Medical and Veterinary Entomology

Medical and Veterinary Entomology (2018), doi: 10.1111/mve.12323

Modelling the distribution of the vector *Aedes aegypti* in a central Argentine city

E. L. ESTALLO[1,2], F. SANGERMANO[3], M. GRECH[4], F. LUDUEÑA-ALMEIDA[1], M. FRÍAS-CESPEDES[5], M. AINETE[5], W. ALMIRÓN[1] and T. LIVDAHL[2]

[1]Instituto de Investigaciones Biológicas y Tecnológicas (IIByT), Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), Centro de Investigaciones Entomológicas de Córdoba (CIEC), Facultad de Ciencias Exactas, Físicas y Naturales (FCEFyN), Universidad Nacional de Córdoba, Córdoba, Argentina, [2]Department of Biology, Clark University, Worcester, MA, U.S.A., [3]Graduate School of Geography, Clark University, Worcester, MA, U.S.A., [4]Centro de Investigación Esquel de Montaña y Estepa Patagónica (CIEMEP), CONICET, Facultad de Ciencias Naturales, Universidad Nacional de la Patagonia San Juan Bosco, Esquel, Argentina and [5]Área de Epidemiología, Ministerio de Salud de la Provincia de Córdoba, Córdoba, Argentina

Abstract. *Aedes aegypti* (Diptera: Culicidae) is an urban mosquito involved in the transmission of numerous viruses, including dengue, chikungunya and Zika. In Argentina, *Ae. aegypti* is the main vector of dengue virus and has been involved in several outbreaks in regions ranging from northern to central Argentina since 2009. In order to evaluate areas of potential vector-borne disease transmission in the city of Córdoba, Argentina, the present study aimed to identify the environmental, socioeconomic and demographic factors driving the distribution of *Ae. aegypti* larvae through spatial analysis in the form of species distribution models (SDMs). These models elucidate relationships between known occurrences of a species and environmental data in order to identify areas with suitable habitats for that species and the consequent risk for disease transmission. The maximum entropy species distribution model was able to fit the training data well, with an average area under the receiver operating characteristic curve (AUC) of > 0.8, and produced models with fair extrapolation capacity (average test AUC: > 0.75). Human population density, distance to vegetation and water channels were the main variables predictive of the vector suitability of an area. The results of this work will be used to target surveillance and prevention measures, as well as in mosquito management.

Key words. *Aedes aegypti*, mosquito, MaxEnt, risk, prediction, species distribution models, SDMs, Córdoba, Argentina.

Introduction

Mosquitoes (Diptera: Culicidae) are vectors of many pathogens worldwide. Blood-feeding females of two invasive species, *Aedes aegypti* and *Aedes albopictus*, are involved in the transmission of numerous viruses, including dengue, chikungunya and Zika. *Aedes aegypti* has expanded its known range in South America to extend at least as far as the southern city of Neuquén (Argentina), where eggs of the species have been recorded (Grech *et al.*, 2012;). The geographic distribution of *Ae. albopictus* is currently restricted to northeast Argentina near the Brazilian border (Vezzani & Carbajo, 2008).

Aedes aegypti is the principal mosquito vector of dengue, chikungunya and Zika viruses in Argentina. Until 2007, when

Correspondence: Elizabet L. Estallo, Instituto de Investigaciones Biológicas y Tecnológicas (IIByT), Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), Centro de Investigaciones Entomológicas de Córdoba (CIEC), Facultad de Ciencias Exactas, Físicas y Naturales (FCEFyN), Universidad Nacional de Córdoba, Edificio de Investigaciones Biológicas y Tecnológicas, Avenida Vélez Sarsfield 1611, X5016GCA Córdoba, Argentina. Tel.: +54 351 5353 800 int 30500; Fax: + 54 351 4334 139; E-mail: eelizabet@gmail.com

a locally transmitted dengue case was detected in Buenos Aires (Natiello *et al*., 2008), dengue virus was restricted to the northern provinces of Argentina. Since 2009, dengue transmission has also affected central areas of the country, where 130 confirmed dengue cases (imported and autochthonous) have been reported in the city of Córdoba, where the outbreak was started by the import of cases from neighbouring provinces (Estallo *et al*., 2014). In 2016, Argentina's health authorities reported a cumulative 79 455 probable cases, including 41 211 confirmed cases, of dengue serotypes 1 and 4. As of epidemiological week (EW) 6 of 2017, 2320 probable cases and 20 confirmed cases of dengue had been reported. During the 2016 dengue outbreak, more than 600 cases were recorded in Córdoba city (Ministerio de Salud de la Provincia de Córdoba, 2016).

The first autochthonous cases of chikungunya virus in Argentina were confirmed in EW 8 of 2016 in the provinces of Salta and Jujuy. In 2016, 338 confirmed cases of chikungunya were reported in Argentina, of which the majority occurred in Salta (329 cases) and the rest in Jujuy (nine cases) [Pan American Health Organization (PAHO), 2017]. During 2017, there were no reports of active chikungunya virus circulation in Argentina. Nine probable imported cases were reported in the province of Buenos Aires (three cases), the city of Buenos Aires (four cases) and Córdoba (two cases) (Ministerio de Salud de la Nación, 2017a).

The first evidence of local vectorial transmission of Zika virus in Argentina was noted in 2016, during which 26 cases were confirmed (Ministerio de Salud de la Nación, 2017a). In May 2017, three provinces in northern Argentina showed confirmed and probable Zika cases, in Chaco (44 cases), Salta (189 cases) and Formosa (22 cases) (Ministerio de Salud de la Nación, 2017b). No cases of Zika were recorded in the city of Córdoba during 2017 (Ministerio de Salud de la Nación, 2017b).

The mosquito *Ae. aegypti* is highly domesticated and is associated with humans and their dwellings not only because humans represent a source of bloodmeals, but also because they provide artificial water-holding containers in and around the home. The mosquito lays eggs on the sides of water containers and the eggs hatch after submersion by rain or flooding [Centers for Disease Control and Prevention (CDC), 2018].

Aedes aegypti commonly occupies urban sites in tropical and subtropical areas. It bites during the day and breeds in a wide variety of small water containers, such as flower vases, discarded automobile tyres, buckets and other trash (Christophers, 1960; Getachew *et al*., 2015). As mosquitoes are poikilothermic organisms, they seek shaded areas during daytime to avoid severe desiccation and heat (Paaijmans & Thomas, 2011). This suggests that the daytime resting habitats for these organisms are usually associated with vegetation, which provides shade and thus a microclimate that is cooler than those in open areas such as bare soil and built-up spaces (Dewald *et al*., 2016).

Because of the climatic characteristics of Córdoba city, the vector population decreases during winter and increases when the temperature rises, resulting in a particular population dynamic that differs from that of tropical regions (Estallo *et al*., 2014). The environmental niche occupied by *Ae. aegypti* can be expressed geographically by identifying the environmental conditions required by this vector mosquito to breed and sustain a longterm population. Identifying a species' environmental niche is essential to understanding its geographic distribution (Peterson, 2006). Studying the distribution of breeding sites within urban areas is a key requirement in assessing dengue transmission risk (Carbajo *et al*., 2004).

Careful monitoring of vector populations permits the identification of alterations in distributions and fluctuations in the densities of the vector species and permits programme evaluation. Careful monitoring programmes can inform and enhance control strategies and measures. The continued success of vector management relies upon consistent surveillance of the vector population [World Health Organization (WHO), 2017].

Disease biogeography is an emerging field, in which the central aim is the study of the geographic dynamics of diseases and their vectors. This field merges epidemiology with ecology and geography using tools that link the analysis of spatial distributions with research on epidemics. Vector distributions can be best understood through tools such as ecological niche modelling (Escobar & Craft, 2016). Because of the link between the environmental niche and spatial distribution of a species, the terms 'ecological niche modelling' and 'species distribution modelling' are often used interchangeably. However, niches are characterized in an environmental dimension, whereas a geographic distribution is the geographic expression of an ecological niche (Warren, 2012).

Spatial analysis allows vector surveillance to be linked with environmental and socioeconomic characteristics to produce spatially explicit maps of potential vector distribution and disease risk (Khatchikian *et al*., 2010; Machado-Machado, 2012). Species distribution models (SDMs) identify relationships between the known occurrence of a species (in the form of either presence or presence/absence data) and environmental data (e.g. meteorological data, land use and cover data, remote sensing data), and use these relationships to make predictions for all unsampled areas in the study region (Cianci *et al*., 2015; Gill & Sangermano, 2016).

Several techniques exist for modelling the spatial distribution of a species (Elith *et al*., 2006; Rogers, 2006), but they differ in assumptions and predictive performance. Outputs from SDMs have been interpreted to represent habitat suitability, probability of presence, potentially occupied habitat and ranked habitat suitability. However, in general terms, outputs refer to the predictive distribution map of the species in question (Franklin, 2010) and, in the context of infectious diseases, can be considered to represent infestation risk (Khatchikian *et al*., 2010; Machado-Machado, 2012).

Maximum entropy (MaxEnt) ecological niche modelling uses an algorithm based on presence data. MaxEnt identifies the probability distribution of highest entropy subject to distribution constraints (in the mean and variance) extracted from the environmental conditions within the training dataset (Phillips *et al.*, 2004, 2006; Elith *et al*., 2012). MaxEnt has been identified as the best predictive method when only presence data are available (Elith *et al*., 2006) and has been shown to work well even when the amount of training data is limited (Elith *et al*., 2006; Phillips *et al*., 2006). MaxEnt has been used extensively in biodiversity conservation (e.g. Osipova & Sangermano, 2016; Stewart *et al*., 2017) and invasive species modelling (e.g. Gill & Sangermano, 2016; Skowronek *et al*., 2017), and has been employed in the study of infectious diseases and disease vectors (e.g. Khatchikian *et al*., 2010; Machado-Machado, 2012; Zhao *et al*., 2016).

Species distribution models require the use of predictive variables that are related to the ecology of the species to be modelled. Remotely sensed data allow for the extraction of localized environmental predictors. The normalized difference vegetation index (NDVI) represents vegetation greenness and has been applied in mosquito studies as a surrogate measure of humidity and precipitation (Estallo *et al*., 2016). The normalized difference water index (NDWI) is sensitive to changes in the liquid water content of vegetation canopies and is complementary to the NDVI (Gao, 1996). The normalized difference built-up index (NDBI) highlights highly reflective urbanized areas (Zha *et al*., 2003).

In order to evaluate areas of potential vector-borne disease transmission in Córdoba city, Argentina, this project aimed to identify the environmental, socioeconomic and demographic factors driving the distribution of *Ae. aegypti* larvae through spatial analysis in the form of species distribution modelling.

Materials and methods

Study area

Córdoba is the second largest city in Argentina and has a surface area of 576 km^2 and a population of 1 330 023 inhabitants [Instituto Nacional de Estadística y Censos de la República Argentina (INDEC), 2010]. It is located in the central province of Córdoba (31°24′ S, 64°11′ W), at an elevation of 360–480 m a.s.l. (Fig. 1). Córdoba city has a temperate climate, with mean annual precipitation of 800 mm. The winter is markedly dry and most precipitation occurs in the summer months (National Meteorological Service, 2018). The Suquía River, its tributary La Cañada and numerous additional water channels run through the city. Human activities have resulted in a landscape characterized by a highly developed urban core represented by buildings with 0.66 km^2 of green areas in the form of urban parks. Suburban areas are characterized by residential neighbourhoods, primarily single-family houses with yards, interspersed with parks and other green spaces (total green areas: 9.27 km^2) (Fenoglio *et al*., 2009; Municipalidad de Córdoba, 2017).

Entomological data

In each month, 30 neighbourhoods were randomly selected and 20 houses within each neighbourhood were surveyed (a total of 600 houses were surveyed in each month). A fine scale for containers in which *Ae. aegypti* breeding had occurred was adopted, using data corresponding to neighbourhoods found to be positive for *Ae. aegypti* larvae during a survey conducted from December 2012 to May 2013. Each neighbourhood in which at least one larva was found in a container was geocoded and recorded as positive.

Predictor variables

Predictor variables were used based on availability and *a priori* expectations of influences on the mosquito population. Factors considered included layers depicting potential vector breeding sites (PBSs), environmental variables, and socioeconomic and demographic parameters (Tables 1 and 2).

Potential breeding sites. Potential breeding sites in the city were identified as places in which unused water-holding containers were available as breeding sites for *Ae. aegypti* mosquitoes. The different variables were created within a geographic information system (GIS) and different layers were generated digitizing informal settlements (suburban slums), garbage dumps, water channels across the city, cemeteries, abandoned train depots, parks, train tracks and tyre storage centres. The layers were generated using ArcGIS 10.4.1 [Environmental Systems Research Institute, Inc. (Esri), Redlands, CA, U.S.A.]. Maps of the Suquía River and Córdoba city streets were acquired from open data sources (www.openstreetmap.org). These particular PBSs were chosen because they accumulate man-made containers that might hold water after rain in the form of trash on riverbanks or along the sides of city water channels. Although *Ae. aegypti* mosquitoes do not breed in running water, numerous small containers were observed amongst rubbish that had accumulated along the river and water channels (see File S1). Tyre disposal areas store tyres outdoors, where they accumulate rainwater and where mosquito larvae were observed. Using ArcGIS 10.4.1, the distance from each of the PBSs was calculated and a fuzzy variable from each distance layer was created using TerrSet (Eastman, 2016). Through fuzzy variables, risk can be scaled in terms of degree of risk along a range. A sigmoidal monotonically decreasing function was used with a control point distance of 500 m, implying that areas closer to roads would be more suitable for the mosquito and that suitability would drop to zero at 500 m from roads. This distance was selected as it approximates the flight range of *Ae. aegypti* female mosquitoes. Studies on the flight range of this vector indicate that females generally fly 100–500 m from their larval habitat (Muir & Kay, 1998).

Environmental variables. The environmental variables considered for this study were calculated from two SPOT 5 (Systeme Probatoire de l'Observation de la Terre) satellite images (February and May 2013) using high-resolution geometric (HRG) sensors. All image processing and analyses were carried out in TerrSet software (Eastman, 2016). The NDVI, NDWI and NDBI were calculated. The quality of the images was good, with no cloud cover over the study area. Continuous NDVI, NDWI and NDBI images were used to calculate mean, maximum, minimum and standard deviation images. The derived images were spatially filtered using a mean filter for a window of 500 m because the 20 houses chosen randomly for the sampling were located within a radius of 500 m around the defined sample site.

The variable 'proximity to vegetation' has a value of 1 for areas with NDVIs of >0, which represent vegetated areas. Non-vegetated areas are represented with values ranging from 0 to just under 1, where values approaching 0 correspond to non-vegetated areas located far from vegetated areas. Values

  doi: 10.1111/mve.12323

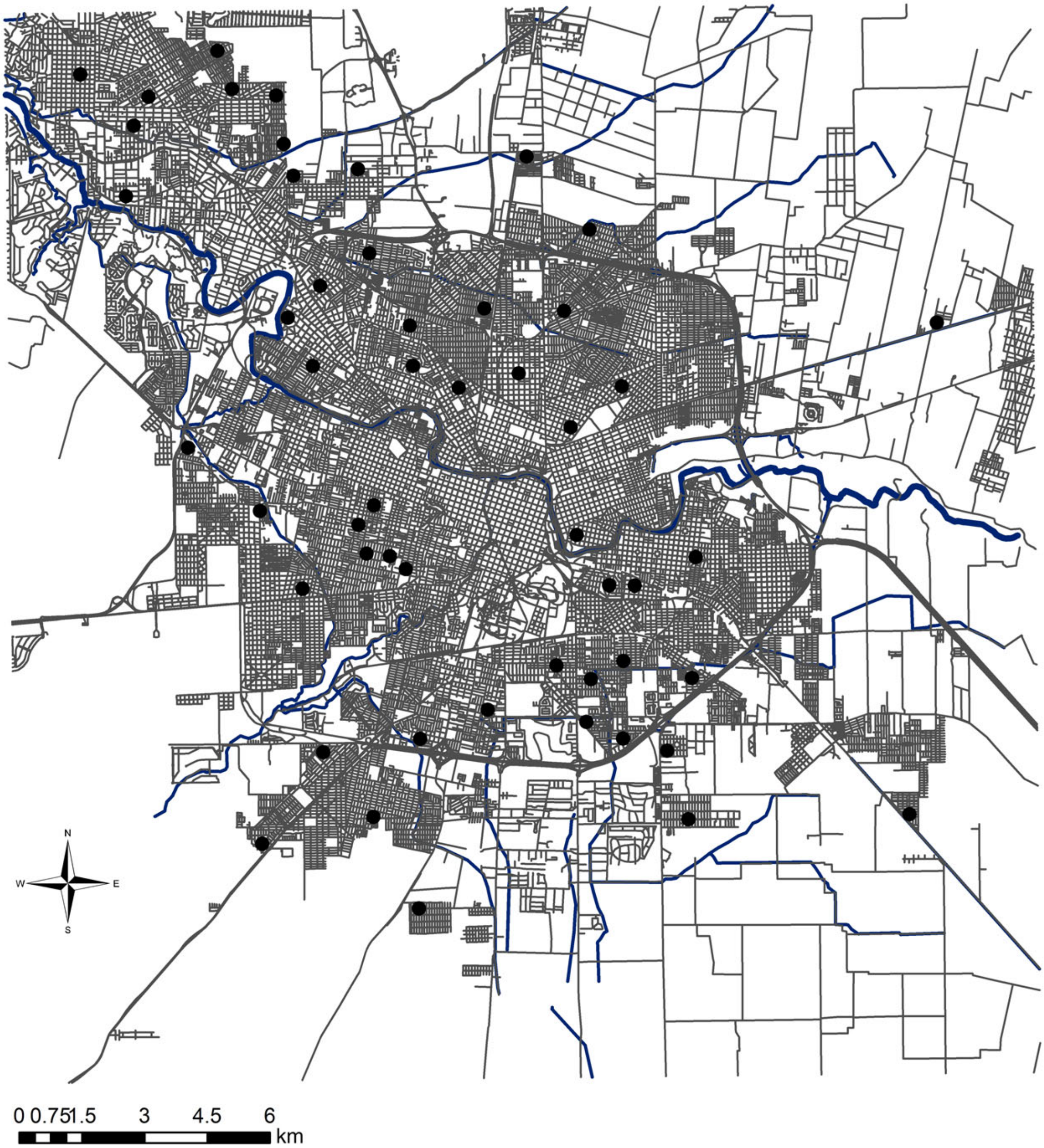

Fig. 1. Points of occurrence of *Aedes aegypti* larvae monitored during December 2012 to May 2013 in Córdoba city, Argentina. [Colour figure can be viewed at wileyonlinelibrary.com].

approach 1 for non-vegetated areas that are in close proximity to vegetated areas. This variable represents not only the presence of vegetated areas, but also the isolation of non-vegetated areas. The variable 'less urbanized' has a value of 1 for areas of heterogeneous urban habitats such as suburbs, where constructions alternate with open spaces, by contrast with areas where construction density is higher (downtown areas), which are designated as the variable 'highly urbanized'. These two variables represented the density of urban construction, obtained from a categorical map defined through a maximum likelihood classification of satellite images (Vergara Cid *et al*., 2013).

Socioeconomic and demographic parameters

Socioeconomic parameters, such as the number of houses by neighbourhood with different types of water supply, the proportions of houses with and without bathrooms, and housing

Table 1. Predictor variables considered included layers depicting potential vector breeding sites (PBSs), environmental variables, and socioeconomic and demographic parameters.

PBS	Environmental parameters	Socioeconomic and demographic parameters
Informal settlements (suburban slums)	*Max NDVI*	*WS 1*
Garbage dumps	*Min NDVI*	*WS 2*
Water channels	SD NDVI	WS 3
Cemeteries	Mean NDVI	WS 4
Abandoned train depots	Max NDWI	WS 5
Parks	Min NDWI	
Train lines	SD NDWI	Homes with a bathroom
Tyre storage depots	Mean NDWI	Homes without a bathroom
Suquía River	*Max NDBI*	*BNU homes*
	Min NDBI	Proportion of homeless people
	SD NDBI	*Proportion of apartments*
	Mean NDBI	*Proportion of houses*
	Proximity to vegetation	*Proportion of ranchos*
	Highly urbanized	*Human population density*
	Less urbanized	

Of the 37 original variables considered, 17 variables were selected based on correlation ($r < 0.70$). Those shown in italics are the variables used with the MaxEnt algorithm.
BNU homes, homes in which basic needs are unmet; Max, maximum; Min, minimum; NDBI, normalized difference built-up index; NDVI, normalized difference vegetation index; NDWI, normalized difference water index; SD, standard deviation; WS, water supply (1, cistern; 2, river, channel or natural source of water; 3, well; 4, water mains; 5, perforation).

conditions, were used to assess conditions of hygiene. The following types of household water supply were identified: (a) cistern; (b) river, channel or other natural source of water; (c) well; (d) water mains, and (e) perforation. Water supply is an important factor as households without water mains or perforation supplies usually store water in uncovered containers that are used by mosquitoes as breeding sites. Housing conditions, which determined in many cases the type and amount of vector breeding in the vicinity, included the proportion of apartments, proportion of houses and proportion of 'ranchos' (houses in informal settlements or suburban slums). Neighbourhood population density according to the national 2010 census was considered an important demographic parameter as humans are a source of bloodmeals for female mosquitoes.

Evaluation of model performance

The capacity of the models to predict *Ae. aegypti* presence was evaluated using the area under the receiver operating characteristic (ROC) curve (AUC).

All PBS, environmental, socioeconomic and demographic factors were considered as potential factors in the development of the MaxEnt model. The 37 original predictor variables, grouped by PBS, environmental, socioeconomic or demographic factors, were evaluated for multicollinearity by calculating the pairwise Pearson's correlation coefficient (r) (Table 1). After reducing pairs of variables that correlated strongly with one another ($r > 0.7$) to a single factor, 17 variables were selected to develop preliminary MaxEnt models.

Preliminary MaxEnt models were run in order to refine the final selection of variables (Phillips *et al*., 2004). Variable importance was measured through permutation importance and response curves. This approach evaluates the contribution of each variable independently of the ordering of the variables and is therefore less sensitive when correlated variables are present (Phillips *et al*., 2006). The final selection of variables was based on the results of these two methods (permutation importance and response curves). Of the 37 original variables considered, only the 11 most relevant variables (Table 2) were included in the final model. Although human population density, proportion of houses and proportion of ranchos were highly correlated with one another ($r > 0.90$), these socioeconomic and demographic variables capture environmental conditions important in the development and persistence of *Ae. aegypti* mosquitoes (Stewart Ibarra *et al*., 2013), and therefore were retained as predictor variables to run the model.

Risk maps, representing areas of potential vector-borne disease transmission, were produced by training the MaxEnt model

Table 2. Spatial data sources and properties for variables used with MaxEnt.

	Source	Spatial resolution	Period of data collection
Human population density	Argentina National Census	Neighbourhood level	2010
Less urbanized	Landsat 5 TM	30 m	February 2010
NDVI	SPOT 5 HRG	10 m	February and May 2013
NDBI	SPOT 5 HRG	10 m	February and May 2013
Informal settlements (suburban slums)	Map from municipal documents source	10 m	2010
Proportion of houses	Argentina National Census	Neighbourhood level	2010
Tyre storage depots	Map from municipal documents source	10 m	2010
Household water supply by river, creek or other	Argentina National Census	Neighbourhood level	2010
Proportion of ranchos	Argentina National Census	Neighbourhood level	2010
Abandoned trains	Mapped through Google Earth	10 m	2012
Cemeteries	Mapped through Google Earth	10 m	2012

HRG, high-resolution geometric; NDBI, normalized difference built-up index; NDVI, normalized difference vegetation index; TM, thematic mapper.

with the presence of *Ae. aegypti* larvae from December 2012 to May 2013 as the response variable. Because MaxEnt ecological niche models eliminate duplicate occurrence points within the same pixel, data collection included a total of 51 spatial occurrence records for *Ae. aegypti* larvae (neighbourhood level). The occurrence points were randomly partitioned into calibration and evaluation datasets. A four-fold cross-validation method (four replicate MaxEnt runs) was used to partition the data into training and testing, which left 38 observations for training and 13 for testing the model. A 1.5 regularization multiplier was used in order to decrease model overfitting.

Finally, overall performance was gauged via visual inspections of risk maps and the AUC (Phillips *et al.*, 2006). The AUC is a threshold-independent measure with values ranging from 0 to 1. All AUC values of > 0.5 represent models that are better than random and higher AUC values indicate a better discriminatory resolution (Phillips *et al.*, 2006). When using the ROC procedure, Swets (1988) recommends interpreting range values as 'excellent' (AUC > 0.90), 'good' (0.80 < AUC < 0.90), 'fair' (0.70 < AUC < 0.80), 'poor' (0.60 < AUC < 0.70), and 'failing' (0.50 < AUC < 0.60). Training accuracy refers to the goodness of fit of the model, which indicates how much the model is capable of predicting the observation used for training. Testing refers to the capability of the model to predict observation points not used during training and is considered an independent evaluation. It is expected that the model capability for data fitting will be better than for prediction and therefore testing accuracy is commonly lower than training accuracy (Phillips *et al.*, 2004).

Ecological niche modelling shows a promising future in modern epidemiology, but its usefulness depends upon the quantitative robustness and biological realism of a model's products. In accordance with Escobar & Craft (2016), risk was defined and considered as the areas suitable for the occurrence of *Ae. aegypti*. In environmental terms, factors at local scale may be a good complement to risk delimitation (Escobar & Craft, 2016). Therefore, the present ecological niche model considered not only potential breeding sites for the vector at a fine scale, but also an enrichment of the model with demographic data such as human population density (Table 1). Suitable habitat for *Ae. aegypti* larvae, and therefore the potential geographic distribution of the vector, was mapped based on the results of the MaxEnt model. These outputs characterize the ecological niche of *Ae. aegypti* larvae, and were used, as suggested by Peterson & Vieglais (2001), to anticipate suitable areas for the vector outside the known sampled range.

Results

MaxEnt produced models with a good goodness of fit (training accuracy and 'fair' extrapolation capacity with an average training AUC of > 0 and average testing AUC of > 0.75, respectively) (Table 3). According to the permutation importance results, human population density appears to be the most influential factor in the model, followed by proximity to vegetation and proximity to water channels (Table 4).

Human population density is considered as a proxy of human influence on the mosquito population because, in addition to serving as a blood source, humans provide both breeding habitats (artificial containers and other breeding grounds) and dispersal opportunities through the movement of containers colonized by eggs or larvae (Khatchikian *et al.*, 2010).

Table 3. Accuracy of each of the four models (fold cross-validation) performed, where training accuracy refers to the goodness of fit of the model (i.e. the model's ability to predict the observations used for training).

Species	Training AUC	Testing* AUC
*Aedes*CBA_0	0.84	0.76
*Aedes*CBA_1	0.85	0.79
*Aedes*CBA_2	0.85	0.82
*Aedes*CBA_3	0.87	0.68
*Aedes*CBA (average)	0.85	0.76

*Testing refers to the ability of the model to predict observation points not used during training and is considered an independent evaluation. CBA, denotes the model for *Aedes* in Córdoba city. 0 to 1 are the fourth models developed, along with the average model for Cordoba city.

Table 4. Importance of variables measured according to permutation importance.

Variable	Permutation importance
Human population density	35.8
Proximity to vegetation	11.2
Proximity to water channels	8.3
Proportion of houses	8.1
Proportion of ranchos	7.7
Proximity to informal settlements (suburban slums)	6.1
Household water supply by river, creek or other	6.0
Less urbanized	5.2
Proximity to abandoned trains	3.9
Proximity to cemeteries	3.5
Proximity to tyre storage places	3.0
Maximum NDBI	1.3

NDBI, normalized difference built-up index.

In general, suitable habitats for *Ae. aegypti* were concentrated in sites proximal to vegetated areas, which accords with the findings of other research in which a close association between the abundance of a mosquito species and NDVI was found (Ferraguti *et al.*, 2016). Higher NDVI values reflect higher vegetation cover that provides shelter that potentially increases the availability of breeding and resting habitats for mosquitoes and other insect vectors (Reisen *et al.*, 1990). Previous studies conducted in the U.S.A. and Europe have also reported positive associations between NDVI values and mosquito presence, abundance and diversity (Diuk-Wasser *et al.* 2006; Roiz *et al.* 2015). Moreover, studies of *Ae. aegypti* reported that more of this species breeds in areas with high vegetation cover (Philbert & Ijumba, 2013).

Proximity to water channels suggested the importance of the availability of artificial water containers at water channels as breeding sites. This factor, together with human population density and proximity to vegetation, contributes

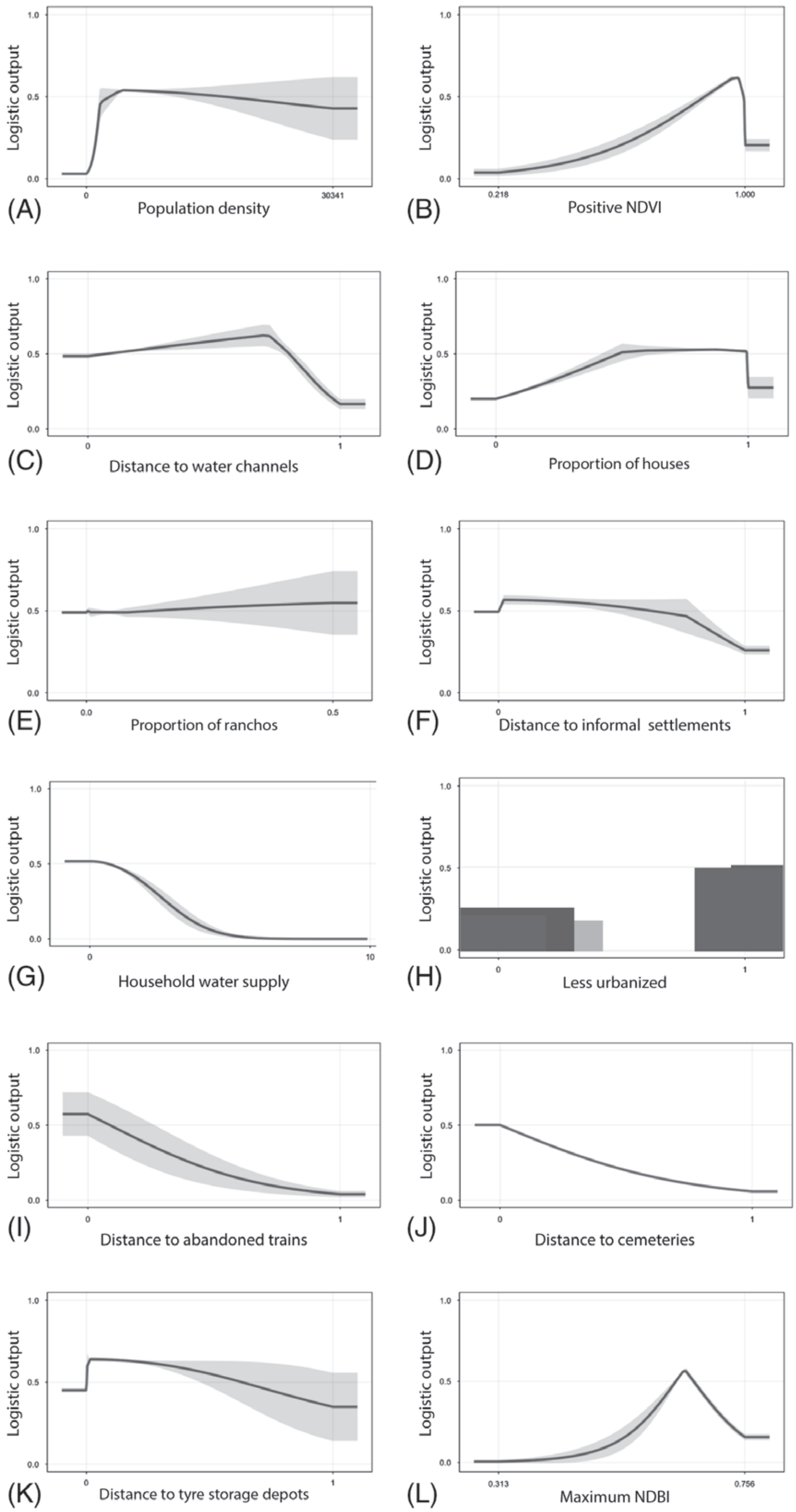

Fig. 2. Model response curves for the presence of *Aedes aegypti* larvae in relation to 12 environmental factors. Black lines show averages and grey shading represents 1 standard deviation in either direction after four iterations of the model. NDVI, normalized difference vegetation index; NDBI, normalized difference built-up index.

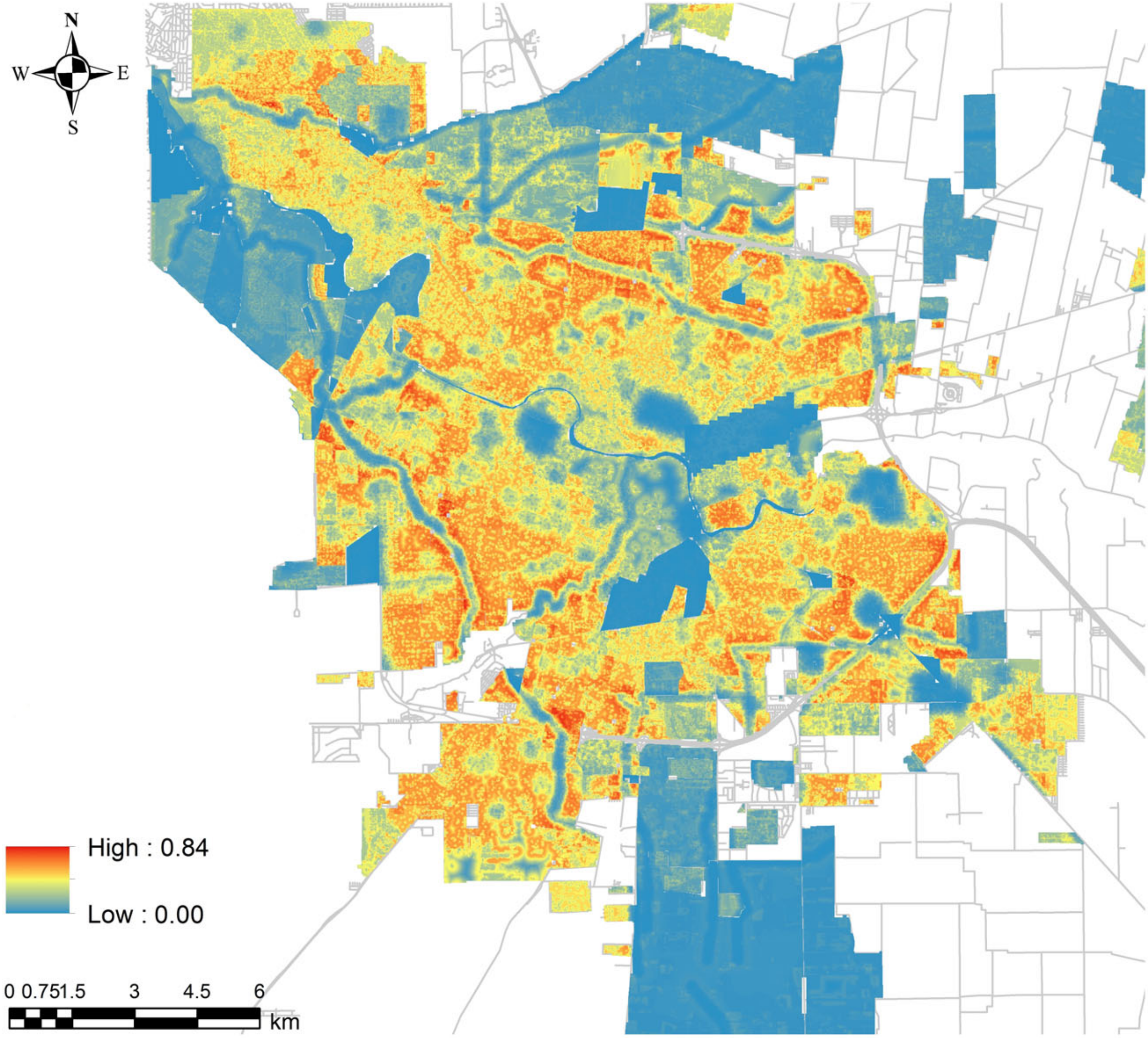

Fig. 3. Risk map identifying habitats suitable for *Aedes aegypti* and therefore risk for disease transmission through spatial analysis in the form of species distribution modelling (maximum entropy modelling). [Colour figure can be viewed at wileyonlinelibrary.com].

significantly towards making an environment suitable for the vector *Ae. aegypti* because this mosquito requires bloodmeals and access to shallow artificial water containers in which to lay eggs.

Areas with high proportions of houses were also important for assessing risk. In general, houses with back yards are characteristic of Córdoba's neighbourhoods and form a heterogeneous urban habitat in which built-up sites alternate with open spaces, by contrast with areas in which the density of construction is high.

The response curve for the proportion of ranchos (Fig. 2E) does not show variability, which suggests that other socioeconomic variables capture environmental conditions important to the development and persistence of *Ae. aegypti* mosquitoes, in accordance with Stewart Ibarra *et al*. (2013). The accumulation around ranchos of unused containers that provide larval habitats is common. Other variables of influence included proximity to informal settlements (suburban slums), household water supply, a lower level of urbanization, proximity to abandoned trains, proximity to cemeteries, proximity to tyre storage depots, and maximum NDBI. The distribution of *Ae. aegypti* is known to be influenced by environmental factors, such as temperature, and demographic factors, such as urbanization (Brown *et al*., 2014). The survival of *Ae. aegypti* is highly dependent on temperature and the availability of water; the variable 'proximity to vegetation' can be used as indicating proximity to areas with suitable soil surface-level moisture that could be associated with the availability of mosquito larval development sites (Nihei *et al*., 2014). Vegetation canopy cover reduces evaporation and wind speed in the sub-canopy, which protects mosquito development sites and favours adult flight activity (Service, 1980). The response curve of the maximum NDBI indicates that the development of an area positively affects mosquito presence (Fig. 2L).

Discussion

The *Ae. aegypti* risk map (Fig. 3) shows a wider geographic distribution in areas with high human population density (Fig. 2), as well as in places in which container habitats are available for egg laying and larval development, such as city channels, informal settlements (which are frequently close to channels or crossed by channels), abandoned train depots and cemeteries.

Study of the biogeography of diseases has much to gain from ecological niche modelling and this approach will become increasingly useful to epidemiologists who are attempting to anticipate disease transmission risk, to predict changes in disease risk brought about by climate change, and to elucidate possible landscape-level causes of outbreaks (Escobar & Craft, 2016). Disease prevention and control will benefit from a more evidence-structured approach developed by integrating risk mapping methods (Alimi *et al*., 2015). Risk assessment is an important component of public health strategy and provides information that may aid decision making by public health agencies.

Conclusions

Small-container mosquito surveillance data were used to produce a general vector exposure risk map that represents the potential risk for the transmission of dengue and other vector-borne diseases, rather than the current risk for dengue (which is reflected in maps of dengue cases). The suitability map is a representation of where human individuals are likely to be exposed to *Ae. aegypti* and therefore at greater risk for infection. This risk map points towards potential measures that can be put in place to reduce the mosquito population, such as targeted, location-specific vector management campaigns. The areas identified as including suitable habitats by the ecological niche model should be considered to carry a risk for disease transmission, as suggested by Escobar & Craft (2016), because even when the vector is present in a population, disease *per se* may be absent. Moreover, this study highlights the importance of both local socioeconomic and demographic studies, as well as the initiation of city cleaning campaigns to reduce the availability of man-made containers in public places. Many of the PBSs and socioeconomic variables included are associated with the presence of litter, which increases the likelihood of containers. Therefore, the variables used in this study may not be applicable to other modelling environments; this highlights the importance of intrinsic knowledge of the area in question in the production of empirical models of mosquito vectors. The risk maps produced in this study will allow public health workers to identify and target high-risk areas with appropriate and timely control measures.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

File S1. Remotely sensed variables. Brief description of normalized difference vegetation index (NDVI), normalized difference water index (NDWI) and normalized difference built-up index (NDBI). Photographic representation of socioeconomic variables.

Acknowledgements

Data used for this study were part of surveillance and control measures, conducted annually by the Epidemiology Section of the Provincial Health Ministry of Córdoba, with the collaboration of the Córdoba Entomological Research Centre (CIEC) from the Biological and Technological Research Institute (IIByT) of Córdoba University (UNC) and the National Scientific and Technical Research Council (CONICET). The authors thank the personnel of the Epidemiology Section of the Provincial Health Ministry of Córdoba. The authors also thank Comisión Nacional de Actividades Espaciales (CONAE) for providing the SPOT 5 HRG imagery (CONAE © Le site du Centre national d'études spatiales-CNES). E.L.E. received support from the Fulbright Program and CONICET as a Fulbright visiting scholar at Clark University (Worcester, MA, U.S.A.). E.L.E. thanks Clark University, the Department of Biology and Clark Labs at Clark University and the kind personnel of each. E.L.E., M.G. and W.A. are CONICET researchers.

The authors declare no conflicts of interest.

References

Alimi, T.O., Fuller, D.O., Quinones, M.L. *et al.* (2015) Prospects and recommendations for risk mapping to improve strategies for effective malaria vector control interventions in Latin America. *Malaria Journal*, **14**, 519–534.

Brown, J.E., Evans, B.R., Zheng, W. *et al.* (2014) Human impacts have shaped historical and recent evolution in *Aedes aegypti*, the dengue and yellow fever mosquito. *Evolution*, **68**, 514–525.

Carbajo, E., Gomes, S.M., Curto, S.I. & Schweigmann, N.J. (2004) Variación espacio-temporal del riesgo de transmisión de dengue en la ciudad de Buenos Aires. *Medicina (Buenos Aires)*, **64**, 231–234.

Centers for Disease Control and Prevention (CDC) (2018) Dengue. Entomology and ecology. https://www.cdc.gov/dengue/entomologyecology/index.html [accessed on 10 July 2018].

Christophers, S.R. (1960) . *Aedes aegypti* (L.) The Yellow Fever Mosquito. Cambridge University Press, Cambridge.

Cianci, D., Hartemink, N. & Ibáñez-Justicia, A. (2015) Modelling the potential spatial distribution of mosquito species using three different techniques. *International Journal of Health Geographics*, **14**, 10.

Dewald, J.R., Fuller, D.O., Müller, G.C. & Beier, J. (2016) A novel method for mapping village-scale outdoor resting microhabitats of the primary African malaria vector, Anopheles gambiae. *Malaria Journal*, **15**, 489.

Diuk-Wasser, M.A., Brown, H.E., Andreadis, T.G. & Fish, D. (2006) Modeling the spatial distribution of mosquito vector for West Nile virus in Connecticut, USA. *Vector-Borne and Zoonotic Diseases*, **3**, 283–295.

Eastman, J.R. (2016) . *TerrSet*. Clark Laboratories, Worcester, MA.

Elith, J., Graham, C.H., Anderson, R.P. *et al.* (2006) Novel methods improve prediction of species' distribution from occurrence data. *Ecography*, **29**, 129–151.

Elith, J., Phillips, S.J., Hastie, T., Dudík, M., Chee, Y.E. & Yates, C.J. (2012) A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions*, **17**, 43–57.

Escobar, L.E. & Craft, M.E. (2016) Advances and limitations of disease biogeography using ecological niche modeling. *Frontiers in Microbiology*, **7**, 1–21.

Estallo, E.L., Carbajo, A.E., Grech, M.G. *et al.* (2014) Spatio-temporal dynamics of dengue 2009 outbreak in Córdoba city, Argentina. *Acta Tropica*, **136**, 129–136.

Estallo, E.L., Benitez, E.M., Lanfri, M.A., Scavuzzo, C.M. & Almirón, W.R. (2016) MODIS environmental data to assess chikungunya, dengue, and Zika diseases through *Aedes* (*Stegomyia*) *aegypti* oviposition activity estimation. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, **9**, 5461–5466.

Ferraguti, M., Martínez-de la Puente, J., Roiz, D., Ruíz, S., Soriguer, R. & Figuerola, J. (2016) Effects of landscape anthropization on mosquito community composition and abundance. *Scientific Reports*, **6**, 29002.

Fenoglio, M.S., Salvo, A. & Estallo, E.L. (2009) Effects of urbanisation on the parasitoid community of a leafminer. *Acta Oecologica*, **35**, 318–326.

Franklin, J. (2010) . *Mapping Species Distributions*, 1st edn. Cambridge University Press, Cambridge.

Gao, B.C. (1996) NDWI: a normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment*, **58**, 257–266.

Getachew, D., Tekie, H., Gebre-Michael, T., Balkew, M. & Mesfin, A. (2015) Breeding sites of Aedes aegypti: potential dengue vectors in Dire Dawa, east Ethiopia. *Interdisciplinary Perspective on Infectious Diseases*, **2015**, Article 706276.

Gill, N.S. & Sangermano, F. (2016) Africanized honeybee models for southern Utah and southern California. *Applied Geography*, **76**, 14–21.

Grech, M., Visintin, A., Laurito, M. *et al.* (2012) New records of mosquito species (Diptera: Culicidae) from Neuquén and La Rioja provinces, Argentina. *Revista de Saúde Pública*, **46**, 387–389.

Instituto Nacional de Estadística y Censos de la República Argentina INDEC (2010) https://www.indec.gob.ar/ [accessed on 10 July 2018].

Khatchikian, C., Sangermano, F., Kendell, D. & Livdahl, T. (2010) Evaluation of species, distribution model algorithms for fine-scale container-breeding mosquito risk prediction. *Medical and Veterinary Entomology*, **25**, 268–275.

Machado-Machado, E.A. (2012) Empirical mapping of suitability to dengue fever in Mexico using species distribution modeling. *Applied Geography*, **33**, 82–93.

Ministerio de Salud de la Nación (2017a) Boletín Integrado de Vigilancia 361. https://www.argentina.gob.ar/salud/epidemiologia/boletines epidemiologicos [accessed on 10 July 2018].

Ministerio de Salud de la Nación (2017b) Boletín Integrado de Vigilancia 375. https://www.argentina.gob.ar/salud/epidemiologia/boletine sepidemiologicos [accessed on 10 July 2018].

Ministerio de Salud de la Provincia de Córdoba (2016) Dengue: 77 new cases of Dengue in Córdoba. http://prensa.cba.gov.ar/salud/dengue-77-nuevos-casos/ [accessed on 10 July 2018].

Muir, L.E. & Kay, B.H. (1998) *Aedes aegypti* survival and dispersal estimated by mark–release–recapture in Northern Australia. *American Journal of Tropical Medicine and Hygiene*, **58**, 277–282.

Municipalidad de Córdoba (2017) Córdoba, una ciudad en cifras. Guía Estadística de la ciudad de Córdoba. https://www.cordoba.gob.ar/cordoba-ciudad/cifras/ [accessed on 10 July 2018].

Natiello, M., Ritacco, V., Morales, M.A. *et al.* (2008) Indigenous dengue fever, Buenos Aires, Argentina. *Emerging Infection Diseases*, **14**, 1498–1499.

National Meteorological Service (2018) Caracterización: Estadísticas de largo plazo. https://www.smn.gob.ar/caracterizaci%C3%B3n-estad%C3%ADsticas-de-largo-plazo [accessed on 10 July 2018].

Nihei, N., Komagata, O., Mochizuki, K. & Kobayashi, M. (2014) Geospatial analysis of invasion of the Asian tiger mosquito *Aedes albopictus*: competition with *Aedes japonicus japonicus* in its northern limit area in Japan. *Geospatial Health*, **8**, 417–427.

Osipova, L. & Sangermano, F. (2016) Surrogate species protection in Bolivia under climate and land cover change scenarios. *Journal for Nature Conservation*, **34**, 107–117.

Paaijmans, K.P. & Thomas, M.B. (2011) The influence of mosquito resting behaviour and associated microclimate for malaria risk. *Malaria Journal*, **10**, 183.

Pan American Health Organization (PAHO) (2017) . *Zika – Epidemiological Report Argentina*. PAHO, World Health Organization, Washington, DC http://www.paho.org/hq/index.php?option=com_docman&task=doc_view&gid=35121&Itemid=270 [accessed on 10 July 2018].

Peterson, A.T. (2006) Ecologic niche modeling and spatial patterns of disease transmission. *Emerging Infection Diseases*, **12**, 1822–1826.

Peterson, A.T. & Vieglais, D.A. (2001) Predicting species invasions using ecological niche modeling: new approaches from bioinformatics attack a pressing problem. *Bioscience*, **51**, 363–371.

Philbert, A. & Ijumba, J.N. (2013) Preferred breeding habitats of *Aedes aegypti* (Diptera, Culicidae) mosquito and its public health implications in Dares Salaam, Tanzania. *Journal of Environmental Research and Management*, **4**, 344–351.

Phillips, S.J., Dudík, M. & Schapire, R.E. (2004) A maximum entropy approach to species distribution modeling. *Proceedings of the 21st International Conference of Machine Learning, Banff, AB. ACM International Conference Proceedings Series*, **69**, 8.

Phillips, S.J., Anderson, R.P. & Schapire, R.E. (2006) Maximum entropy modeling of species geographic distribution. *Ecological Modelling*, **190**, 231–259.

Reisen, W.K., Meyer, R.P., Tempelis, C.H. & Spoehel, J. (1990) Mosquito abundance and bionomics in residential communities in Orange and Los Angeles counties, California. *Journal of Medical Entomology*, **27**, 356–367.

Rogers, D.J. (2006) Models for vectors and vector-borne diseases. *Advances in Parasitology*, **62**, 1–35.

Roiz, D., Ruiz, S., Soriquer, R. & Figuerola, J. (2015) Landscape effects on the presense, abundance and diversity of mosquitoes in mediterranean wetlands. *Plos One*, **10**, e0128112.

Service, M.W. (1980) Effects of wind on the behaviour and distribution of mosquitoes and blackflies. *International Journal of Biometeorology*, **24**, 347–353.

Skowronek, S., Ewald, M., Isermann, M. *et al.* (2017) Mapping an invasive bryophyte species using hyperspectral remote sensing data. *Biological Invasions*, **19**, 239–254.

Stewart Ibarra, A.M., Ryan, S.J., Beltran, E., Mejía, R., Silva, M. & Muñoz, A. (2013) Dengue vector dynamics (*Aedes aegypti*) influenced by climatic and social factors in Ecuador: implications for targeted control. *PLoS One*, **8**, e78263.

Stewart, D.R., Underwood, Z.E., Rahel, F.J. & Walters, A.W. (2017) The effectiveness of surrogate taxa to conserve freshwater biodiversity. *Conservation Biology*, **32**, 183–194.

Swets, K.A. (1988) Measuring the accuracy of diagnostic systems. *Science*, **240**, 1285–1293.

Vergara Cid, C., Estallo, E.L., Almirón, W.R., Contigiani, M.S. & Spinsanti, L.I. (2013) Landscape determinants of Saint Louis encephalitis human infections in Córdoba city, Argentina during 2010. *Acta Tropica*, **125**, 303–308.

Vezzani, D. & Carbajo, A.E. (2008) *Aedes aegypti*, *Aedes albopictus*, and dengue in Argentina: current knowledge and future directions. *Memorias del Instituto Oswaldo Cruz*, **103**, 66–74.

Warren, D.L. (2012) In defense of 'niche modeling'. *Trends in Ecology and Evolution*, **27**, 497–500.

World Health Organization (2017) http://www.who.int/rpc/guidelines/9789241547871/en/ [accessed on 10 July 2018].

Zha, Y., Gao, Y. & Ni, S. (2003) Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing*, **24**, 583–594.

Zhao, J., Liao, J., Huang, X. *et al.* (2016) Mapping risk of leptospirosis in China using environmental and socioeconomic data. *BMC Infectious Diseases*, **16**, 343.

Accepted 25 May 2018

