

The different time lags of the SATMET and SAT model variables are justified insofar as the influence of the environmental variables over survival and abundance of the vector are given throughout the life cycle, which is known to vary considerably according to these factors. Thus, the happenings in the environment prior to sampling may have a significant effect, which suggests the need to consider time lags in predictive models. For instance, when Dominguez *et al*. (2000) considered time lags in Córdoba city, they found that climatic variables influenced the *A. aegypti* oviposition.

Accordingly, the NDWI is useful for modelling in order to predict the HI as well as to monitor and control the dengue vector. The NDWI allows a better characterization of the environment where the vector develops since it takes into account the vegetation water content and indirectly measures soil humidity and precipitation (Breshears *et al*. 1997, Jackson *et al*. 2004), which are very important variables that regulate the biology of the vector. Many ecologists have used field measurements of the foliar water content

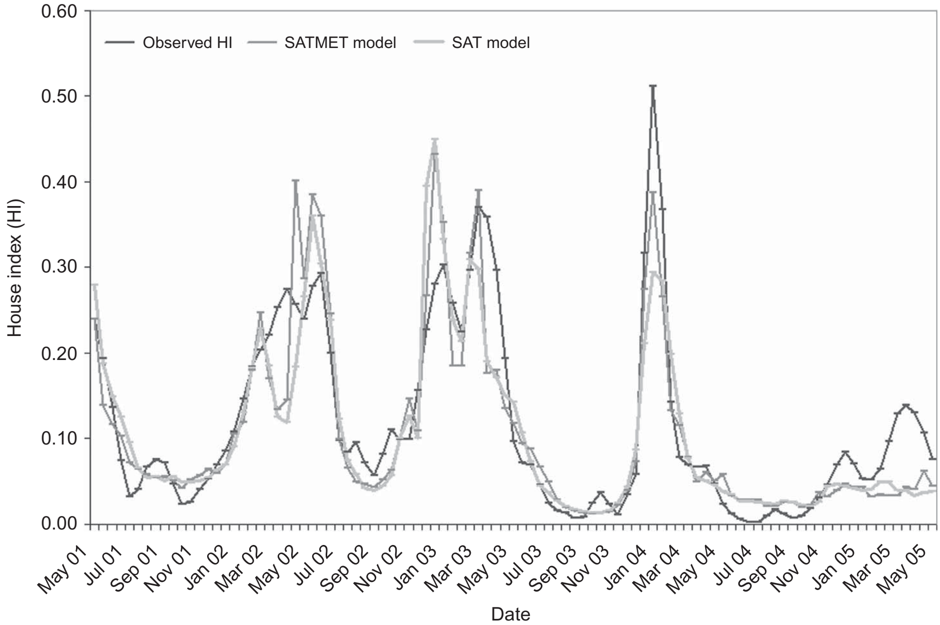

Figure 2. Observed and forecast house index for the SATMET forecast model (adjusted $R^2 = 0.82$; $p < 0.0001$; $F = 47.10$; AIC = 88.45) and the SAT forecast model (adjusted $R^2 = 0.79$; $p < 0.0001$; $F = 34.98$; AIC = 99.26). The RMSE for each model was the same: 0.0411 for the SATMET model and 0.0413 for the SAT model; therefore, both models according to the RMSE have the same predictive power.

and the foliar water potential as sensitive indicators of water status, which are also important for the development of the immature stages of the vector. A similar index was used by Brown *et al*. (2008) in attempting to identify clusters of sites with similar mosquito vector communities. Brown *et al*. (2008) examined the association between vegetation indices such as the NDVI and the disease water stress index (DWSI) and a mosquito vector community. Although the NDWI is not a frequently used index, in this work it is seen as a major indicator of the environmental climatic conditions than simply using the NDVI.

In a previous project, Estallo *et al*. (2008) developed predictive models at a regional level, using satellite and meteorological data to characterize the environment. Those models did not include the use of the NDWI, a variable that would have allowed for a better characterization of the environment. Therefore, we propose to develop new predictive, parsimonious and easy to apply models, at a local level for Orán, including the NDWI, and test its effectiveness as a variable that allows for estimating the HI. Even though Estallo *et al*. (2008) developed local models for two cities in the Argentine northwest, those were descriptive and not predictive models, which allowed for a better understanding of the system and the variables that might be affecting it. Those models were not validated. This project validated the local models and calculated their predictive power.

On the other hand, the local models developed by Estallo *et al*. (2008) include both satellite and meteorological variables, whereas only one of the models of the current project combines both kinds of variables (SATMET). The SAT model, which includes only satellite variables, could be easier to apply since there is no need for meteorological data, which sometimes are hard to obtain or unavailable or simply not recorded in remote areas.

In this project, we estimated only the HI, which is the most used larval index in addition to being the easiest for health agents to obtain. In the models developed by Estallo *et al*. (2008), the authors considered the NDVI as an important estimator because vegetation is strongly associated with temperature, precipitation and soil properties. This project focuses on the importance of the NDWI satellite environmental variable for modelling *A. aegypti* HI and could be considered an extension of Estallo *et al*. (2008).

Dominant effects of the NDWI and the BT on HI forecast were significant in this study at lags of 3 months for the variance of the NDWI of the forest (X_{15}) and 3.5 months for the mean NDWI of the city (X_{16}). Temperature proved to have a significant effect, as reflected by the variance of the BT of the forest (X_4) with a 1-month time lag. NDWI showed the major model coefficient and therefore the major influence as estimator and consequently the value of this variable as environmental indicator for modelling *A. aegypti* HI. The vegetation index (NDVI) and BT were included in the models developed by Estallo *et al*. (2008), where NDVI was demonstrated to be the major factor to estimate the Breteau and HIs for Orán; yet, temperature also proved to be a meaningful influence with the same time lags used in this work. Therefore, temperature and NDWI conditions recorded in an area determine the vector population growth. Temperature is the abiotic factor that has received the most attention as a modulator of *A. aegypti* bionomics, as well as the larval indices, as at higher temperature there is a higher rate of reproduction and hatching, which would result in a greater number of mosquitoes per breeding site (Jetten and Focks 1997, Tun-Lin *et al*. 2000).

Wu *et al*. (2007) evaluated the impact of weather variability on the occurrence of dengue fever in a city of Taiwan using autoregressive integrated moving average (ARIMA) models. The best-fit ARIMA models showed that dengue incidence was negatively associated with monthly temperature deviation and relative humidity, both with their most prominent effects at a time lag of 2 months. Our SATMET forecast model included as significant climatic variables rainfall (X_9) at a lag of 1 month and the minimum temperature (X_{13}) at a lag of 15 days for Orán. Rainfall is important in the transmission of mosquito-borne diseases because mosquitoes require water for the larval and pupal development. However, both humidity and rainfall should be used to model mosquito vector population dynamics. Quantity, timing and pattern of rainfall will affect mosquito larval habitats (Lindsay and Mackenzie 1996).

Considering that there are many regions in Argentina where meteorological data are not available, SATMET and SAT models developed here explore the potential application of satellite data. The SAT forecast model did not include meteorological variables, other than those obtained from satellite data, the NDWI and the BT being the ones that most contributed to explain the response variable fluctuation in the model. Our results highlight that the variables with the highest influence, in both the SAT and the SATMET models, were the temperature and the NDWI, suggesting that these are important variables that should be taken into consideration when developing a predictive model.

According to our results, satellite data are useful variables to characterize the environment and to generate models that allow forecasts of, in this case, the *A. aegypti* HI. While these kinds of models could be used in other northwestern cities of Argentina, which share similar climatic features, we recommend validating them in the new areas prior to their application. Therefore, we suggest applying remote sensors, especially in areas where the unavailability of meteorological data precludes monitoring this vector. This type of research is needed to help the authorities to monitor and control the diseases accurately. Remote sensing provides readily usable and relatively inexpensive data for large areas. Therefore, such data can be used to accurately model and predict diseases and vector outbreaks and may be helpful to assist in the decision making of health authorities.

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