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Relation between Environmental Variables and the Spatial Distribution of the *Aedes aegypti* Mosquito in Rural Colombia

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Abstract

Background: Changes in global and local environmental variables are linked to the distribution and density of disease vectors. The study's objective was to estimate the relation between the entomological indicator of immature and adult forms of the *Aedes aegypti* mosquito per unit area and the environmental variables in rural areas of two municipalities in Colombia.

Methods: Four spatial regression models were used, immature and adult *A. aegypti* forms were collected at homes during June 2013 (dry season), the houses were chosen at random, georeferenced and climate information was obtained from the Institute of Hydrology, Meteorology and Environmental Studies (IDEAM- Instituto de Hidrología, Meteorología y Estudios Ambientales). Weather information was completed with interpolation of irregularly and regularly spaced data (package akima).

Results: The most appropriate model was the Spatial Autoregressive Model with Autoregressive Disturbances of order [1,1] (SARAR [1,1]). It showed the lowest values of the Akaike information criterion (AIC = 473.34) and variable that best explained the entomological indicator (immature and adult forms per unit area) was the altitude of the houses in the rural area where the entomological samples were collected. The ranges of the environmental variables in which the presence of the mosquito occurred were between 602 to 1414 m.a.s.l (meters above sea level) for altitude, from 17 °C to 27 °C for temperature, 27 mm to 86 mm for precipitation, and 70% to 85% for relative humidity.

Conclusions: The importance of understanding the relation between local environmental features and the presence of the vector for designing comprehensive management strategies was highlighted, contributing to a better surveillance, prevention, and control of vectors and diseases transmitted.

Keywords: spatial analysis, disease vectors, public health, environmental variables

Relación entre las variables ambientales y la distribución espacial del mosquito *Aedes aegypti* en zonas rurales de Colombia

Resumen

Antecedentes. Los cambios en las variables ambientales globales y locales condicionan la distribución y densidad de los vectores de enfermedades. Este estudio tuvo como objetivo estimar la relación entre el indicador entomológico de formas inmaduras y adultas del mosquito *Aedes aegypti* por unidad de área, y variables ambientales en zonas rurales de dos municipios de Colombia.

Métodos. Se ajustaron cuatro modelos de regresión espacial. Se recogieron formas inmaduras y adultas de *A. aegypti* en viviendas durante junio de 2013 (estación seca). Las casas se eligieron al azar, se georreferenciaron y la información climática se obtuvo del Instituto de Hidrología, Meteorología y Estudios Ambientales (IDEAM). La información meteorológica se completó con la interpolación de datos espaciados irregulares y regulares (package akima).

Resultados. El modelo más apropiado fue el Modelo Autorregresivo Espacial con Perturbaciones Autorregresivas de orden [1,1] (SARAR[1,1]) que mostró los valores más bajos del criterio de información de Akaike (AIC = 473,34) y la variable que mejor explicó el indicador entomológico (formas inmaduras y adultas por unidad de superficie) fue la altitud de las casas de la zona rural donde se recogieron las muestras entomológicas. Los rangos de las variables ambientales en las que se produjo la presencia del mosquito estuvieron entre 602 y 1414 m.s.n.m. (metros sobre el nivel del mar) para la altitud, 17 °C a 27 °C para la temperatura, 27 mm a 86 mm para la precipitación y 70% a 85% para la humedad relativa.

Conclusiones. Se destacó la relación entre las características ambientales locales y la presencia del vector para diseñar estrategias de manejo integral contribuyendo a una mejor vigilancia, prevención y control de los vectores y las enfermedades transmitidas por ellos.

Palabras clave: análisis espacial, vectores de enfermedades, salud pública, variables ambientales

Relação entre as variáveis ambientais e a distribuição espacial do mosquito *Aedes aegypti* na Colômbia rural

Resumo

Antecedentes. As mudanças nas variáveis ambientais globais e locais condicionam a distribuição e a densidade dos vetores de doenças. Este estudo teve como objetivo estimar a relação entre o indicador entomológico das formas imaturas e adultas do mosquito *Aedes aegypti* por unidade de área, e variáveis ambientais em áreas rurais de dois municípios da Colômbia.

Métodos. Foram instalados quatro modelos de regressão especial. *A. aegypti* imaturos e adultos foram coletados em residências durante junho de 2013 (estação seca). As casas foram escolhidas ao acaso e foram georreferenciadas. As informações climáticas foram obtidas do Instituto de Hidrologia, Meteorologia e Estudos Ambientais (IDEAM- Instituto de Hidrología, Meteorología e Estudios Ambientales). As informações meteorológica foram completadas com interpolação dados irregular e regularmente espaçados (package akima).

Resultados. O modelo mais apropriado foi o the Spatial Autoregressive Model with Autoregressive Disturbances of order [1,1] (SARAR[1,1]), pois apresentava os valores mais baixos do critério de informação Akaike (AIC = 473,34). Neste modelo, a variável que melhor explicava o indicador entomológico (formas imaturas e adultas por unidade de área) era a altitude das casas na área rural onde as amostras entomológicas eram coletadas. As faixas das variáveis ambientais em que ocorreu a presença do mosquito estão entre 602 a 1414 m.a.s.l (metros acima do nível do mar) para altitude, 17 °C a 27 °C para temperatura, 27 mm a 86 mm para precipitação, e 70% a 85% para umidade relativa.

Conclusões. A importância de entender a relação entre as características ambientais locais e a presença do vetor para a concepção de estratégias de gerenciamento abrangentes foi destacada, contribuindo para uma melhor vigilância, prevenção e controle dos vetores e doenças por eles transmitidas.

Palavras-chave: análise espacial; vetores de doenças; saúde pública; variáveis ambientais

Introduction

The *Aedes aegypti* (L) mosquito is the main vector of dengue (DENV), chikungunya (CHIKV), zika (ZIKV), and urban yellow fever (YFV) which are viral diseases of global importance for their impact on the health of populations located in tropical and subtropical countries (1, 2). There has been a growing interest in studying its distribution and the incidence of the diseases it transmits associated with climatic variability and climate change (3). These variations in climate are related to the increase in the average temperature of the earth's surface, which has risen approximately 0.7 °C in the last ten decades globally, and future growth of an additional 1 - 3.5 °C is anticipated for the next 100 years (4).

An example of the connection between climate variables and vector-borne diseases is DENV, considered the most prevalent arbovirus in humans. Recent research estimates that between 30% and 55% of the world's population is at risk of contracting DENV (5) and adds that this figure is likely to increase with projected global climate change contributing to extend the geographical distribution of the mosquito to some regions currently considered low risk or without its presence. Thus, some projections estimate an increase in the vector by 2050 in southern Africa, India, China, and even Japan (6). Likely, this change in the distribution of the vector will also affect the Americas, where it is projected that the southern United States will become a favorable environment for this mosquito and there will be variations in the distribution of the insect in Latin America (6, 7).

This raises concerns from a public health perspective because the region has been the epicenter epidemics of diseases transmitted by this mosquito and the presence of new arboviruses such as Mayaro and Oropouche has been documented (2). Despite a reduction in cases of DENV, CHIKV, and ZIKV in the region for the period 2015-2017, in 2019, an increase in ZIKV was observed that reached epidemic levels (8). These diseases have endemic features in many regions of Latin America: DENV in Colombia is a disease that is considered a public health priority due to its transmission intensity and the growing trend towards a higher frequency and severity of epidemics (9). The factors that have facilitated the endemic condition of DENV in Colombia may have also strengthened CHIKV and ZIKV in the country (9).

Besides social and demographic factors, some climate-related variables also influence the emergence of viral outbreaks. For example, the intensification in precipitation, changes in average temperature, and increases in humidity influence them (3) and affects the mosquito's distribution in latitude and altitude (10, 11).

In the case of the *A. aegypti* and *Aedes albopictus* (S) mosquitoes also considered a vector of DENV, CHIKV, and ZIXV (12, 13), weather factors such as temperature, precipitation, humidity, and wind speed can affect their survival, development, and reproduction (14, 15). The life cycle stages and the density and flight distance of mosquitoes are affected by ambient temperature (15). Cold environments result in a more extended incubation period; at higher temperatures (as long as it does not exceed 32 °C), there is a higher density of mosquitos and for the case of *A. albopictus*, the insect can move more than 400 meters in temperatures raging 20 °C and 27 °C, depending on wind speed (15).

Mosquito biting behavior is influenced by temperature, as shown in a study conducted in the Yunnan Province (China) where they were reported between 15 °C and 35 °C, with an optimal range between 25 °C and 30 °C (15). In addition, in the Hainan province of China, it has become evident that as winter temperatures continue to rise, mosquitoes may be active throughout the year (15, 16). The association of rainfall with the incidence of viruses transmitted by *A. aegypti* is a crucial variable to understand its distribution and activity (17, 18). Precipitation provides potential breeding grounds contributing to mosquito density (15). Humidity, being related to rainfall and temperature, also influences mosquito behavior, as one study showed an increase in the number of *A. albopictus* bites from 19 bites to 60 bites / (person * hour) from the dry to the wet season (15, 19).

The *A. aegypti* mosquito is widely distributed around Colombia (10), but its presence may increase following the trend observed in previous years. For example, in relation to its altitudinal distribution, in 1981 the mosquito was recorded at 2200 m.a.s.l in the municipality of Málaga, Santander (20) and by 2016 it was already found at 2302 m.a.s.l in the municipality of Bello, Antioquia (21), this is the highest altitude record for this insect in Colombia. The change in the vector distribution pattern can also alter the geographic distribution or transmission dynamics of the viruses it transmits (3).

Despite an increase in global research on DENV, CHIKV, and ZIKV (7) that is related to the rise in cases of these arboviruses between 2000 and 2017, there is still limited knowledge of the geographical distribution of *A. aegypti* and the influencing factors for its distribution. This is concerning because the importance of the geographical component is a determining factor and must be included in the development of appropriate control strategies adapted to the specific characteristics of the local context (22). The use of spatial analysis techniques in epidemiology (visualization, exploration, and modeling) makes it possible to describe spatial patterns, identify clusters or groups of diseases, and learn about the risk factors of the diseases under study to explain or predict the risks of infection (23).

Including these and temporal dynamics of vector-borne diseases in the design of comprehensive management strategies would lead to better surveillance, prevention and control of infections (24). However, one of the challenges in reducing the diseases transmitted by the vector *A. aegypti* is the complex and dynamic manner in which the disease manifests itself in different populations which cannot be understood entirely from the main components of the infection (presence of the virus, vector, and susceptible population) (22, 25). Understanding local environmental features and their relation to these diseases is critical to design effective control programs (25).

This situation is critical in Colombian rural areas because entomological surveillance of *A. aegypti* and vector control programs have focused on urban areas (12). Given the marginal conditions of many rural populations (e.g., limited access to health services, lack of a continuous supply of water for human consumption), it is necessary to expand our knowledge about these seldom-studied populations and how the transmission of dengue or other arboviruses occurs.

These areas of transmission may have a smaller magnitude compared to other regions (12, 26), but the burden and effects of the disease could be exacerbated by local socioeconomic factors. One of the challenges of studying the dynamics of diseases transmitted by *A. aegypti* is the under-reporting of cases of infection occurring in rural and urban areas (10). Entomological information of distribution of the vector, as well as identification of the ranges of environmental variables (precipitation, temperature, humidity, and altitude), are essential pieces that contribute to the design of prevention and control strategies. The present research sought to estimate the potential relation between the response variable (entomological indicators of immature and adult forms per unit area) with the explanatory variables of temperature, precipitation, humidity, and altitude in rural towns of the municipalities of Anapoima and La Mesa (Cundinamarca department) in June 2013.

A combination of collected field data (infestation rates of adult and immature forms of the vector in rural homes), digital elevation models and monitoring weather stations were used. In order to estimate the relation between the variables of interest, four spatial regression models were adjusted: Spatial Autoregressive Model with Autoregressive Disturbances of order [1,1] (SARAR[1,1]), Spatial Error Model (SEM), Spatial Lag Model (SLM) and the Pure Spatial Autoregressive Model.

Materials and methods

Study area

The present study was carried out in rural and peri-urban areas of two municipalities in the department of Cundinamarca, Colombia (Figure 1). The municipality of Anapoima is located 710 m.a.s.l., geographical coordinates at the municipal seat are latitude 4°33'01"N and longitude 74°32'10"W, with area of 124.2 km^2, average annual total precipitation is 1300 mm, average temperature fluctuates between 22 °C and 28 °C and has approximately 12539 inhabitants, 57% which live in rural areas (27, 28).

The municipality of La Mesa is located at 1200 m.a.s.l., geographical coordinates at the municipal seat are 4°37'4"N latitude and 74°27'45"W longitude, has an area of 148 km^2, an annual precipitation is 1300 mm, average annual temperature is 22 °C, and has 29566 inhabitants, 45% which live in rural areas (28, 29). The two municipalities' economic activity is mainly based on agriculture with crops of sugar cane, coffee, and fruit. Other economic activities, such as livestock and tourism are also present (28). According to the Holdridge life zone system, these municipalities are located in the tropical dry forest and premontane wet forest formations (30).

Topographic Information

The altitudes (contours) of the study area were obtained from the digital elevation model (90 meters of spatial resolution) generated by the international project Shuttle Radar Topographic Mission (SRTM) of the National Agency for Geospatial Intelligence (NGA) and the National Aeronautics and Space Administration (NASA) (31).

Weather Data

Data of total precipitation, average temperature and percentages of relative humidity were compiled from the network of monitoring stations of the Regional Autonomous Corporation (CAR) and the Institute of Hydrology, Meteorology and Environmental Studies (IDEAM- Instituto de Hidrología, Meteorología y Estudios Ambientales. Twenty-four (24) stations were included (17 CAR stations and 7 IDEAM stations).

With linear regression, missing values of the total precipitation of June 2013 were logged when an absolute value of the correlation coefficient greater than 0.7 was present. The methodology described by Fries *et al* (32) was used for missing values of the average temperature and the percentage of relative humidity were estimated for the stations that did not have measurements of these.

Ranges of weather variables with the presence of the Aedes aegypti mosquito in the study area

Maximum and minimum values of the weather variables (precipitation, temperature, percentage of relative humidity) that characterize houses with the presence of the mosquito in the study area were obtained from the interpolation of surfaces generated for the month of interest. The interpolation layers of the weather variables were generated to complete the information of the meteorological data and was performed by filling irregularly spaced data from the akima package (33) of the R 3.6.0 program (34). The mathematical action with precise data measured by the described monitoring stations allows an estimation of the weather variables of interest for the entire territory. Once the respective interpolation surfaces were generated, the values of the environmental variables (total precipitation, average temperature) were extracted from the raster files using the "Extract values to points" tool of the ArcMap 10.5.1 program (35) and the percentage of relative humidity for each geographical location of the sampled houses. This information was used to set the maximum and minimum values of each of the variables.

Mosquito density (immature and adult forms)

Information on the *A. aegypti* mosquito (immature and adult forms) was collected from 103 houses, distributed in 34 geopolitical divisions called veredas in the rural and peri-urban areas of the municipalities Anapoima and La Mesa, Cundinamarca, during June 2013 (dry season). The houses were georeferenced, mosquito breeding grounds were searched inside and outside and adult samples were collected using Prokopack vacuum cleaners (36) inside each dwelling. The material collected in the field was processed, according to Olano et al (37). The information collected was filled and debugged using spreadsheets and the vector's immature and adult form data was consolidated because some houses did not have both immature and adult forms.

Area Spatial Data

Area data within spatial statistics refer to entities with polygonal geometry with limits that can be defined by the researcher or arbitrarily like the administrative division of Colombian territory. The data associated with this polygonal entity is characterized by adding information as is the case of population counts, rates, and so on (38).

Given that the data used in spatial regression models are characterized by being of the area type, and because the density indicator (count of immature and adult forms) is of the point type, it is necessary to transform the data from point to area type. To achieve this, an irregular tessellation, which is an arrangement of closed shapes that completely covers the plane without overlapping or leaving gaps, was created with the deldir package (39) of the R 3.6.0 program (34) and it is aimed at reducing the uncertainty generated by having a small sample in the number of sampling points within the interpolation maps. Examples of this strategy's application are studies on electrical conductivity in soil (40), spatial-temporal distribution of calls for medical care (41) and global modeling of infectious disease spread (42).

The respective value of the density indicator was added to the new polygonal entities, obtaining the density indicator per unit area (count of immature and adult forms/m^2). The transformation (logx+1) to this indicator was subsequently performed due to small values that were present and with the indicator, spatial dependence was evaluated through the spatial weights matrix. The graphical output of the Voronoi diagrams was performed in the R 3.6.0 program (34) and later edited in ArcMap 10.5 (35).

Spatial Linear Regression Models

Following an exploratory approach, the Moran Index was used to evaluate if the spatial distribution of each variable of interest (explanatory and response) presented spatial dependence or autocorrelation (43). The generation of neighbors within the spatial weights matrix was generated with the criterion of adjacency that considers neighboring polygons in eight directions (queen-type criterion) and rows standardized it (44).

The analysis of spatial models was performed using the spatial dependence package - spdep (38, 45) of the R 3.6.0 program (34) adjusting the Spatial Autoregressive Model with Autoregressive Disturbances of order [1,1] (SARAR[1,1]), Spatial Error Model (SEM), Spatial Lag Model (SLM) and the Pure Spatial Autoregressive Model.

The Akaike information criterion (AIC) and the p values associated with the model parameters were used as evaluation basis and selection of the model and the explanatory variables that presented the best fit. The interpretation of the parameters of these models differs from the interpretation performed in standard linear regression models because its interpretation is less immediate and requires additional clarifications (44). For this reason, p-value associated with the most important variables was emphasized and was complemented by other studies where these variables were significant. Although, for further studies it is recommended to explore the "impacts" function of the spatial regression analysis package (spatialreg); through which it is possible to properly interpret the spatial regression coefficients through the calculation of model impacts (46).

Spatial regression models, in addition to allowing the establishment of relations between the variables of interest, allow the variability of spatial dependence to be included in the analysis. This is of great importance because ignoring this factor could lead to biased estimates in the results for the presence of spatial dependence indicates the existence of a functional relation between two locations in two different places; the assumption of independence of the residuals of classical statistics would not be met (47, 48). Applications of these models include environmental issues related to particulate pollution and the nitrogen footprint of food (47, 49). However, there are few studies that include spatial econometric models in their analyses (47).

Spatial variability or spatial structure within these models may be present in the response variable, the explanatory variables, the error term and their combination (50). Accordingly, the general spatial regression model is expressed according to the Elhorts taxonomy (51), as follows:

$$y = \lambda Wy + \alpha 1_n + X\beta_1 + WX\beta_2 + u; |\lambda| < 1$$
$$u = \rho Wu + \varepsilon; \quad |\rho| < 1$$

with a weight matrix, is the matrix of explanatory variables, corresponds to the spatial lag of the residuals, is the spatial lag of the variable, is the vector of residuals with $\varepsilon \vee Xi.i.d.N(0, \sigma_\varepsilon^2 I)$ and $\beta_1, \beta_{2,} \lambda \wedge \rho$ parameters to be estimated.

The following models are obtained from the general model equation:

1. The Spatial Autoregressive Model with Autoregressive Disturbances of order [1,1] ([SARAR[1,1]). This model is characterized by being an autoregressive spatial model for the response variable *(y)* and the residuals *(u)*; that is, none of its parameters *(λ,ρ)* are null. Where *(y)* is the vector of the explained variable, (λW_y) is the spatial lag of the variable and, *(X)* is the matrix containing the explanatory variables, *(W)* is the matrix of spatial weights, and *(μ)* corresponds to the spatial lag of the residuals. The parameters *(λ)* and ρ determine the level of the autoregressive relation, *(ε)* is the vector of residuals, assuming that *(ε)* are independent variables and identically distributed to a normal variable with zero mean and constant variance.
2. Pure Spatial Autoregressive Model. When $(\beta_1=0)$ and $(\beta_2=0)$ and either *(λ)* or *(ρ)* are null. If there is autocorrelation in the variable of interest nd the autoregressive parameter associated with the end of error *(ρ=0)*, it means that the residuals are independent and the equation would be:

$$y = \lambda Wy + \varepsilon; |\lambda| < 1$$

3. Spatial Error Model (SEM). There is autocorrelation in the response variable, the explanatory variables are lagged and the residual ones are considered independent *(ρ=0)*:

$$y = \lambda W y + \alpha 1_n + X\beta_1 + WX\beta_2 + \varepsilon; |\lambda| < 1$$

4. Spatial Lag Model (SLM). In the case where the parameter *λ=0 (ρ≠0)*, the model ceases to be autoregressive leaving only the spatial dependence at the end of the error:

$$y = X\beta_1 + WX\beta_2 + (I - \rho W)^{-1}\varepsilon; |\rho| < 1$$

If the autoregressive parameters *(λ)* and *(ρ)* are zero, there is no autocorrelation in the response variable or the error term, leaving *(μ=ε)* and the explanatory variables are lagging, the model is reduced to:

$$y = X\beta_1 + WX\beta_2 + \varepsilon$$

The above model preserves the spatial nature because the matrix of spatial weights associated with the explanatory variables is considered.

Results

The municipalities' altitude range is between 500 m.a.s.l and 2000 m.a.s.l (Figure 2). The lowest area is located in the central region of the two municipalities and southwest of Anapoima. The highest elevation was in the northeastern part of the municipality of La Mesa. The relation between the mosquito's presence with the level curves (altitude) shows that the maximum altitude at which it was observed was 1414 m.a.s.l. in the municipality of La Mesa (Figure 1).

Figure 1. Municipalities (second-level administrative division) of Anapoima and La Mesa, department of Cundinamarca, Colombia.

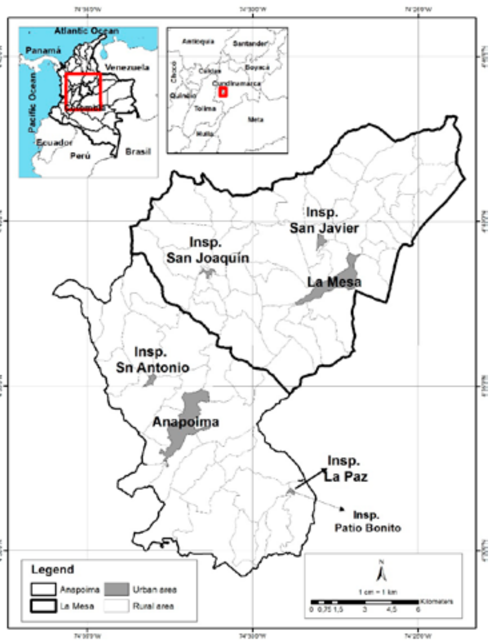
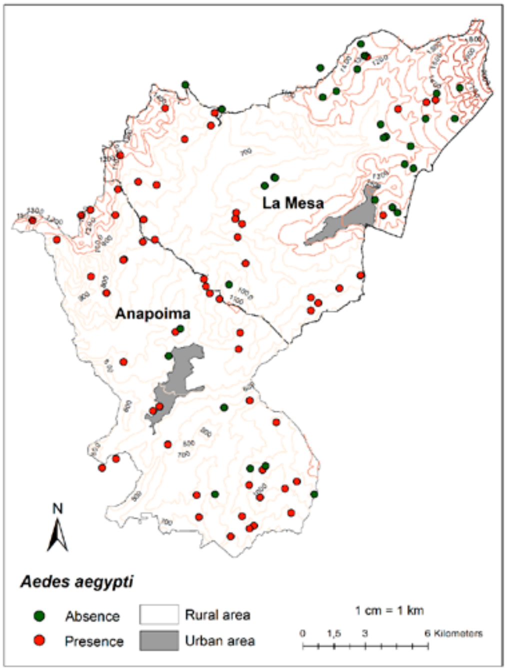


Figure 2. Presence (red) and absence (green) of *Aedes aegypti* and relief (altitude) of the study area.



The maximum and minimum values of the weather variables derived from the interpolated surfaces for each dwelling are summarized in Table 1.The total precipitation recorded during the study was between 27 mm to 86 mm and the average temperature was between 17 °C and 27 °C. The range corresponding to the percentage of relative humidity was between 70% and 85%. The altitude of the study area where the vector was present was between 602 m.a.s.l and 1414 m.a.s.l (table 1).

Table 1. Ranges of environmental variables that characterize homes where the presence of the Aedes aegypti mosquito is present.

Environmental Variable	Presence	
	Min.	**Max.**
Precipitation (mm)	27	86
Temperature (°C)	17	27
Relative humidity (%)	70	85
Altitude (m.a.s.l)	602	1414

The exploratory spatial analysis performed with the Moran index for the variables of interest indicated some degree of spatial dependence which justifies spatial regression models. It is important to emphasize that the evidence of spatial dependence in an exploratory manner does not guarantee the existence of spatial dependence within the spatial modeling process.

In the figure shown below (Figure 3), the distribution of the density indicator (count of immature and adult forms) by the generated tile is presented, taking into account the presence of the vector in one of its stages (gray) and the absence of it (white).

Figure 3. Tessellation based on the geographic location of the houses sampled with the absence (white) and the presence of *Aedes aegypti* in one of its stages (gray)

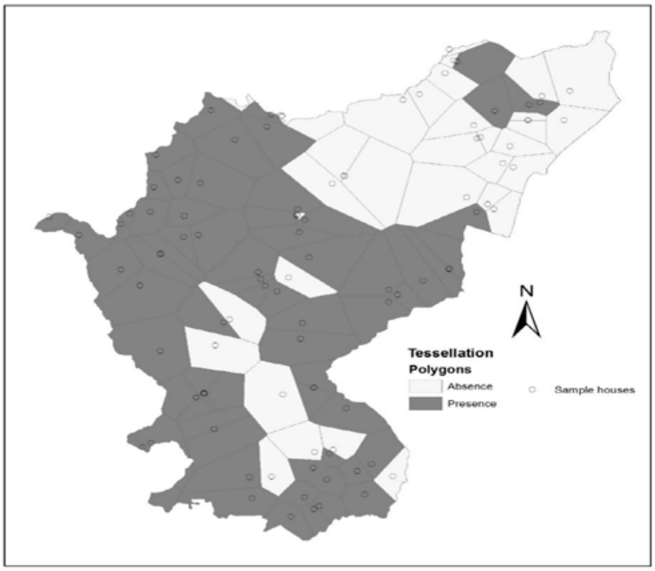


Table 2 contains the results obtained for the four estimates with spatial regression models. The most suitable model was SARAR[1,1] since it has the lowest value of the Akaike information criterion (AIC = 473.34). In this model, the variable that best explained the entomological indicator (immature and adult forms per unit area) was the altitude of the houses in the rural areas where the entomological samples were taken. In the Spatial Error Model, the altitude variable also showed a good fit from a statistical perspective. In the Spatial Lag Model (SLM), this variable was near significant *(p-value=0.0508)*.

In addition to presenting a good fit, the SARAR[1,1] model showed the following p-values of the autocorrelation parameters associated with both the response variable *(λ) (p-value<2.2204e-16)* and the parameter related to the error structure *(ρ) (p-value=0.00054).* A significant spatial lag is also observed in the estimation of these parameters *λ=0.8137* and *ρ=-0.78331*. The residuals *(ε_i)* obtained from the SARAR[1,1] model did not show spatial autocorrelation, according to Moran's I, and are normal according to the Jarque-Bera Adjusted normality test (52) (Table 2).

Table 2. Estimated parameters, significance level, and residuals of the estimated spatial regression models.

		SARAR[1,1] Model	**Spatial Error Model**	**Spatial Lag Model**	**Pure Spatial Autoregressive Model**
Intercept	Estimation	-6.2974	1.5164	3.3158	3.7724
	Standard Error	19.59	12.419	9.4419	0.4826
	Test (z)	-0.3214	0.1221	0.3511	7.8133
	p-value	0.7478	0.90282	0.7254	5.5511 e-15
AIC		473.34	473.9337	476.24	483.9502

		SARAR[1,1] Model	Spatial Error Model	Spatial Lag Model	Pure Spatial Autoregressive Model
Altitude	Estimation	-0.00325	-0.003277	-0.003	
	Standard Error	0.00143	0.00163	0.00158	
	Test (z)	-2.266	-2.055	-1.952	
	p- value	0.0234	0.039	0.0508	
Precipitation	Estimation	-0.02033	0.0048	0.01081	
	Standard Error	0.0327	0.02	0.01955	
	Test (z)	-0.6211	0.197	0.55311	
	p-value	0.5345	0.84	0.58	
Relative humidity (%)	Estimation	0.07121	-0.012	-0.01449	
	Standard Error	0.1817	0.1198	0.0881	
	Test (z)	0.3918	-0.102	-0.1645	
	p-value	0.6951	0.9181	0.8693	
Mean Temperature	Estimation	0.488	0.2353	0.11907	
	Standard Error	0.3292	0.2025	0.16519	
	Test (z)	1.48223	1.1618	0.7208	
	p-value	0.1382	0.2453	0.471	
Lambda (λ)	Estimation	0.8137	0.3374		0.5113138
	Test (z)	9.2133	6.3852		18.876
	p-value	<2.2204 e-16	0.0115		(1.3946 e-05)
Rho (ρ)	Estimation	-0.78331		0.3156	
	Test (z)	-3.4592		6.0372	
	p-valor	0.00054		0.014	
I Moran (Residuals)	Observed	0.00116	0.00212	0.002435	0.02811
	p-value	0.3748	0.3348	0.3224	0.00225
Test for normality (Residuals)	p-value	0.0685	0.083	0.116	0.02

Discussion

There is a wide variety of studies that have shown that the environment directly influences the *A. aegypti* mosquito: weather factors such as temperature, precipitation, humidity and wind speed can affect survival, development and reproduction (6, 7, 14, 15) because its life cycle stages, density and flight ranges are affected by temperature (14, 15). Although there is global evidence of the effect of weather variables on the distribution of the *A. aegypti* , it is essential to combine this information from broad temporal and spatial scales with local entomological studies that allow a more precise understanding of the risk of spreading of the diseases transmitted (14, 25). Supporting this study with entomological samples collected from 103 houses in rural and peri-urban areas of La Mesa and Anapoima, spatial correlation was found between the presence of the vector and the altitude.

This association was significant for the SARAR[1,1] and Spatial Error Models (SEM), and close to the selected level of significance for the Spatial Model in Lag It was found that the SARAR[1,1] spatial model had the best fit. However, despite having observed in the exploratory analysis stage a spatial autocorrelation in the resulting variables of interest (immature and adult forms per unit area) and explanatory variables (altitude, precipitation, relative humidity, average temperature), the weather variables were not significant in any of the models evaluated in this study.

It should be noted that the majority of studies in Colombia that seek to link vector-borne diseases with environmental variables are based on reported cases of the diseases of interest and not on the presence of the vector. One example is a study in which a spatial-time analysis was performed between dengue cases and environmental variables between 2007 and 2010 (53). A relation was found between the quadratic term of the precipitation and the incidence of dengue for a wide range of altitudes comprised between four meters and 3831 m.a.s.l (53). However, the *A. aegypti* mosquitoes with or without a natural DENV infection are within an altitudinal range with a smaller amplitude. Their circulation with natural infection of dengue serotype 2 is found up to 1984 m.a.s.l and the highest altitude record for the mosquito is above 2302 m.a.s.l in Colombia (21).

The observed altitudinal range was between 602 m.a.s.l. and 1414 m.a.s.l., which is consistent with the altitude where endemic transmission of DENV occurs in the country (10). Although only altitude was found to be a significant variable in the model, in the area of interest some conditions have been reported in other investigations as favorable for the development of the vector, including the environmental variables analyzed (temperature, precipitation, relative humidity, and altitude).

In researches conducted in Colombia and elsewhere, models have shown different importance of the environmental variables included in this study (17, 54). For example, studies have found positive associations between average, maximum, and minimum temperatures with dengue fever incidence in Taipei City, Taiwan. However, an adverse effect of average, maximum, and minimum temperature was found 360 km from this city in Kaohsiung, as well as no correlation between dengue disease and the climatic variable of temperature in Cixi City, Zhejiang Province, China (15). These differing environmental variables explain the presence of the virus in nearby geographical areas and speak to the importance of studying the vector's local distribution. Due to the complexity to analyze the relation between weather factors with *A. aegypti* and DENV, the need to model at regional and local scales is highlighted to complement the evidence regarding this problem. To model and project patterns of the spatial and temporal distribution of the transmission of this arbovirus, examples at various scales should include the distribution of the mosquitoes and the disease and the effects of climatic factors.

Similarly, the importance of complementing national and global scale models with models that analyze the situation in specific contexts such as this study is highlighted. These are especially important in rural and peri-urban contexts due to the emphasis on urban areas. Also, these populations are characterized by other comorbidities and deficiencies in managing health problems that can make them more vulnerable to viruses transmitted by this vector. Altitude (significant variable within the model) is one of the determining factors in the temperature variation that is reflected in the temperature gradient and determines the structure and concept of the unified thermal floors, known as the climatological classification of Caldas (55). According to this classification, the area of this study is characterized by being a warm-temperate thermal floor.

Additionally, the municipalities of Anapoima and La Mesa present a climatic classification between semi-humid and semi-arid, according to a study that unified said classification of Caldas and Lang. This last model groups the climate based on precipitation and mean annual temperature through a coefficient (56). It is possible that the relation observed at the exploratory level between the vector and the variables of temperature, humidity, and precipitation for this region is mediated by altitude, which showed a significant spatial autocorrelation.

According to the relation between temperature with geographic variables (latitude and altitude), studies have found that the increase of the former can cause an increase in the probability of new geographic regions with cases of vector-borne diseases (21, 57). However, the temperature was not seen as a significant variation within the model. The minimum and maximum temperatures recorded (17 °C to 27 °C) are within the range that was defined as optimal within an intra and interstate autoregressive prediction study for dengue outbreaks in Colombia from a 12 year meteorological and epidemiological time series (2000 to 2011) (25). In this same study, it was found that significant dengue outbreaks occur in warm-dry periods with a temperature range between 18 °C and 32 °C, leading to the conclusion that this is the optimal range for the survival of *A. aegypti* and virus transmission (25).

Like temperature, precipitation was not significant in any of the models evaluated even though the frequency and intensity have been defined as one of the main determinants of mosquito abundance because it causes an increase in insect breeding sites during and after the rainy season (17, 53, 25). This increase in infestation can be extended to dry seasons when water shortages are evident or when the supply is intermittent and containers are used for the storage of rainwater for consumption. (58).

Some limitations that have to be considered: the absence of relation between temperature and vector distribution may be due to the mean temperature variable. Future research could include maximum and minimum temperature values and the mean temperature within the spatial models. Some investigations have obtained significant models for meteorological variables such as evidence of the correlation between temperature, rainfall and the transmission of dengue disease (17, 59), minimum temperature recorded in past times (lag of 2 months), maximum temperature and relative humidity without lag period significantly affect the incidence of dengue (60).

Additionally, it is possible that not having found a significant relation between precipitation and relative humidity with the presence of mature and immature forms of the vector has to do with samples that were only taken during the dry season. This becomes more important in the study region during times of other weather conditions, for it is harder to infer about temporal changes in the distribution of *A. aegypti* in the region due to logistical limitations for sample collection throughout the year in rural areas of Colombia. Given the need to further understand the distribution of this vector, it is essential to consider methodological designs that can have a longitudinal perspective of the problem. This will depend on access to resources that will overcome the challenges in rural and peri-urban areas in low and middle-income countries.

An association was not shown in the spatial model for environmental variables other than altitude; their relevance can be determined by making a general association using Caldas and Lang's climatic classifications and obtaining an approximation of the environmental conditions that characterize places with the presence of the vector, such as the case study of this research.

Despite limitations, this research is an important step towards understanding a seldom-studied phenomenon in the global context: the relation between the vector *A. aegypti* and environmental variables in rural areas of low- and middle-income countries. This information is relevant for comparison to studies focused on reporting mosquito-associated diseases and vector distribution models. Likewise, the registered presence of adult and immature forms of the vector provides evidence for the need to strengthen the study, control, and monitoring of these diseases in rural and peri-urban areas, especially in regions that have not been provided with basic public services such as constant access to drinkable water.

In the case of the rural and peri-urban areas of Anapoima and La Mesa, this information may prioritize prevention and control actions in regions at higher risk of mosquitoes in response to the early alarms for associated diseases. The evaluation of the possible impact that environmental variables might have, not only on the incidence of diseases but also on the increase in the reproductive rates of vectors that transmit them, is a great challenge for territorial management because of the high variation that occurs in the spatial, weather, social, and economic contexts. Understanding the effect of these variables and monitoring them is essential for focusing and adapting measures for preventing disease transmission, particularly in the current climate change scenario. For this reason, geographic techniques applied to the study of the distribution of *A. aegypti* and the diseases this mosquito transmits over time constitute fundamental tools in the design of public health actions and policies.

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Conflict of interests

The authors declare that they have no conflict of interest.

Ethical approval

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