Dengue risk-mapping in an Amazonian locality in Colombia based on regression and multi-criteria analysis

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Abstract

The potential of dengue infection is of prime public health concern in tropical and subtropical countries. In Colombia, the management of this disease is based mainly on epidemiological monitoring and vector control. This study, covering the period 2015-2022, adds to this approach by investigating a tool that identifies dengue risk zones considering its environmental and socio-demographic determinants. For this purpose, an analytical, comparative, ecological study was carried out in three stages: i) selection of indicators associated with the occurrence of dengue through hierarchical analysis; ii) execution of a spatial-based Ordinary Least Squares (OLS) regression technique; and iii) multi-criteria analysis of the risk data obtained. Consequently, two optimal models, one for the rainy season (R^2=0.5761; AIC=366.3929) and the other for the dry season (R^2=0.8560; AIC=440.7557) were obtained for the Dengue Incidence Rate (DIR) during the study period mainly based on socio-demographic and environmental variables. A dengue risk map was generated, showing the impact on three neighbourhoods in the municipality of Piamonte in the Cauca Department covering both seasons. In conclusion, the dengue risk map made it possible to identify high-risk areas and also to identify the determinants of disease occurrence, which can contribute to improving disease management in tropical and subtropical regions.

Introduction

Dengue, an arbovirus primarily transmitted by the mosquitoes *Aedes aegypti* and *Aedes albopictus*, is considered one of the main communicable disease problems at the global level due to its rapid expansion in tropical and subtropical countries. Other reasons are progressive increases in morbidity and mortality rates and their possible further exacerbation due to climate change (Racloz *et al*., 2012; Intergovernmental Panel of Climate Change (IPCC), 2022). In Colombia, a long-term study conducted by Padilla *et al.* (2017) indicate that more than 900 of 1,100 municipalities are endemic for the disease, with 108 municipalities identified as transmission foci, representing a risk for 58% of the country's population. In 2022, there were 69,497 reported cases of dengue and 1,371 cases of severe dengue (Instituto Nacional de Salud, 2022). As of 2023, the country had recorded 131,784 cases of dengue,1,714 cases of which were severe (Instituto Nacional de Salud, 2023)

This research was carried out in the department of Cauca, located in the south-western part of Colombia. Due to increasingly more dengue cases than expected, this area has been under a continuous epidemiological alert since 2019. In 2022, 550 dengue cases were recorded, including six with severe symptoms, contributed 0.8% to the nationwide count (Instituto Nacional de Salud, 2022). The department of Cauca remains on epidemiological alert, with 1,795 cases recorded in 2023 (up to December) that again exceeded the expected case level (Instituto Nacional de Salud, 2023). The epidemiological situation was characterized by the habitual transmission of the disease combined with spatial spread at an unusual frequency (Padilla *et al*., 2012). This was also the case in Piamonte municipality, in which there has been a remarkable increase of cases since 2015, going from a Dengue Incidence rate (DIR) increasing from 6.7 cases per 10,000 inhabitants in 2015 to 76 cases per 10,000 inhabitants in 2021.

Currently, dengue management is oriented toward epidemiological monitoring of cases, entomological larval and pupal control, occasional adult-stage vector control in outbreak situations and promotion of behavioral change in affected communities through health education. However, the environmental and sociodemographic determinants that are critical for a comprehensive understanding of dengue risk and response capacity are often overlooked. The World Health Organization (WHO) and the Pan American Health Organization (PAHO) emphasize the need for robust surveillance systems to enhance early detection and response to public health events. They advocate an integrated approach to dengue that combines traditional surveillance with environmental and behavioural data, paving the way for the implementation of preventive strategies rather than reactive strategies (WHO, 2015).

Understanding the factors contributing to dengue transmission is crucial for effective prevention and control. Socio-economic variables, such as income levels, education and urbanization have impacted health outcomes and access to preventive measures (Ávila *et al*., 2004; Collazos *et al.*, 2017). Additionally, environmental conditions, such as water management and habitat suitability, play a critical role in mosquito breeding and survival (Guzmán *et al*., 2006). Climate change, with its effects on temperature and precipitation patterns, further complicates the transmission dynamics (Soneja *et al.,* 2021). Gaps remain in our understanding of how these factors interact and influence the spread of dengue. To this end, this study aimed at providing a tool, consisting a of spatial stratification map of dengue in the municipality as this could assist prioritizing prevention and control strategies for high-risk areas.

The development was based on methodologies that have been used in Asian countries (Dom *et al*., 2016; Ajim & Ahmad, 2018; Sahdev & Kumar, 2020), but are innovative in the Latin American and Caribbean public health sectors. We thus carried out a Analytic Hierarchy Process (AHP) followed by Ordinary Least Squares (OLS) spatial regression (Anselin *et al*., 2006) and a Multi-Criteria Analysis (MCA). Data identified from the first two processes supported by overlapping from the latter, we developed a cartographic representation of a set of statistically significant determinants of dengue to be tested in the municipality of Piamonte, Cauca. This was done by evaluating epidemiological, entomological, environmental and socio-demographic determinants to allow an early response to disease outbreaks, an initiative that could serve as a starting point toward developing effective early-warning systems in public health. The health authorities could deploy this approach to targeted responses through a stratified process focusing on the most affected areas and the key determinants of dengue in Amazonian municipalities.

Materials and methods

Study area and design

The municipality of Piamonte is located in the south of the Cauca Department in the subregion known as the “Bota Caucana”, which is part of the Amazonian foothills. It has an area of 1,162 km^2 and a current population of 9,484 inhabitants, only 2,129 of which reside in the urban area. It is worth highlighting the presence of indigenous communities in the territory and that the population growth is caused mainly by migration from neighbouring municipalities. Piamonte has an average elevation of 310 m above the sea level (masl), has an average temperature of 25.3°C, and annual rainfall of 4,000 to 4,500 mm/year. This municipality was selected based on the results of a spatio-temporal analysis. Previously, a Poisson model of dengue cases recorded in Cauca between 2012 and 2018 was developed from which four statistically significant risk clusters were identified (Marceló-Díaz *et al*., 2023). In addition to belonging to one of these clusters, Piamonte had outbreaks in the last five years, which allowed to be classified as a high risk municipality. This is an analytical, ecological study comparing explicit spatial and temporal elements to analyze the causality of events, which generally respond to social or environmental factors (Blanco *et al*., 2015). In ecological studies, the unit of measurement is presented as a set or aggregate of individual units, and the methodological approach used allows the identification of an existing and causal association between variables (Borja, 2000; Londoño, 2014).

Variables and data source

The spatial unit of this study was the population block, defined as a developed or undeveloped area of land delimited by vehicular or pedestrian traffic routes of a public nature, as well as by natural or cultural artifacts, as long as these elements are permanent and are easily identified in the field (Departamento Administrativo Nacional de Estadística, 2018).The variables used in this study, here called indicators, are presented in Table 1 together with the sources of information used for each indicator category. Additional information about these indicators is given below.

Epidemiological indicators

The number of dengue cases, recorded in the municipality of Piamonte between 2015 and 2022 and the DIR per 100 inhabitants of each block calculated from population data obtained from the National Administrative Department of Statistics (DANE) were included in this category. The data were cleaned and georeferenced using ArcGIS 10.8.1 ® software (ESRI, Redlands, CA, USA). Furthermore, a kernel density analysis (Silverman, 1986) was carried out on this data, which allowed for identifying the clusters with the highest risk of the disease in the municipality and prioritizing areas for fieldwork.

Environmental indicators

Colombia en Mapas, a cartographic platform of the Agustín Codazzi Geographical Institute, Government of Colombia, was downloaded and the land cover layer was created by adapting the CORINE land cover for Colombia. Elevation, at a resolution of

12.5 m, was obtained from the Digital Elevation Model (DEM) downloaded from the ALOS PALSAR dataset through NASA's cartographic resources repository. The normalized difference vegetation index (NDVI), the Enhanced Vegetation Index (EVI), and normalized difference water index (NDWI) indices were obtained with a code through the Google Earth Engine platform. The layers created was refined and verified using a function to mask clouds using the Sentinel-2 QA band and *ee.Image* and *map* functions to obtain the vegetation indices (https://code.earthengine.google.com)

Meteorological indicators

The weather parameters were obtained from the multi-source weather (MSWX) satellite product. Co-researchers from the Industrial University of Santander carried out a downscaling process, giving the data a higher spatial resolution (Blanco *et al.*, 2023). Likewise, verification was carried out with data obtained in the field with the Davis Vantage Pro-2 automatic station (https://www.davisinstruments.com/) installed in the municipality.

Entomological indicators

This information was collected in the field from 360 homes distributed in dengue high-risk neighbourhoods in the municipality of Piamonte through entomological inspection for vector mosquitoes in their pupal and adult stages during the rainy season in July 2021 and the dry season in February 2022.To find pupae, entomology technicians of the Secretaría de Salud del Cauca (SSC) investigated containers that could be potential breeding sites and recorded houses with positive findings. A Prokopack aspirator was used for the adult stage collection (Vásquez, 2009). Female *Ae. aegypti* and *Ae. albopictus* mosquitoes were stored in vials with an RNAlater® solution from (ThermoFisher) https://www.thermofisher.com/co) for subsequent analysis of the presence of Dengue Virus (DENV) using molecular techniques.

Spatial information on the potential distribution of *Aedes* mosquitoes in the municipality of Piamonte were generated using MaxEnt software (Philips *et al*., 2024), which allows modelling the geographic distribution of the species from environmental and georeferenced data from field sampling. This layer of information was used in the MCA to represent the statistically significant entomological variables of the regression models.

Socio-demographic indicator

These data were collected in the field during the two seasons (dry and rainy) from 360 homes distributed in dengue high-risk neighbourhoods. Digital socio-demographic surveys were conducted using the ArcGIS Survey 123® application, which enables the user to obtain the geographic coordinates of the homes visited. The socio-demographic database created was refined and verified using the OpenRefine® application (http://openrefine.org/).

Spatial regression

After conducting a bibliographic review of indicators used to monitor the risk of dengue in different contexts at the international level, the most appropriate variables were selected by AHP approach, as done by other authors (Dom *et al*., 2016; Ajim & Ahmad, 2018; Sahdev & Kumar, 2020; Tsheten *et al*., 2021). Each indicator was evaluated in relation to the others using the fundamental scale of comparison by pairs proposed by Thomas L. Saaty (1980), which assigns values from 1 to 9 based on criteria defined according to the objective. In this case, four criteria were established to prioritize the indicators: i) explanatory capacity of dengue risk; ii) use in previous studies; iii) applicability; and iv) accessibility. This allowed us to make decisions involving multiple factors including weighting and sensitivity. The database was structured and completed with the information collected for each indicator. After transforming the data according to quantitative values, such as percentages or Boolean, they were organized, calculated and analyzed at the block level. OLS spatial regression (Anselin *et al*., 2006) was carried out to determine the influence of the variables

Table 1. Categories and sources of indicators used in the study.

Category	Variable	Source
Epidemiological indicators	Dengue cases Incidence rate per 100 inhabitants	Departmental Health Secretary of Cauca for cases and National Administrative Department of Statistics for population
Environmental indicators	Land cover Elevation Normalized difference vegetation index (NDVI) Enhanced vegetation index (EVI) Normalized difference water index (NDWI)	*Colombia en mapas* (https://www.colombiaenmapas.gov.co/) Alaska Satellite Facility (NASA archive athttps://asf.alaska.edu/) Google Earth Engine (https://earthengine.google.com/)
Meteorological indicators	Minimum temperature Average temperature Maximum temperature Humidity Precipitation	Multi-source weather (MSWX) verified with field data of Davis vantage Pro-automatic stations(https://www.davisinstruments.com/). Meusurements made at the neighbourhood level from 2015 to 2022.
Entomological indicators	Number of *Ae. aegypti* and *Ae. albopictus* mosquitoes Number of dwellings with the pupal and adult stage Breteau index (Barrera, 2016) Pupae productivity Number of pupae per person Positive containers for pupal stages	ArcGIS Survey 123 (https://survey123.arcgis.com/)
Socio-demographic indicators	Housing and sanitation conditions Family history of dengue Migration and mobility Domestic practices for mosquito control	ArcGIS Survey 123 (https://survey123.arcgis.com/)

on the number of dengue cases per block. Initially, an exploratory analysis was carried out for each indicator category, then a scatterplot matrix was analysed to identify the variables with the strongest statistical significance in each group. Subsequently, the regression was carried out with the identified variables and a backward stepwise selection process that optimizes the model performance by excluding variables that were not statistically significant ($p \geq 0.1$). A set of coefficients were taken into account for the magnitude and direction of the final variables in the model results, *i.e.* making sure of non-multicollinearity by Variance Inflation Factor (VIF) statistical significance accepting only VIF ≤ 7.5 and $p \leq 0.1$, respectively, as well as normality of the residuals, and the non-autocorrelation among the residuals by the Jarque-Bera test (1980). Finally, the goodness-of-fit of the model was examined by the Akaike information criterion (AIC), R^2 and the Koenker test (Koenker & Bassett, 1982). The Wald test (Anselin, 1988a; Juhl, 2020) was used to determine the overall significance.

To assess model bias, the Jarque-Bera statistic tests whether the residuals are normally distributed. A small *p-value* from this test indicates that the residuals are not normally distributed, suggesting potential model bias. In such cases, it will be necessary to include additional variables in the model to improve its accuracy. The Koenker test is used to diagnose whether the relationships being modelled exhibit nonstationarity (*i.e.* they change across the study area) or heteroscedasticity (*i.e.* they vary depending on the magnitude of the variable being predicted). Where the Koenker test was statistically significant ($p \leq 0.05$), a Geographically Weighted Regression (GWR) was run.

Finally, the Wald test let us assess model statistical significance; if the Koenker statistic is significant, the joint Wald statistic should be used to determine overall model significance.

Multi-criteria analysis

MCA is a decision-making framework used to prioritize many alternatives that are not easily valued even though may be quantified. It allows ranking locations by a series of steps, such as assigning weights based on the importance of each variable, scoring different locations, calculating the weighted scores for each variable and summing them for each location. In this way, MCA helps making transparent, structured and justifiable decisions when faced with multiple variables. To determine the spatial dynamics of dengue risk, this kind of analysis was performed using geographic information systems (GIS) taking into account only indicators identified as statistically significant at the 90% confidence level (CL) ($p \leq 0.1$). The spatial information associated with the indicators was compiled and converted into raster format guaranteeing that all layers had the same cell size (5x5 m) and that they overlapped through the Snap Raster tool in ArcGIS 10.8.1 software. Subsequently, the data were reclassified into three dengue risk levels according to the coefficients obtained in the spatial regression allowing the expression of cartographic superposition of the layers by the Weighted Sum tool in the software used.

Software

Socio-demographic data were collected through the ArcGIS Survey 123® application. The databases were refined using OpenRefine and finally processed and analysed using ArcGIS 10.8.1 and Geoda (Anselin *et al*., 2006).

Results

Epidemiology

We recorded 190 dengue cases were in Piamonte between 2015 and 2021, 104 of which corresponding to the urban area and 86 to the rural area. There was evidence of an increasing trend in dengue cases, with 10 cases between 2015 and 2017, 54 in 2018, 30 in 2019, 58 in 2020 and 38 in 2021. At the local level, the neighbourhoods with the greatest DIR during the period analysed were Los Fundadores (DIR= 8.71), Centro (DIR= 7.83) and Villa los Prados (DIR= 6.1). Two dengue risk clusters were identified in the urban area of Piamonte through kernel density analysis of the previously georeferenced cases. One comprised Los Fundadores and Centro neighbourhoods, which contributed 63% and 37% of cases, respectively, with the other consisting of neighbourhoods Villa Los Prados, La Paz and El Nogal. Here, the former contributed 82% of the cases and the two latter ones only 12% and 6% of the cases, respectively.

Environment

The average elevation of Piamonte was 328 masl, with a range of 318 to 338 masl. Three land cover types were identified: 76% of the municipality had continuous, built environment, 17% secondary or transitional vegetation and 7% pasture mosaics with natural spaces. Significant values were found for NDVI, with a mean of 0.45 and a range from –0.08 to 0.87, while EVI had a mean of 0.49 and a range of 0.1 to 0.95. Relative to the identified land cover, the lowest values were associated with the urban areas, and the maximum values with secondary vegetation.

Meteorology

Multi-year average values were calculated for all these parameters overthe 2015-2022 period. The values obtained were 25.9°C for average temperature; 20.9°C minimum temperature; 33.0°C maximum temperature; 85%relative humidity; and 4,678 mm annual rainfall, with high precipitation between April and July and-high-temperature peaks in September.

Entomology

The pupal sampling indicated that 9% of the 360 houses inspected were positive for pupae (n=33); with none found in the rest of the houses. Of the total number of containers inspected (n=690), 9% were positive for the vector. The main container type harbouring mosquitoes were barrels, accounting for 30% of the potential breeding sites, with 171 of the 500 pupae recorded in the municipality. The sampling for adult mosquitoes revealed that 18% of the houses were positive for *Ae. aegypti* (n=65) and 3% for *Ae. albopictus* (n=11), with 120 and 29 collected individual insects, respectively. Table 2 summarizes the main results by neighbourhood. Additionally, from the mosquito samples collected, six DENV-positive blocks were identified, three in the rainy season in 4 of 19 dwellings (n=4♀, 2♂), and three in the dry season in 5 of 21 dwellings (n=7♀).

Socio-demography

In the municipality of Piamonte, 79% of the people surveyed were women. Of those surveyed, 51% were dedicated to housework and 40% to work. Regarding the factors associated with dengue, the municipality's sanitation conditions stand out since 24% of the homes (n=85) did not have sewage services but relied on septic tanks. A total of 29% of those surveyed said they had been infected with dengue. Regarding mobility patterns, 33% come from another city (n=120), and 13% had moved outside the municipality 15 days before the interview (n=45). Finally, the most common preventative measure by individuals to prevent mosquito bites was the use of bed nets combined with other domestic practices, such as fumigating or burning eucalyptus (81% - n=290).

Selection of indicators

The most relevant indicators were selected in each of the proposed categories through ranking based on AHP with the following result: i) explanatory capacity (0.49); ii) accessibility (0.29); iii) applicability (0.15); and iv) use in previous studies (0.07). In the epidemiologic category, DIR obtained a higher value concerning the weighting of the criteria mentioned; with respect to the environment, altitude and NDVI were selected; for meteorology, preference was given to mean, minimum and maximum temperatures, the temperature range and precipitation; in the entomological area, to seasonality and vector distribution; finally in socio-demography, population density and the mobility patterns of the inhabitants were prioritised.

Spatial regression

Based on the application of the *backward stepwise* selection process, the twelve variables included in the initial model for the rainy season were reduced to seven variables, four of which were statistically significant at 95% CL (*p-value*<0.01): population per block; number of pupae per person; use of mosquito netting as a preventive measure against dengue; and migrant status. The remaining three variables played an important explanatory role in the occurrence of dengue: forest cover (an environmental variable), mobilization or displacement for a period greater than 15 days to other municipalities (socio-demographic variable) and DENV-positive *Ae. Aegypti* (entomological variable) at 90% CL (p<0.1).

Table 3 shows the coefficients obtained for each of the explanatory variables of the rainy season model, which support non-multicollinearity (VIF≤7.5) and acceptable statistical significance for most variables, except forested areas and travel outside the municipality.

The OLS spatial regression (Anselin *et al*., 2006) performed showed an R^2= 0.5761 and an AIC= 366.3929 for DIR, which indicates that the variables obtained (Table 3) explain 58% of disease incidence behaviour in the municipality of Piamonte for the rainy season, pointing out their causal relationship. The results of the Koenker test (p<0.01) showed that the relationship between the independent variables and the the dependent variable in the study area varied over the study period (heteroskedasticity) and these results might therefore be invalid. Considering the significance of the Koenker test (p=0.012), a GWR was run. However, although the R^2 was slightly higher than the OLS parameters (OLS=58%; GWR=59%), the AIC value was lower compared to the GWR model (OLS=366.392; GWR=368.835). However, with the Moran's I spatial autocorrelation result for the residuals at 0.0598, z-score= 0.8062 and p=0.4202), possible dispersion or clustering patterns was discarded. An additional regression derived from the DIR for the dry season was obtained, whose analysis was carried out based on the parameters mentioned in the model for the rainy season. In this sense, the model presented fit values R^2=0.8560 and

Table 2. Descriptive entomological indexes by sampling locality for immature mosquito stages (pupae) and adults.

Entomological measure	Neighbourhood La Paz	 Fundadores	 Villa los Prados	Total
Aedes sp.				
Number of houses screened	66	95	199	360
Number of residents in screened houses	255	379	778	1,412
Number of houses with pupae	5	6	22	33
Proportion of houses with pupae	7.6%	6.3%	11.1%	9.2%
Number of containers screened	138	198	354	690
Number of containers with pupae	5	9	20	43
Proportion of containers with pupae	3.6%	4.6%	5.6%	43
Number of pupae	95	132	143	370
Pupae productivity (see Barrera, 2016)	333	399	415	1147
Number of pupae per person	1.31	1.05	0.53	2.89
Breteau index (BI)	7.58	9.47	10.05	27.10
Ae. aegypti				
Number of infested houses	11	17	37	65
Proportion of infested houses	16.7%	17.9%	18.6%	
Number of mosquitoes	16	34	70	120
As proportion of all *Aedes* sp.	59.3%	91.9%	82.4%	
Number of female mosquitoes	8	18	48	74
Sex ratio: proportion of females	50.0%	52.9%	68.6%	
Sex ratio (F:M)	1:1	1.13:1	2.18:1	1.61:1
Ae. albopictus				
Number of infested houses	4	2	5	11
Proportion of infested houses	6.1%	2.1%	2.5%	
Number of mosquitoes	11	3	15	29
As proportion of all *Aedes* sp.	40.7%	8.1%	17.7%	
Number of female mosquitoes	1	3	7	11
Sex ratio: proportion of females	9.1%	100%	46.7%	
Sex ratio (F:M)	0.1:1	1:0	0.88:1	0.61:1

AIC=440.7557, which indicates that the behaviour of the disease in the municipality of Piamonte could be explained by 86% of the independent variables selected for the dry season. In contrast to the first model, the relationship between the independent and dependent variables in this regression did not change in the study area (p =0,181 in the Koenker test). Likewise, the 15 variables included in the initial model were reduced to eight, four of which were statistically significant at the 99% CL (p<0.01): population per block, rainwater storage, agricultural covers (pasture mosaic and natural spaces) and family dwelling. Average multi-annual precipitation and the percentage of positive barrels with pupae were statistically significant at the 90% CL (p≤0.1). Finally, the percentage of DENV positive mosquitoes was included as an indirect measure of infection. Table 4 shows the coefficients obtained for each explanatory variable of the dry season model, as well as statistical significance and the VIF values. Finally, a Moran I of 0.112972 was obtained, showing a strongly random residual distribution.

Multi-criteria analysis

Based on the regression results, the indicators and parameters required for mapping dengue risk were identified through MCA analysis. Table 5 shows the normalization proposed for each indicator according to the coefficients obtained in the regression model for the rainy season. This information allowed the establishment of criteria based on the increase (positive coefficient) or decrease (negative coefficient) of the DIR. The same process was carried out for the dry season. Subsequently, for the dengue risk map, five risk levels were established, categorized by the natural breaks approach, ranging from very low with a range of 11 to 12, low with values between 12 and 14, medium from 14 to 16, high from 16 to 18 and very high with a range of 18 to 22. These values correspond to the sum of the layers previously normalized from 1(low dengue risk) to 3 (high dengue risk) for the MCA analysis (Figure1). Finally, the zonal statistics based on the dengue risk map of the

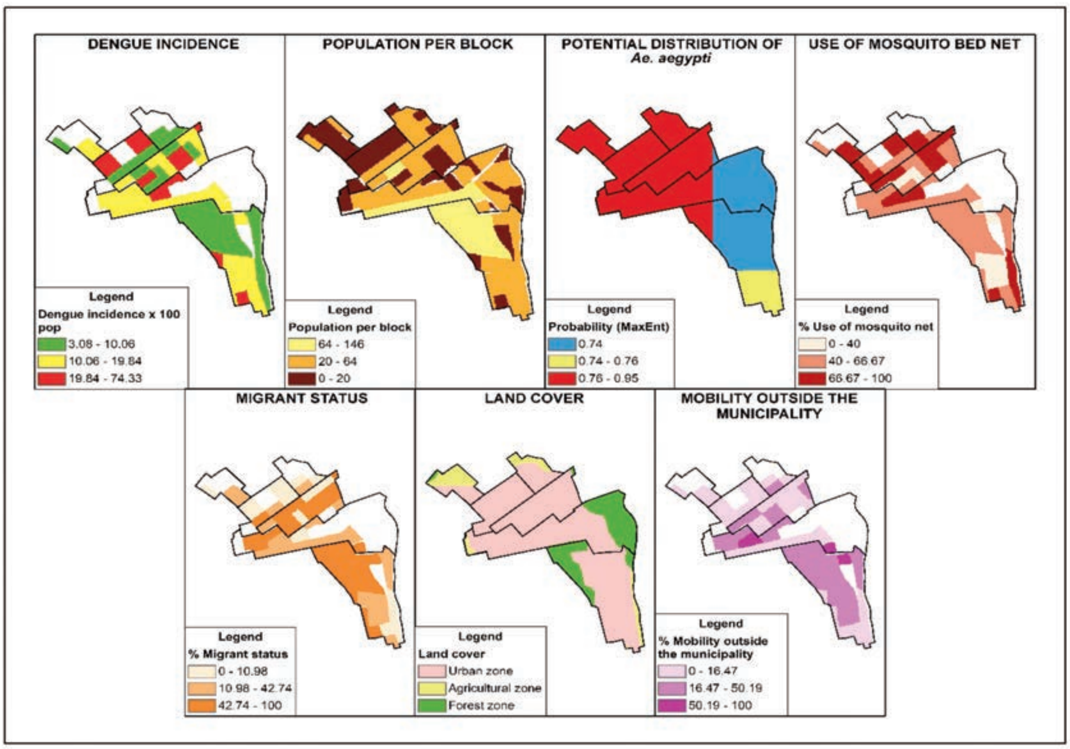

Figure 1. Multi-criteria analysis of dengue-risk mapping in the municipality of Piamonte, Cauca for the rainy season.

Table 3. Outcome of regression statistics for Piamonte data for the rainy season.

Variable	Coefficient	Probability	Standard error (SE)	Variance inflation factor (VIF)
Intercept	19,527770	0,002597**	6,056692	Not applicable
Municipality block population	-0.625533	0.000000**	0.092857	1.209704
Pupae per person	-0.193051	0.000041**	0.041638	2.440397
Use of mosquito bed net	0.212817	0.012891*	0.081545	1.211338
Migrant status	0.165766	0.024083*	0.070545	1.259538
DENV-positive *Ae. aegypti*	4.879344	0.026231*	2.109489	2.359187
Forest cover	0.126827	0.097977	0.076625	1.034321
Mobility outside municipality	0.064283	0.077398	0.035415	1.303587

DENV, dengue virus; *Statistically significant at p≤0.01; **Statistically significant at p ≤ 0.001.

urban area of Piamonte obtained for the rainy and dry seasons (Figure 2) showed that the neighbourhoods with the highest average risk in the municipality were Villa los Prados (15.98) and La Paz (15.92) for the rainy season, while for the dry season were El Nogal (14.45) and Villa los Prados (13.18).

Discussion

A total of 190 dengue cases and two risk clusters were identified in Piamonte between 2015 and 2021. From the environment, forested areas, agricultural covers, and average precipitation stood out, and the socio-demographic factors, such as population, family dwelling, migrant status or travel outside the municipality, played a major role with respect to dengue risk. All variables subjected to spatial regression results for the rainy season (R^2=0.5761) and the dry season (R^2=0.8560) were statistically significant, with the block populations and land cover being strongly relevant. The independent variables explained the behaviour of DIR with 58% accuracy in the rainy season and 86% accuracy in the dry season, information that assists in the identification of which combination of factors may increase the dengue risk.

According to the systematic review conducted on dengue risk mapping (Louis *et al*., 2014) generalized linear models, logistic regression, kernel estimation, and maximum entropy are the most commonly used geostatistical models for constructing predictive maps in the public health field. In this sense, it can be noted that the OLS and GWR regression techniques used in this research constitute a suitable approach for the spatial representation of dengue risk since they are based on generalized linear models that study

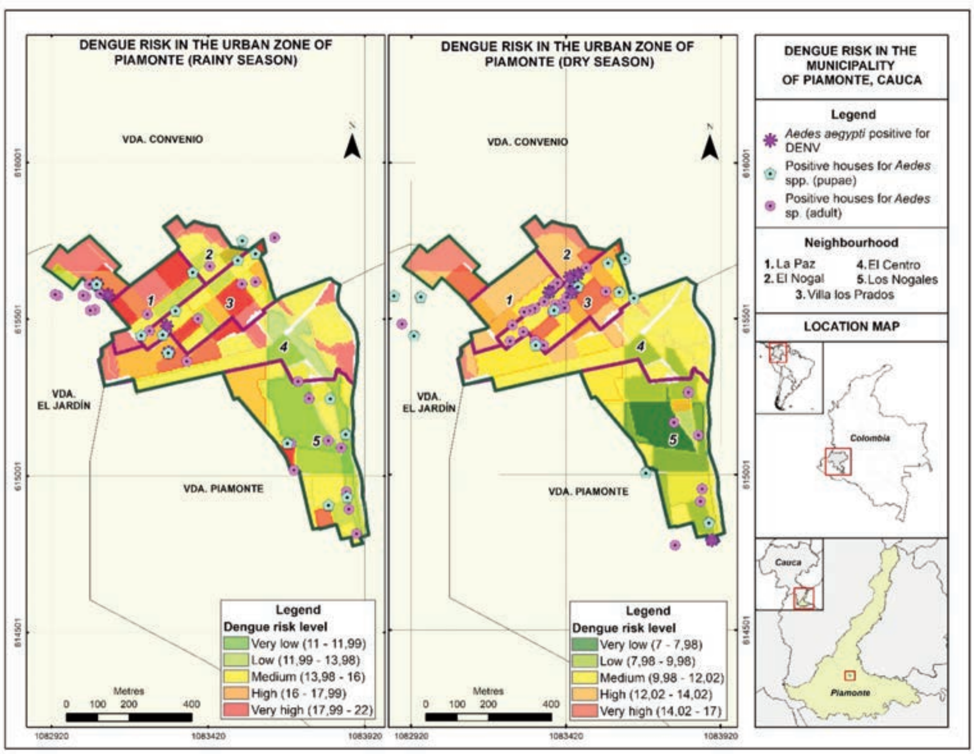

Figure 2. Dengue-risk map for the municipality of Piamonte, Cauca.

Table 4. Outcome of regression statistics for Piamonte data for the dry season.

Variable	Coefficient	Probability	Standard error (SE)	Variance inflation factor (VIF)
Intercept	499.08970	0.06922	268.89027	Not applicable
Rain water storage	0.306920	0.000000**	0.050790	1.193254
Agricultural cover	0.242792	0.000002**	0.045401	1.849221
Municipality block population	-0.341288	0.000003**	0.064986	1.640751
Family dwelling	0.249477	0.000010**	0.050800	1.310453
Residents per household	-0.299282	0.098000	0.177561	2.010956
Average multi-annual precipitation	-1.397841	0.080515	0.083757	1.509615
Positive pupae barrels	-0.087512	0.182316	0.064724	1.124657
Percentage of DENV- positive *Ae, aegypti*	0.062740	0.313866	0.061680	1.305897

DENV, dengue virus; **Statistically significant at p≤0.001.

the relationships between the determinants of disease at global and local levels, respectively. The method used highlights the scope and performance concerning the spatial overlap of the factors that influence the occurrence of the arbovirus. This is why other authors have previously used MCA analysis on dengue (Sahdev & Kumar, 2020; Tsheten *et al*., 2021) and Chagas disease (Costa, 2014). In contrast to the referenced studies, which mainly used environmental factors, this research covered the various categories of dengue indicators.

Socio-demographic and behavioral factors

Forest cover emerged as a significant factor during the rainy season, while agricultural land cover was relevant in the dry season. Population per block showed an inverse relationship with DIR; blocks with lower population densities experienced higher incidence rates. This aligns with findings in other regional studies, where individual dwellings and limited sanitation can create favorable conditions for mosquito infestation despite low population density (Braga *et al*., 2010; Schmidt *et al*., 2011; Vieira *et al*., 2015). However, the results also emphasize the importance of considering local contexts and interacting factors.

A study conducted in Kendari, Indonesia (Istiqamah *et al*., 2020) points out that a high population density contributes to dengue transmission by increasing the contact between infected mosquitoes and human hosts as long as the number of cases is significant. Another study by Braga *et al*. (2010) in Recife, Brazil, found a direct relationship between dengue seropositivity and the number of people per room, due to increased feeding opportunities for mosquitoes. However, the studies made by Handayani *et al*. (2017) and Lippi *et al*. (2018) show that population density does not have a statistically significant correlation with the occurrence of dengue or a statistically significant relationship between the number of people per room or household and the disease.

Water-related variables were also significant, particularly during the dry season. A combination of reduced precipitation and increased water storage contributed to higher DIR. Households storing water in barrels were particularly affected, as 30% of pupal positivity was associated with these containers. These results mirror findings from studies in Vietnam (Schmidt *et al.*, 2011), where limited tap water access increased the rate of hospital admission for dengue by a relative risk of 1.66 (1.50-1.84) suggesting that the supply of tap water in a neighbourhood can largely explain its effect on dengue risk, although not entirely.

Population mobility and migrant status significantly influenced the DIR during the rainy season. Approximately 33% of the survey respondents had migrated to Piamonte, mainly from neighbouring departments, thereby contributing to rapid population changes over the past decade. In addition, 13% reported travelling to other cities for work or trade, highlighting the role of mobility in spreading arboviruses. Previous studies have shown that mobility patterns can increase exposure to dengue, as individuals may carry the virus or encounter infected mosquitoes in high-risk areas (Semenza, 2015; Chen *et al.,* 2018).

Surprisingly, bed net use showed a positive correlation with dengue incidence during the rainy season. This finding may be due to improper use, such as lack of insecticide treatment or due to the fact that *Ae.aegypti* is most active during the day. Similar observations have been made in studies where preventive measures such as bed nets failed due to inappropriate timing or application (Tsuzuki *et al*., 2010). Further research is necessary to evaluate the specific effectiveness of bed nets in Piamonte, as this is not a control dengue measure distributed across the municipality by the SSC.

Entomological indicators and mosquito dynamics

Concerning entomological indicators, each model obtained a statistically significant variable for the dengue IR. The *pupae per person* index was a critical variable during the rainy season, which is consistent with the findings of other authors (Gubler, 1998; Ministerio de la Protección Social, 2011) in which it is noted that the pupal counts reflect better the number of adult mosquitoes in a locality than the larval indexes or even the number of larvae, since survival at this stage is relatively high. For the dry season, the positivity of pupae in water barrels was the most relevant variable.

Field data showed that infected mosquitoes were heavily concentrated in Villa Los Prados, with 50% of DENV-positive mosquitoes captured indoors during the rainy season and 86% in neighboring blocks during the dry season. These findings suggest that mosquito movement, which may exceed an average dispersal distance of 100 meters, may spread infections across neighborhoods. This is particularly true when clusters are identified where pupal productivity leads to high block densities of mosquitoes, such as in the Villa Los Prados area during the dry season (Sánchez *et al*., 2023). Thus, one block of infected mosquitoes could become an outbreak for neighboring blocks.

Although both models included the percentage or absolute number of *Ae. aegypti* mosquitoes positive for at least one dengue serotype, few studies have been carried out on the serotypes in mosquitoes in this Amazonian community (Golding *et al*., 2023). Although serotyping of entomological samples was carried out, dengue has a complex immunology that needs to be considered in our model, which can be one of its limitations.

Table 5. Normalization of the indicators for multi-criteria analysis of data obtained during the rainy season.

Indicator	Criteria for high risk of dengue	Normalization		
		1	2	3
Dengue incidence per municipality block	Higher the dengue incidence	3.08-10.06	10.06-19.84	19.84-74.33
Municipality block population	Low municipality block population	64-146	20-64	0-20
Distribution of *Ae. aegypti*[a]	High numbers of Ae. aegypti	0.74	0.74-0.76	0.76-0.95
Use of mosquito net	Common use of mosquito net	0-40	40-66.67	66.67-100
Migrant status	High numbers of migrant population	0-10.98	10.98-42.74	42.74-100
Forest cover	Large forest cover	Urban zone	Agricultural zone	Forest zone
Travel outside municipality	Mobility outside the municipality	0-16.47	16.47-50.19	50.19-100

[a]MaxEnt model of the distribution of all the entomological variables (pupae and adults) with OLS statistical significance.

The high values of Piamonte Breteau's index (above 8%) and *pupae per person* index (above 0.5) indicate a significant mosquito risk burden. In particular, 1 out of 10 adults *Ae. aegypti* mosquitoes were infected with DENV-2 or DENV-3 serotypes, highlighting the importance of monitoring immature mosquito stages and serotype distribution for effective control measures.

Environmental and land cover influences

Land cover significantly influenced dengue IR, with distinct seasonal patterns. During the rainy season, forested areas increased risk, likely due to their suitability as mosquito habitats, providing food and resting sites (Estallo *et al*., 2018). Agricultural cover was more significant in the dry season, possibly due to water-holding containers in rural areas. These findings are consistent with studies in other regions (Palaniyandi, 2012), where vegetation indices and land cover have been associated with mosquito abundance and dengue risk. However, contrasting results from studies in Brazil, where vegetation was linked to reduced dengue incidence (Cunha *et al*., 2021) highlight the need to consider local ecological contexts and seasonality.

This study presents, for the first time, two dengue risk maps for the municipality of Piamonte highlighting high-risk areas and seasonal trends, which allow contrasting the spatial behavior of the disease according to seasonality. Thus, while the map of the rainy season shows the peaks of "very high" risk values in each neighbourhood, the values are smoothed out in the dry season. Additionally, the high-risk blocks for dengue were identified in both seasons, as well as the risk trend of each neighbourhood, which is very useful for targeting actions oriented to disease management by the responsible health authorities.

Key strategies include focusing on neighbourhoods like Villa Los Prados, which consistently show high mosquito densities and infection rates. Seasonal patterns suggest that interventions should be tailored to address specific factors, such as mobility patterns during the rainy season and water storage practices during the dry season. The latter findings highlight the importance of improving water supply infrastructure to reduce dengue risk.

Conclusions

The maps obtained allow the identification of high-risk areas for dengue and the determinants of the disease's occurrence in the municipality of Piamonte. These findings may interest health authorities operating in Amazonian regions, as prioritizing the main determinants can help address the increase in incidence rates each season. This information can contribute to developing prevention strategies at the neighbourhood or block level, particularly related to vector control of pupae and cultural practices among the population, since these are statistically significant indicators of dengue risk in both the rainy and dry seasons.

In this sense, three noteworthy factors of the dengue risk maps obtained are i) the analysis scale at the block level, which provides a very beneficial measure for the dengue management by the SSC; ii) the seasonality of sampling and its effects on DIR; and iii) evidence showing how the best entomological indicator is the capture of adult mosquitoes compared to their immature stages.

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