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Downscaling incidence risk mapping for a Colombian malaria endemic region

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Abstract

OBJECTIVE To map at a fine spatial scale, the risk of malaria incidence for the important endemic region is Urabá-Bajo Cauca and Alto Sinú, NW Colombia, using a new modelling framework based on GIS and remotely sensed environmental data.

METHODS The association between environmental and topographic variables obtained from remote sensors and the annual parasite incidence (API) for the years 2013–2015 was calculated using multiple regression analysis; subsequently, a model was constructed to estimate the API and to project it to the entire endemic region in order to design the risk map. The model was validated by relating the obtained API values with the presence of the three main Colombian malaria vectors, *Anopheles darlingi*, *Anopheles albimanus* and *Anopheles nuneztovari*.

RESULTS Temperature and Normalized Difference Water Index (NDWI) showed a significant correlation with the observed API. The risk map of malaria incidence showed that the zones at higher risk in the Urabá-Bajo Cauca and Alto Sinú region were located south-east of the region, while the northern area presented the lowest malaria risk. A method was generated to estimate the API for small urban centres, instead of the used reports at the municipality level.

CONCLUSIONS These results provide evidence of the utility of risk maps to identify environmentally vulnerable areas at a fine spatial resolution in the Urabá-Bajo Cauca and Alto Sinú region. This information contributes to the implementation of vector control interventions at the microgeographic scale at areas of high malaria risk.

keywords Malaria incidence, Malaria vectors, ecoepidemiology, risk map, *Anopheles*, Colombia

Introduction

Malaria is one of the most important problems of public health in Colombia, the country reported 17% of cases of the Americas in 2016 [1], and the disease remains a threat in areas where various human activities such as mining and coca-cultivation have become prevalent [2]. Particularly, the Urabá-Bajo Cauca and Alto Sinú (UCS) region has historically reported the highest numbers of malaria cases in the country [3], but currently, is second in number after the Pacific region with 16.600 cases [4].

Recent advances in Geographic Information Systems (GIS) and methods of spatial analysis enable mapping vector-borne diseases and thus, help in the evaluation of the malaria risk by identifying the environmental variables that influence malaria incidence [5]. Thereby mapping capabilities provided by high- to medium-resolution satellite imagery allow to identify target areas and populations at risk [6]. Various methods have been used to model malaria risk and include the Generalized Linear Model [7, 8], the Generalized Additive Model and the Bayesian estimation method [9]. These statistic tools allow the evaluation of the relationship between the environmental conditions and malaria transmission at a wide geographic scale [10]; however, at the local level, the factors influencing this relationship are not clear [5] and new approaches should be assessed.

In Colombia, various studies using GIS to model malaria risk have been conducted. Two of them focused on the effects of climatic change associated with El Niño/Southern Oscillation-ENSO on the number of malaria cases [11, 12]. Another study that mapped malaria risk for the Pacific Coast municipality of Buenaventura and showed a 78.8% reduction in areas under malaria risk when environmental and anthropic variables were included in the model [13]. In addition, a high spatial resolution (90 × 90 m) malaria risk map for Colombia, based on environmental and human population data, helped to demonstrate the relationship between mean risk scores with total cases by the municipality, and provided an accurate spatial representation of risk potential to vector exposure [14].

The limited resources available in Colombia for the control of infectious diseases and the need for regular surveillance of vector-transmitted parasites make it essential to implement novel and effective methods to improve vector control interventions. Therefore, this study proposes a new modelling framework based on GIS and remotely sensed environmental data to map at a fine spatial scale, the risk of malaria incidence for the important endemic region UCS, covering the years 2013–2015.

Methods

Study area

The malaria endemic region Urabá-Bajo Cauca and Alto Sinú (UCS), in the northwest of Colombia, includes 35 endemic municipalities of the Antioquia and Córdoba departments (Figure 1). UCS has an estimated area of 43506 km^2 and is characterised by broad areas of flat lands, with some low mountains in the south of Alto Sinú. The region has a humid subtropical climate [15]. In 2010, the population at risk was 2500000 people [16].

Epidemiological data

The number of malaria cases by *Plasmodium vivax*, per municipality and for the years 2013 to 2015, was obtained from the Sistema Nacional de Vigilancia en Salud Pública (Sivigila), Instituto Nacional de Salud [4]. *Plasmodium vivax* was selected to construct the risk map considering that for decades this species has been the predominant malaria parasite in the UCS region, representing an annual incidence of 28.7/1000 in 2015; while in the same year, the incidence for *Plasmodium falciparum* was of 10.2/1000 [4]. For each municipality, the annual parasite incidence, here denominated 'observed API', was calculated according to the following formula: observed API = No. cases $\times$ 1000/population at risk per year. These incidence rates were calculated separately for each year (2013–2015). Then, the arithmetic mean of the observed APIs for these three years was calculated using ArcGIS 10.2 software (ESRI Corporation, Redlands, CA). This arithmetic mean was converted in a grid layer with a spatial resolution of 1 km^2, with each pixel representing the mean value of the observed API for the respective municipality.

Environmental predictors of malaria risk

Topographic attributes and environmental variables were used to evaluate their possible association with malaria incidence. The selection of covariates was based on previous studies, their biological significance for the parasite and the vectors [5, 17, 18], and included annual precipitation, annual mean temperature, Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI). The arithmetic means for the NDVI and NDWI were calculated for the years 2013 to 2015. The Topographic Wetness Index (TWI) [19] and the percentage of forest were estimated (Table 1). All covariate layers were gridded to spatial resolution of 1 km^2, consistent with the highest resolution of the WorldClim dataset. Boundary shapefiles (polygons of urban areas) were used to generate a buffer of 2.5 km of radius from each urban centre [20]. The information on environmental covariate layers was extracted from the mask of urban areas. Finally, a database was created and contained the information of an urban centre per municipality, which was selected under the criterion of greater nocturnal luminosity, as estimated by the maximum average value per pixel. These average values were chosen to carry out the statistical analyses. The urban centre with greater luminosity was selected in order to reduce the error that the observed API presents in small urban centres.

Data analysis and risk map design

To estimate the association between the observed API and covariates, a Generalized Linear Model (GLM) was implemented in R software v. 3.3.2 (R Development Core Team, 2008); a $P < 0.05$ was considered statistically significant. The API for each municipality was modelled with a Poisson distribution, and an iterative approach was used to choose the explanatory covariates in the GLM [21]. The best GLM model was selected using pseudo-R-squared measures [22]. The values for the variables in the GLM were included in the following function [23]:

$$\text{Log (API)} = \text{intercept} + \text{coef. Var1} + \text{coef. Var2}$$

where Var1 and Var2 are the environmental variables that most influenced the model.

The estimated API for the entire endemic area was generated using ENVI software v. 5.3. The product was a map of estimated API with a 1 km^2 spatial resolution, which was reclassified into four risk categories by dividing the estimated API values into four classes using the quartiles of incidence data. Because the risk of malaria is associated with the presence of human populations, the risk map was cut using the layer of nocturnal luminosity.

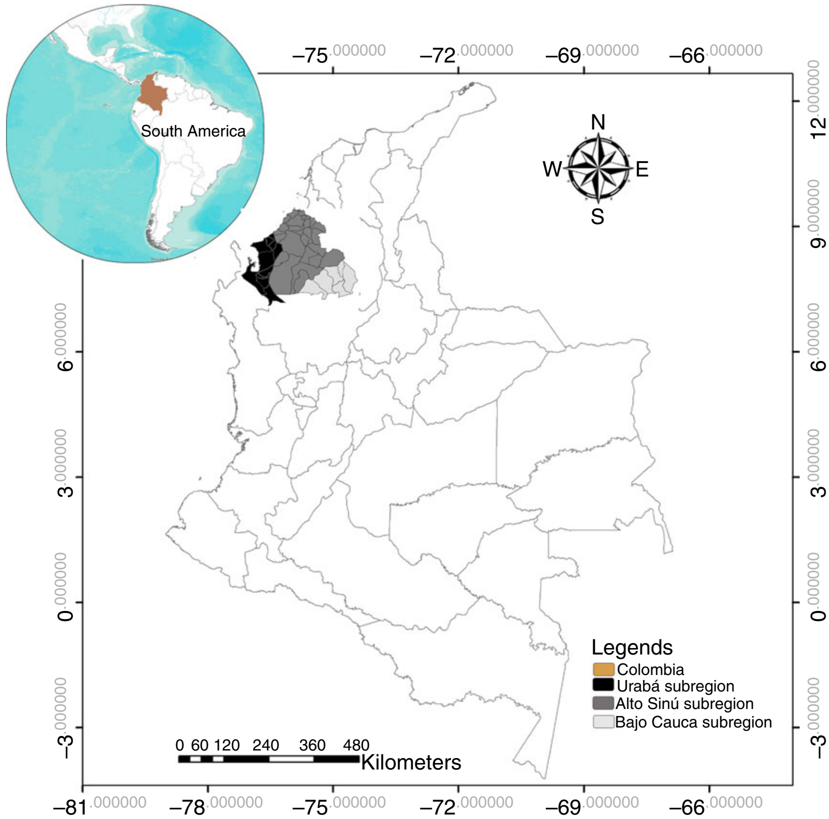

Figure 1 Study area. Malaria endemic region the Urabá-Bajo Cauca and Alto Sinú, Colombia. [Colour figure can be viewed at wileyonlinelibrary.com].

Risk map evaluation

A simple linear regression analysis was performed to evaluate the relationship between the observed and estimated API. Additionally, the relationship between the presence of the three main Colombian malaria vectors, *Anopheles darlingi*, *Anopheles nuneztovari* and *Anopheles albimanus* (data obtained during the mosquito collections for this work) with the malaria risk categories, was evaluated. Species occurrence and the proportion of occupied area were calculated for each incidence risk category, and a Chi-squared test was used to evaluate the independence of these data.

Results

At the municipality level, the observed API showed that Caceres in the Bajo Cauca subregion is the municipality with the highest value (Figure 2a, represented by red colour). The GLM indicated that the annual mean temperature and NDWI had a significant correlation with the observed API ($R^2 = 0.66$, $P < 0.05$), suggesting that these variables are good predictors of the API spatial variability (Table 2). Based on the GLM results, the following model was defined:

$$\text{Log (API)} = 7.4252 + 21.1421\ \text{(NDWI layer data)} + 0.2722\ \text{(Temperature layer data)}$$

Application of the inverse equation (1) to all the pixels of the endemic region helped to generate the malaria risk map.

$$\text{API} = \exp(7.4252) \times \exp[(21.1421)\ \text{(NDWI layer data)}] \times \exp[(0.2722)\ \text{(Temperature layer data)}] \tag{1}$$

The malaria incidence risk map for the region showed that the areas under higher malaria risk were located in the Urabá and Bajo Cauca subregions (Figure 2b). A malaria risk map based on the layer of nocturnal luminosity evidenced that the areas under very low risk were

Table 1 Variables used to analyse malaria incidence risk in the Urabá-Bajo Cauca and Alto Sinú region of Colombia

Variable	Source	Initial spatial resolution	References
Annual precipitation	Worldclim	1 km	Hijmans *et al.* (2005)
Annual mean temperature	Worldclim	1 km	Hijmans *et al.* (2005)
Normalized difference vegetation index (NDVI)	Moderate Resolution Imaging Spectroradiometer (MODIS)	250 m	Hassan *et al.* (2007)
Normalized difference water index (NDWI)	Moderate Resolution Imaging Spectroradiometer (MODIS)	250 m	Gao (1997)
Topographic wetness index (TWI)	Calculated from Shuttle Radar Topography Mission Digital Elevation Data	90 m	Jarvis *et al.* (2008)
Forests	National Geographic and Atmospheric Administration (NOAA)	1 km	http://www.noaa.gov/

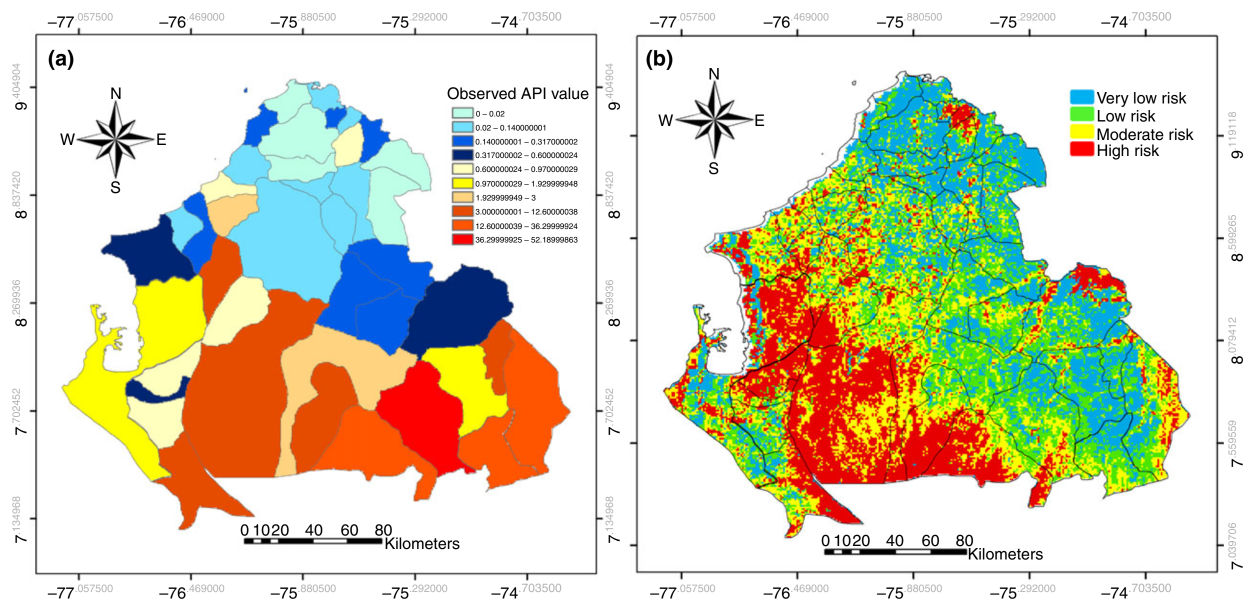

Figure 2 Map of malaria incidence risk derived from a general linear model for the Urabá-Bajo Cauca and Alto Sinú region of Colombia. (a) Represents the observed API by municipality. (b) Represents the estimated API by 1 km^2 of spatial resolution. [Colour figure can be viewed at wileyonlinelibrary.com].

those north of the endemic region, in the Alto-Sinú subregion (Figure 3).

The simple linear regression analysis revealed a significant statistical relationship between the observed and estimated API ($R^2 = 0.45$, $P < 0.05$, $t = 1.19$) (Figure 4). There was a significant and positive relationship among the risk categories of malaria incidence and the presence of two of the three main malaria vector species (Figure 5), *Anopheles albimanus* ($X^2 = 12.2$, $P < 0.05$, df = 3) and *An. nuneztovari* ($X^2 = 15.3$, $P < 0.05$, df = 3). Finally, a significant difference was found between the number of vector species and the risk categories of malaria incidence ($X^2 = 18.7$, $P < 0.05$, df = 3) (Figure 6).

Discussion

Mapping vector-borne disease environmental determinants and entomological risk is a central feature for an efficient and integrated vector control management [24]. However, the malaria risk maps produced in Latin America have been of wide spatial scale, difficulting their practical application [10]. This is the first study, using GIS and remotely sensed data, performed to understand the malaria risk incidence in the UCS endemic region. The results indicated that temperature and NDWI values are important in the prediction of malaria risk incidence. This corroborates results of a study in Swaziland which showed that malaria transmission occurs mainly in areas

Table 2 General linear model results showing the relationship between observed API and environmental and topographic covariates

Covariates	Estimate	Std. Error	*z* value	*P*-value
(Intercept)	7.17E+00	2.12E+00	3.381	0.000723***
NDVI	−4.15E+00	2.12E+00	−1.242	0.214171
NDWI	2.00E+01	1.85E+00	10.823	<2e-16***
TWI	5.81E-02	3.80E-02	1.531	0.12569
Forest	−4.74E-02	2.87E-02	−1.649	0.099146
Precipitation	−3.83E-05	2.75E-04	−0.139	0.889225
Temperature	−2.24E-01	6.65E-02	−3.366	0.000764***

Std: standard error, *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

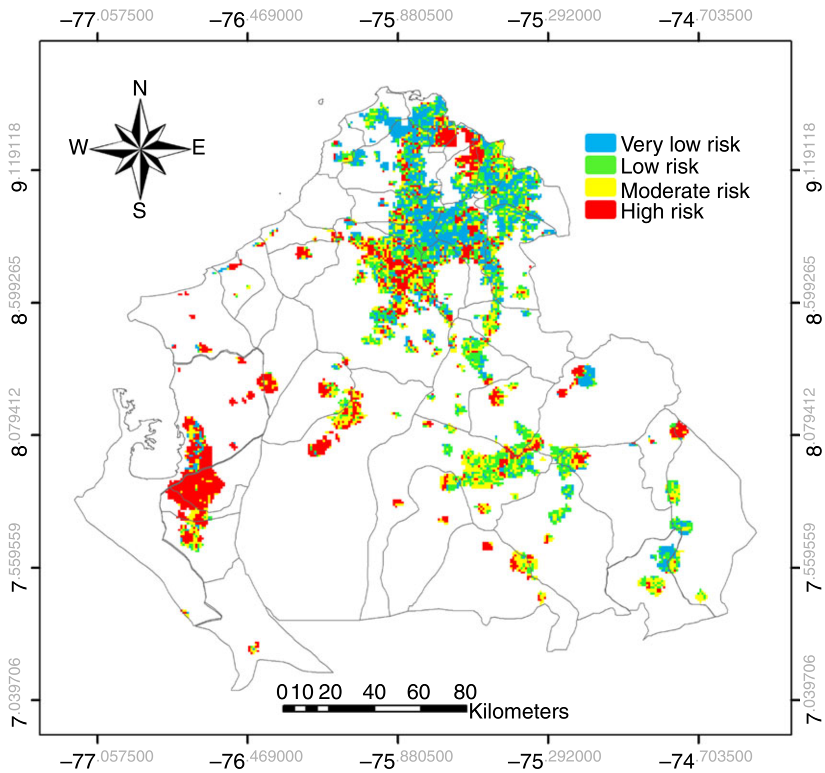

Figure 3 Risk map of malaria incidence derived from a general linear model, cut using a layer of nocturnal luminosity for the entire the Urabá-Bajo Cauca and Alto Sinú region of Colombia. [Colour figure can be viewed at wileyonlinelibrary.com].

with highest NDWI values [25]. Also, NDWI was the determinant variable for the presence of *Anopheles* larval habitats in Senegal [26]. Regarding temperature, this variable is a known factor that affects both, the parasites and their hosts [27]; its spatial and temporal variations greatly affect transmission dynamics [28].

Human activities such as deforestation, agriculture, migration and urbanisation have a profound effect on malaria transmission [29]. The risk map of malaria incidence for the UCS region showed that the areas under higher risk were located in the Urabá and Bajo Cauca subregions; during the last decades, these areas have undergone extensive transformation due to deforestation for agriculture, urbanisation and open-pit mining [30]. Thus, we hypothesise that anthropic activities may be favouring the ecological and epidemiological suitable conditions for malaria transmission in these subregions; further studies should be conducted to test this. Moreover, localities north of the endemic region, in Alto Sinú subregion, presented a low risk. In the

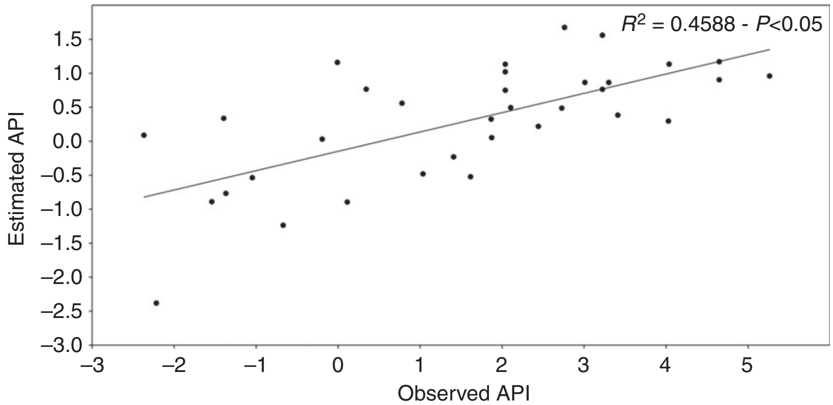

Figure 4 Simple linear regression plot between the observed and estimated API for the Urabá-Bajo Cauca and Alto Sinú endemic region of Colombia.

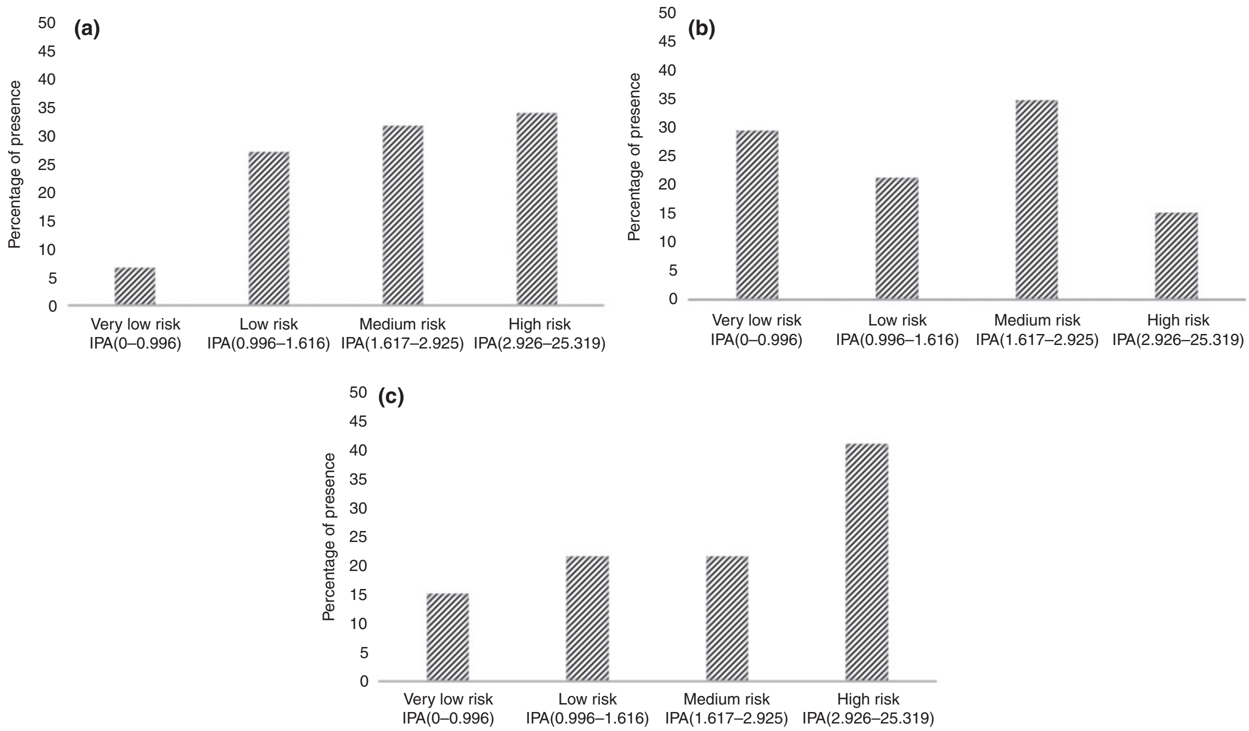

Figure 5 Relationship among risk categories of malaria incidence and the presence of the main malaria vectors. (a) *Anopheles albimanus*, (b) *Anopheles nuneztovari* and (c) *Anopheles darlingi*, in the Urabá-Bajo Cauca and Alto Sinú region of Colombia.

period 2001–2012; this subregion reported on average 26000 annual malaria cases, corresponding to an API of 16.23 [31]. Various localities of this subregion are in areas far away from the wetlands of the Sinú and San Jorge rivers [32], where formation of appropriate larval habitats and subsequent mosquito proliferation are less likely, and consequently fewer people are exposed to mosquito bites and thus at lower risk of malaria [33].

There was a significant and positive relationship among the risk categories of malaria incidence and the presence of the main vectors *An. albimanus* and *An. nuneztovari*. These two species co-occurred in some areas of UCS. Accordingly, a previous study in five Departments of NW

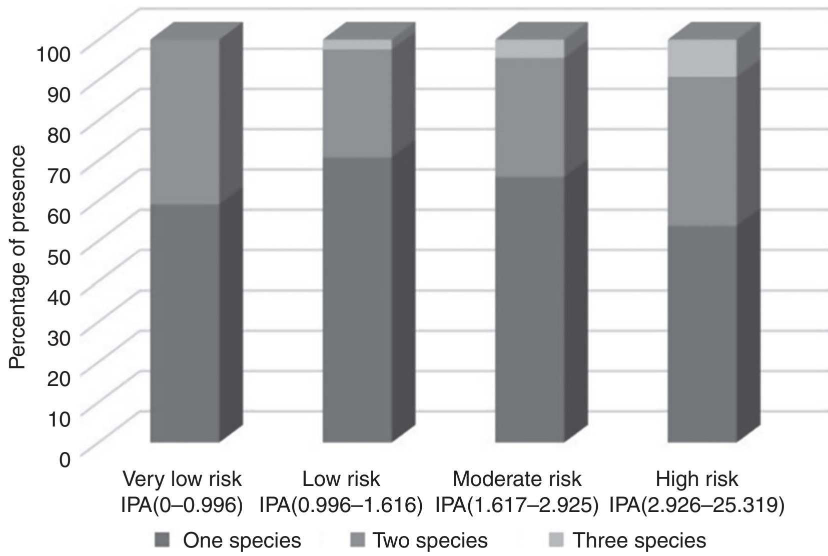

Figure 6 Proportion of vector species co-occurrence, *Anopheles darlingi*, *An. albimanus* and *An. nuneztovari* in relation to risk categories of malaria incidence in the Urabá-Bajo Cauca and Alto Sinú region of Colombia.

and W Colombia showed a positive association between the number of malaria vector species and the API; this association was attributed to the vectors preference for feeding on humans, and also to the co-occurrence of various species, which increases the exposure to infected bites [23]. Also, the presence of the three main vector species, *An. albimanus*, *An. nuneztovari* and *An. darlingi* was previously considered a risk factor for malaria occurrence in localities of the Alto Sinú subregion [34]. Additionally, *An. nuneztovari* and *An. darlingi* have been detected naturally infected with *Plasmodium* in various localities of the UCS region [35, 36]. Together, these results suggest that the presence and co-occurrence of the main vectors species constitute important risk factors that should include in futures studies about malaria incidence risk characterisation.

Malaria risk maps are used to optimise human and financial resources available for disease prevention and control [37]. In Colombia, decisions on malaria control are based on municipality API values [4], which have low spatial resolution, do not allow discrimination of adequate risk levels and thus are of little practical use [7]. In this context, the results from this work provide evidence of the utility of risk maps to identify environmentally vulnerable areas at a fine spatial resolution. The method we implemented also constitutes a useful and improved approach to identify areas at higher risk of malaria in an important Colombian endemic region.

Knowledge of favourable local environmental conditions for the occurrence of malaria may be used for the design of area-specific malaria prevention and control interventions. The method proposed here is recommended as the foundation of national and subnational programme strategies for malaria control. Furthermore, this proposal could be expanded to include epidemiological information related to other malaria parasites and be projected to other spatial and temporal scales.

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