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Malaria, relationship with climatic variables and deforestation in Colombia, Latin America and the Caribbean from 2000 to 2020: a systematic review

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Abstract

Background This systematic review investigates the relationship between malaria incidence, climate variables, and deforestation in Colombia, Latin America, and the Caribbean from 2000 to 2020. Malaria, a significant public health issue in these regions, is influenced by ecological factors including climatic conditions and environmental changes, such as deforestation.

Methods The review employs a comprehensive search strategy across PubMed, Web of Science, Embase, Scopus, Cochrane, and Scielo databases. It applies strict inclusion and exclusion criteria to ensure the relevance and quality of selected studies, focusing on analysing the relationship between climate variables, deforestation, and malaria incidence.

Results Twenty-four articles were included in this review, fourteen of which assessed the relationship between climatic variables and malaria and ten between deforestation and malaria. The analysis reveals a nuanced understanding of malaria dynamics. A significant finding is the seasonal effect of climatic variables on malaria incidence. The study notes that increased rainfall is positively correlated with malaria incidence. Similarly, warmer temperatures are associated with increased malaria risks, and malaria rates can change by 10% to 80% for every degree of temperature increase, after adjusting for altitude. The impact of deforestation on malaria is complex, with positive and negative correlations observed, depending on the remaining forest cover.

Conclusions The review highlights the multifaceted nature of malaria transmission, emphasizing the need for integrated approaches that consider both environmental and health perspectives. It underscores the importance of understanding the complex relationships between malaria incidence, climate variables, and deforestation.

Keywords Malaria, Deforestation, Climatic variables

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Background

Malaria is one of the most important vector-borne diseases worldwide, with around 247 million new cases and 619,000 deaths reported in 2023 in 85 endemic countries [1]. There are currently five species of *Plasmodium* parasites that cause malaria in humans, of which *Plasmodium. falciparum* and *Plasmodium vivax* cause the majority of cases worldwide.

After the Africa and Asia regions, the Americas region is one of the most affected by the disease, where 18 of the 21 countries in the region are endemic for the disease. More than three-quarters of all cases occur in the Bolivarian Republic of Venezuela, Brazil, and Colombia. In the Americas region for the year 2021, 520,000 cases of malaria and 120 deaths were recorded, 74% of the reported cases were caused by *P. vivax* and 26% by *P. falciparum*. Compared to 2015, there was an increase of 8% in the number of cases and a 26% decrease in deaths [2].

The transmission of malaria is affected by ecological factors that influence the distribution and abundance of mosquito vectors and parasites. These factors can be classified as either extrinsic—including environmental components such as temperature, humidity, precipitation, and altitude, as well as social, cultural, economic, and political factors—or intrinsic, which involve interactions between humans, the vector, and the parasite [3]. Due to their geographical, environmental, and social characteristics, countries in Latin America and the Caribbean are particularly susceptible to the transmission and endemicity of malaria.

The epidemiology of malaria is complex and multifactorial, and understanding the association between climate, land use change, and malaria is essential. It depends on the ecology of the main prevalent vector species, the biology of the causative organism (*Plasmodium*), the resistance and immunity of the host, and climatic factors such as temperature, precipitation, humidity, and anthropogenic changes [4–6]. Regarding climatic factors, a positive association has been described between malaria incidence with seasonal rains causing an increase in vector abundance and greater malaria transmission in risk areas [7–9]. Additionally, climatic events such as El Niño and La Niña significantly influence climate on a broad scale, impacting temperature, precipitation patterns, and extreme weather events. El Niño typically results in warmer and drier conditions in some regions, while La Niña brings cooler and wetter conditions. These events can alter mosquito breeding sites and affect malaria transmission dynamics, necessitating consideration of these phenomena in studies examining climate and malaria in Latin America and the Caribbean [5, 6].

Deforestation is another factor that has been found to increase malaria cases, especially in the early stages of deforestation in the interior of the Amazon. This is because deforestation promotes the breeding habitat of the mosquito vector, such as *Anopheles darlingi*, which increases the survival and rate of human bites. However, as the forest is lost, the effects are attenuated [10, 11].

It is important to note that deforestation and malaria have bidirectional causal relationships, where deforestation increases malaria through ecological mechanisms, and malaria reduces deforestation through socioeconomic mechanisms. The strength of these relationships depends on the stage of land use transformation. More research is needed to fully understand the implications of land use change on malaria risk in optimal transmission [11–13]. Studies examining deforestation and its impact on malaria often employ a variety of methodologies. The variability in methods used to study deforestation, as highlighted in Tucker-Lima, includes satellite imagery analysis, field surveys, and modelling approaches [3]. These methodological differences can lead to varying conclusions about the impact of deforestation on malaria transmission, emphasizing the need for standardized approaches in future research.

Climatic factors have been well established as determinants of malaria transmission. However, the relationship between deforestation and land use to malaria is a more emergent field and there is no systematic review of his role as a contributor to malaria in Latin America. It is also unclear whether studies linking those factors to malaria transmission have taken into account the potential confounding effect of biological and climate factors.

The objective of this systematic review was to identify the characteristics of published knowledge for malaria and its relationship with climatic variables and deforestation in Colombia, Latin America, and the Caribbean, from 2000 to 2020.

Methods

Databases and techniques for searching published studies

To investigate the impact of "climate variables" and "deforestation" on "malaria," a thorough search was conducted across six databases: Cochrane, PubMed, Scielo, Scopus, Embase, and Web of Science, covering the period from 2000 to 2020. The search employed a combination of controlled vocabulary (MeSH terms) and free terms, including spelling variations, synonyms, acronyms, and truncations. Additionally, tags were added in the title and abstract fields, with the use of proximity operators (ADJ) and Boolean operators (OR, AND) to broaden the search criteria. To ensure a comprehensive scope, articles in Spanish, English, and Portuguese from all Latin American and Caribbean countries were included, as indicated in Table 1.

Inclusion and exclusion criteria for published literature

Articles published in the period described, in English, Spanish, or Portuguese, were taken into account, selecting the titles and summaries of all the references obtained in the search. Studies were evaluated and classified by a team member into three categories.

Category 1, included articles: studies that contained original primary or secondary source information on malaria, climate variables, and deforestation. Category 2, included reviews. Items in Category 3 were excluded, comprising all articles on malaria that did not contain environmental data and/or deforestation or that, although including these variables, did not analyse associations between malaria and these variables. Descriptive ecological studies, case reports, editorials, letters of opinion, letters to the editor, as well as basic and/or clinical research were excluded from the search.

Full-text retrieval was performed on all references of relevant articles identified in Set 6 and Set 7 (see Table 1) that belonged to Category 1 and 2, to identify potentially relevant data.

The articles selected for full text reading were analysed and classified using the above criteria. Articles classified in Category 1 were selected and chosen for data extraction. A review of the bibliographic references of the articles classified in Category 2 was carried out to identify the articles that were not captured in the search strategy and that were potentially eligible.

Structured abstraction of relevant information

Eligible articles were distributed among the reviewers for the abstraction of relevant information. The variables extracted from the selected studies were: year of publication, year of the study, country of the study, name of the main author, name of the journal and digital object identifier DOI, title of the article, type of study, type of model employed, sources of environmental and deforestation data and main results. If the eligibility of an article was questioned, a second reviewer or all reviewers analysed the article to reach a consensus.

Information analysis

A descriptive analysis of the frequency of articles by country and subregion of Latin America and the Caribbean was carried out; as well as by the type of design employed, using the classification of ecological studies described by Morgenstern et al. [14], where these designs can be classified along two dimensions: the method of exposure measurement and the process of grouping. For the first dimension, a study is termed exploratory if the main exposure of interest is not measured, and analytic if the main exposure variable is measured and included in the analysis. This dimension is a continuum, as most

Table 1 Search strategy

Step	Search terms
1	"Malaria"
2	Caribbean region OR west indies OR "antigua and barbuda" OR bahamas or barbados OR cuba OR dominica OR dominican republic OR grenada OR guadeloupe OR haiti OR jamaica OR martinique OR netherlands antilles OR puerto rico OR "saint kitts and nevis" OR saint lucia OR "saint vincent and the grenadines" OR "trinidad and tobago" OR "virgin islands of the united states" OR central america OR belize OR costa rica OR el salvador OR guatemala OR honduras OR nicaragua OR panama OR panama canal zone OR latin america OR south america OR argentina OR bolivia OR brazil OR chile OR colombia OR ecuador OR french guiana OR guyana OR paraguay OR peru OR suriname OR uruguay OR venezuela
3	Anguilla OR Antigua OR Argentina OR Bahamas OR Barbados OR Barbuda OR Belize OR Bolivia OR Brazil OR Caicos OR Cayman Islands OR Chile OR Colombia OR Costa Rica OR Cuba OR Dominica OR Dominican Republic OR Ecuador OR "El Salvador" OR French Guyana OR French Guiana OR Grenada* OR Grenadines OR Guadeloupe OR Guatemala* OR Guyana OR Haiti* OR Hondura* OR Jamaica* OR Martinique OR Mexico OR Mexican* OR Montserrat OR Netherlands Antilles OR Nevis OR Nicaragua OR Panama OR Paraguay OR Peru OR Puerto Rico OR Saint Kitts OR Saint Lucia OR Saint Vincent OR Suriname OR Trinidad OR Tobago OR "Turks and Caicos" OR Virgin Islands OR Uruguay or Venezuela
4	"Region of the Americas" OR "Pan American Health Organization" OR PAHO OR "American States Organization" OR Latinoamerica* OR "El Caribe" or Sudamerica* OR Centroamerica* OR Latin America* OR Central America* OR South America* OR West Indies OR Caribbean
5	1 AND 2; 1 AND 3; 1 AND 4 (Set 1; Set 2; Set 3)
6	Limit 8 to English, Spanish or Portuguese, 2000 to 2020 (Set 1 + Set 2 + Set 3) = (Set 4)
7	Climate OR ENSO OR Weather OR Temperature OR Rain OR Humidity OR Wind Clima/Temperatura/Humedad Relativa/Precipitación/Vientos OR "El Nino" OR "El Niño" Clima/Temperatura/Precipitações/Humidade relativa/Ventos
8	(Set 4 + Step 7) = (Set 5)
9	Deforestation
10	(Set 4 + Step 9) = (Set 6)
11	(Set 5 + Step 9) = (Set 7)

ecological studies do not aim to test a single hypothesis. For the second dimension, the groups in an ecological study can be classified by place (multiple-group design), by time (time-trend design), or by both place and time (mixed design) [14]. The environmental and deforestation variables used in the different analyses and the types of statistical analyses used to relate patterns of malaria were described. The environmental variables found most frequently associated with epidemiological changes in malaria were identified and the strength of such associations was described. Additionally, the relationship between deforestation was described, as was the type of analysis, and it was established whether this association came from an analysis that controlled for possible confounder bias produced by other variables.

Results

Search strategy

Table 1 outlines the search strategy utilized in the databases examined for this review, with the outcomes of this strategy depicted in Fig. 1. After applying the combinations described in Set 4, a total of 900, 2140, 5606, and 55 articles were found in PubMed, Web of Science, Scopus, and Embase, respectively. Subsequently, the combination of climatic variables (Set 5) was applied, which obtained 92, 98, 411, and 6 results. After that, the "deforestation" variable (Set 6) was applied, and 20, 35, 67, and 3 articles were found. Finally, combining climate variables with deforestation (Set 7), 8, 9, 24, and 1 studies were obtained in those databases. These last three combinations (Set 5, Set 6, and Set 7) were considered for the selection by title. While for the Cochrane database, four articles were found using the combination of Set 4. No results were found for any combination in the Scielo database.

Characteristics of the reviewed articles

From the PubMed, Web of Science, Scopus and Embase databases, a total of 524 articles were initially retrieved for consideration in this review. After reviewing the titles and abstracts and removing duplicates, 469 of these articles were excluded, 382 because they treat subjuct outside the main objetives of the review (vector biology, biomedical aspects of malaria, among others). Additionally, 29 articles were topic reviews, 21 were case reports, 9 were editorial letters, and 26 were excluded because they were specific to countries that were not within the focus of this study and, 2 were book chapter as show in detail in Fig. 2

For full-text reading, 55 articles published between 2000 and 2020 were recovered. After reading the full text, 31 of the 55 studies were excluded, 18 because they did not use primary or secondary data, and 13 because

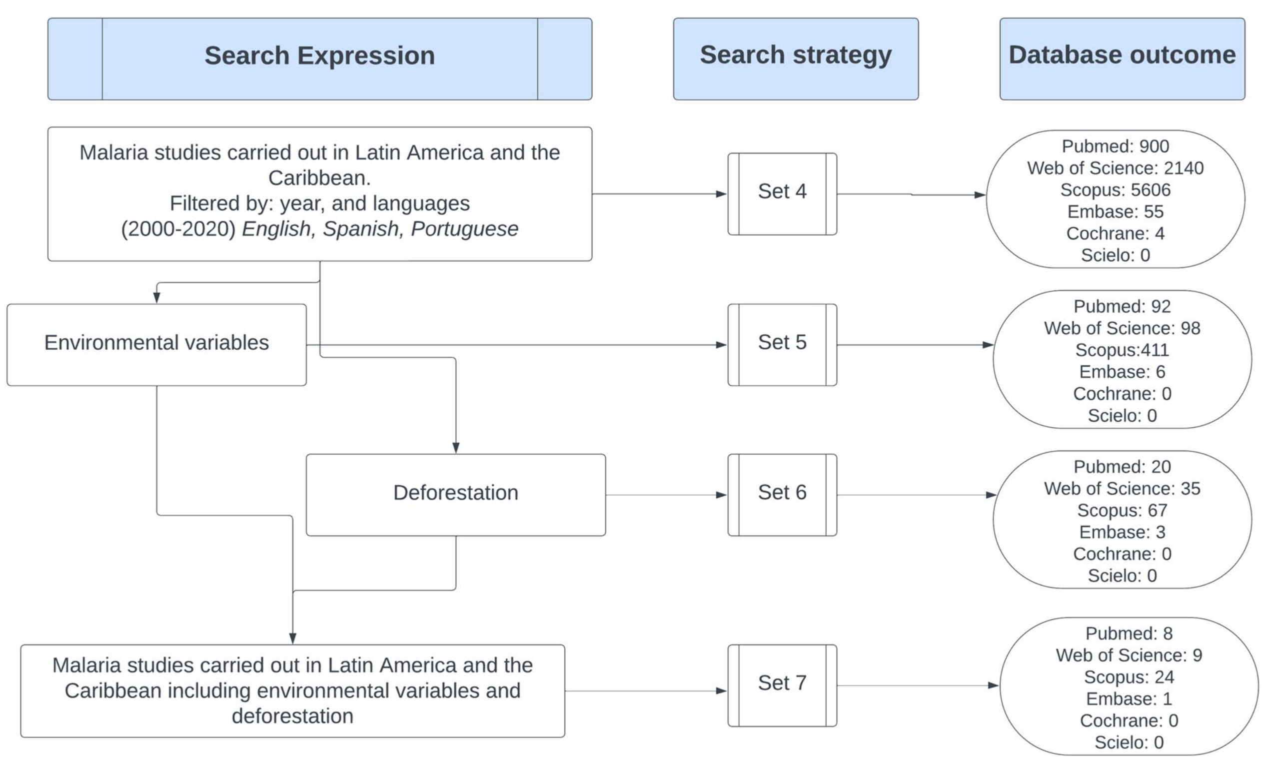

Fig. 1 Search strategy flow diagram. Search strategy flow from databases

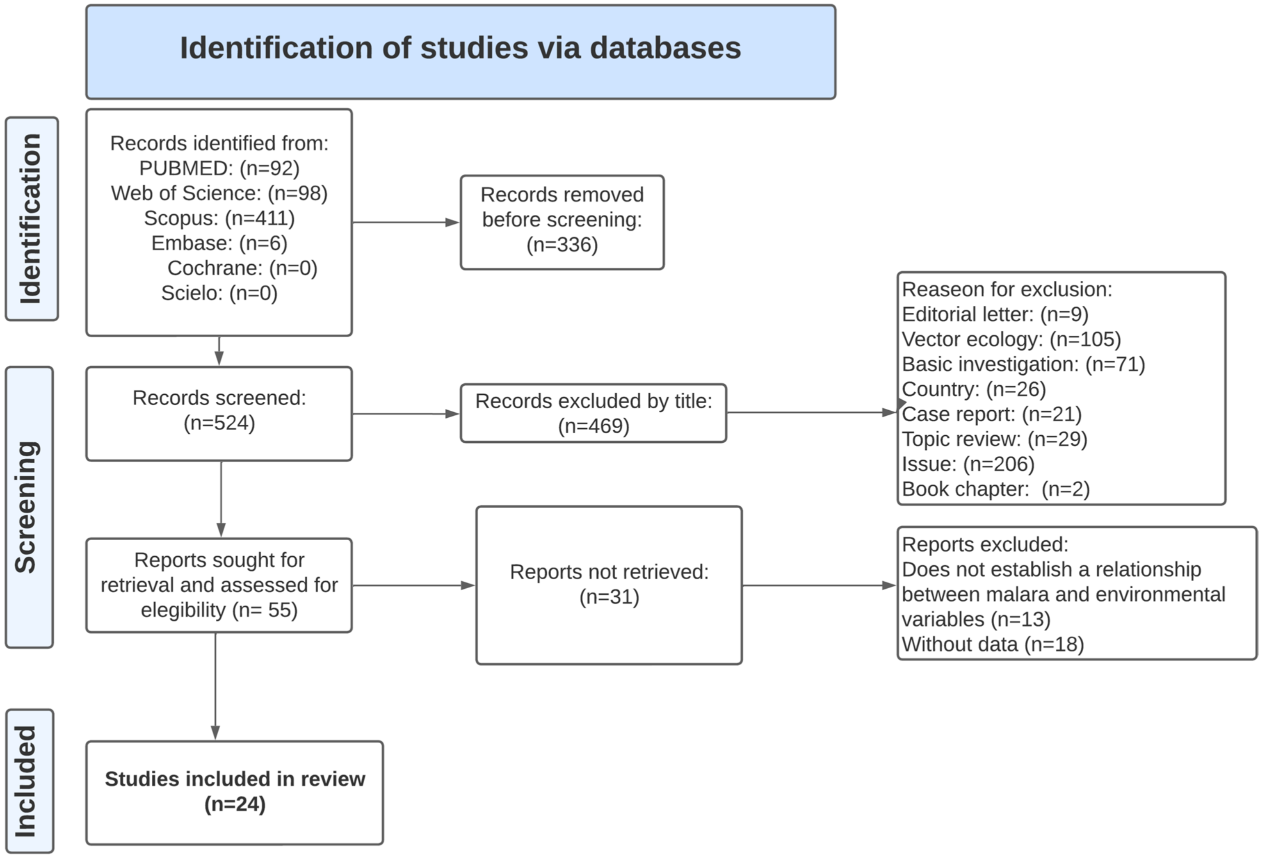

Fig. 2 PRISMA flow diagram. Study flow from literature search to data extration and analysis

did not establish the relationship between malaria and environmental variables and/or deforestation. The years 2011, and 2018 had the highest bibliographic production with four and five articles respectively, as shown in detail in Fig. 3. The study periods evaluated in the articles varied between 1 to 46 years as seen in Fig. 4. Twenty four studies were carried out in the Latin American Subregion (Ecuador, Bolivia, Brazil, Colombia, Peru, Suriname, Venezuela); two in the subregion of Central America (Panama).

The most frequently used study designs were: 22 ecological studies and 2 cohort studies. According to the classification of ecological studies by Morgenstern et al. [14], the types of ecological studies found were 5 exploratory studies and 17 analytical studies: (6 multiple groups, 4 mixed, and 7 time series). The 24 articles were included, of which 22 were done in the Latin American subregion (Brazil, Colombia, Perú, Ecuador, Guyana, French Guiana, Suriname, and Venezuela) and 2 in Panama.

Data source of the included articles

The main sources of information used in the selected articles after applying the inclusion and exclusion criteria were national databases for the malaria incidence variable and data from meteorological stations for the climatic variables as shown in Table 2.

Types of studies and statistical methods used for malaria risk analysis

The study designs used were: twenty-two ecologic studies and two cohorts [35, 37]. According to Morgenstern classification, five of the ecological studies were exploratory [23, 25, 28, 30, 31] and sixteen were analytic, seven studies were time series [20, 27, 29, 32, 33, 36, 38], six studies were multiple groups [11, 16–19, 24], and four mixed [15, 21, 22, 26].

Sixteen of the selected studies had malaria incidence as their main outcome and eight had malaria cases. The statistical approaches most frequently used for the analysis of this variable with the predictor variables were: negative binomial regression, Poisson regression,

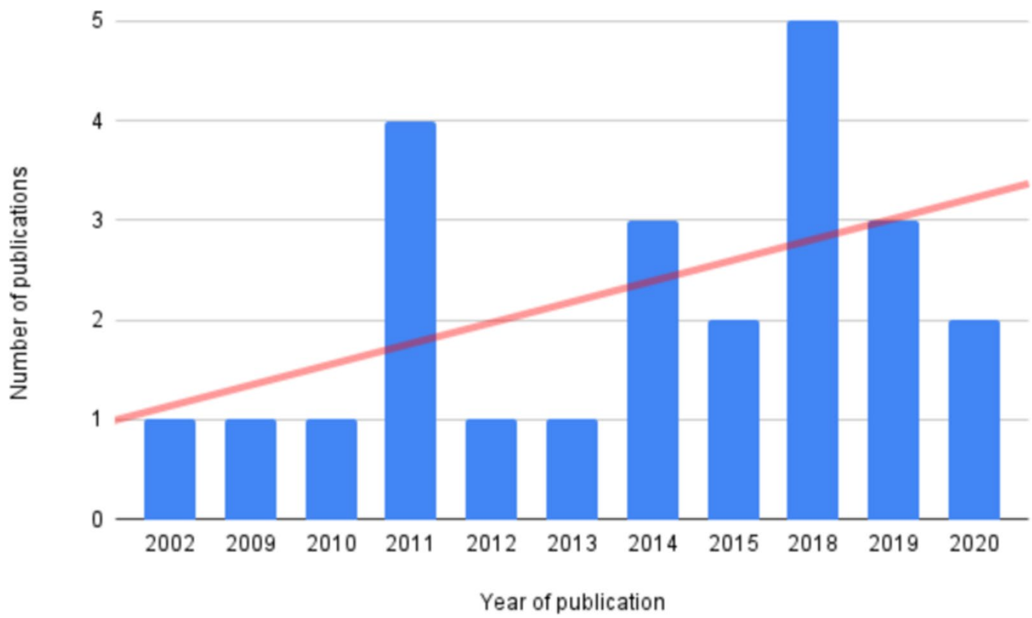

Fig. 3 Number of publications per year. Bar-chart showing the total number of included studies

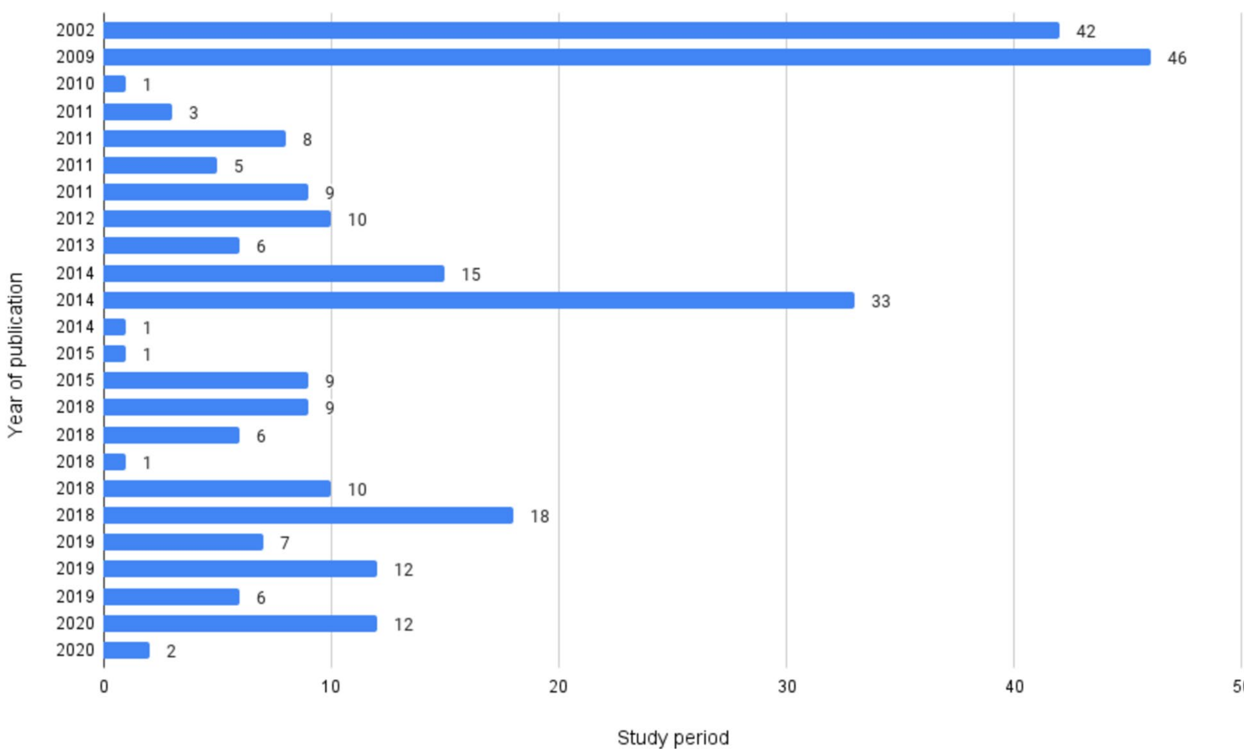

Fig. 4 The study periods of studies analysed. Bar-chart showing the study period of the articles included for full-text reading by year of publication

Table 2 Data source

Type	Source	Nº	Refs.
Global or continental databases	• Pan American Health Organization • SEAS Project	2	[15] [16]
National databases	•Surveillance system (Guyana) •National Institute of Health (Colombia) •Ministry of Health (Panama) •Ministry of Health (Brazil) •Ministry of Health (Peru) •National malaria eradication system (SNEM) •Malaria epidemiological surveillance system (SIVEP-Brasil) •Malaria information system •Institute of Hydrology, meteorology and environmental studies (IDEAM-Colombia) •United Nations Office on Drugs and Crime (UNODC) •Institute of Man and the Environment of the Amazon (IMAZON)	23	[16] [17–20] [21] [22–25] [26] [27] [11, 22, 28–33] [33] [19] [19] [25]
Subnational databases	•Region health centre (Guyana) •Laboratory of the Cayenne University Hospital •Regional office of environmental sanitation and sanitary control of malaria	3	[34] [35] [36]
Remote sensing	•Joint Institute for the Study of the Atmosphere and the Oceans (JISAO) •Oceanic United Nations •National Institute for Space Research (INPE) •National Oceanic and Atmospheric Administration (NOAA) •WorldClim •Moderate Resolution Imaging Spectroradiometer (MODIS) •Tropical Rainfall Measuring Mission (TRMM) •Global Precipitation Climatology Project (GPCP) •Global Forest Change data	10	[15] [21] [22, 28, 30, 31] [11, 20] [17] [26] [29]
Data from weather stations	•Global Historical Climatology Network (GHCN) •National Climatic Data Center (NCDC) •National meteorological services of Colombia, Guyana and Suriname •Weather service (Guyana) •Institute of Hydrology, meteorology and environmental studies (IDEAM-Colombia) •Institute of Meteorology and Hydrology (Panama) •National Institute of Meteorology (INMET-Brazil) •Brazilian Institute of Geography and Statistics (IBGE) •Brazilian National Water Agency (ANA)	10	[15] [34] [37] [18] [21] [22, 25] [24, 33]
Not reported	•Meteorological sources •Land use source	1	[23]

multivariate regression, Spearman's rank correlation coeffiecient, and Lineal regression as shown in Table 3.

Covariates analysed to estimate malaria risk

The primary outcome studied in the articles was annual malaria incidence in twelve studies, total malaria cases in seven studies, monthly malaria incidence in three articles, and weekly malaria incidence in two studies. It should be noted that one article also applied similar methods to infectious diseases other than malaria. Regarding the predictor variables, precipitation and temperature were the most studied covariates, followed by land cover and El Niño-Southern Oscillation (ENSO). Twelve studies were carried out at the municipal level, eight at the district level and 4 at the country level. See Table 4.

Relationship between climatic variables and malaria incidence

The articles included in this review show that the relationship between climatic variables such as precipitation, temperature, the El Niño phenomenon (ENSO), river level, among others, and the incidence of malaria has been widely studied in Latin America and the Caribbean.

The findings of the reviewed studies indicate that rainfall has a positive correlation with malaria rates in Colombia [15], Ecuador [15, 27], French Guyana [15, 16, 34, 35], Guyana [15], Peru [15, 26], Brazil [29, 32], and Venezuela [15].

One study noted that floods can trigger malaria epidemics in the coastal regions of northern Peru, while droughts in Colombia and Guyana favor the development of epidemics, and in Venezuela, droughts delay epidemics by a year. These variations underline the complex interaction between climate and malaria [15, 16]. Another study

Table 3 Statistical methods used for malaria risk analysis

Type of study	Statistical method for variable analysis	Refs.
Ecologic studies	•Quenouille's Correlation	[15]
	•Rossel's Method	[15]
	•Negative binomial regression	[15]
	•Poisson regression	[18, 20, 30]
	•Multivariate regression	[20, 27, 33]
	•Spearman's rank correlation coefficient	[25, 28, 32]
	•Analysis of Variance (ANOVA)	[16, 25, 29]
	•Time-Series Analysis	[36]
	•Autocorrelation function (ACF)	[21, 22]
	•Regression quartiles	[21, 38]
	•Lineal Regression	[23]
	•Spatial Durbin error model (SDEM)	[17, 25, 31]
	•Geographically Weighted Regression (GWR)	[24]
	•Principal component analysis (PCA)	[22]
	•Bernoulli null model	[22]
	•Topographic data analysis	[19]
	•Kolmogorov–Smirnov Test	[19]
	•Conditional autoregressive (CAR)	[25]
	•General linear model (GLM)	[27]
	•Ordinay Least Squares (OLS)	[17]
	•Least Squares Dummy Variable (LSDV)	[11]
	•Boosted Regression Tree	[11]
		[26]
Cohort studies	•Autoregressive integrated moving average (ARIMA)	[35]
	•Multivariate Survival Analysis using Cox model	[34]
	•Spearman's rank correlation coefficient	[34]
	•Time-Series Analysis	[34]

Table 4 Variable used in malaria risk

Indicator	Metric	Nº	Refs.
Malaria outcome	•Annual malaria incidence	12	[11, 15, 22, 23, 25, 26, 28, 30, 31, 34, 35, 37]
	•Weekly malaria incidence	2	[16, 19]
	•Monthly malaria incidence	3	[18, 21, 29]
	•Total malaria cases	7	[17, 20, 24, 27, 32, 33, 36]
Precipitation	•Total monthly precipitation	6	[15, 16, 21, 27, 37, 38]
	•Total daily precipitation	1	[37]
	•Average annual precipitation	7	[17, 23–26, 29, 32]
Temperature	•Monthly average temperature	3	[15, 27, 38]
	•Monthly average minimum temperature	3	[21, 35, 37]
	•Monthly average maximum temperature	3	[21, 35, 37]
	•Average annual temperature	4	[17, 23, 24, 29]
El Niño-Sourthern Oscillation (ENSO)	•SOI Southern Oscillation Index	2	[15, 36]
	•SST4 Sea surface temperature	4	[20, 21, 29, 38]
Altitude	•Height above mean sea level	1	[18]
Land cover	•Land use: deforestation alerts/anthropogenic changes	1	[19]
	•Percentage deforestation/Absolute deforestation	1	[28]
	•Deforestation rate	3	[30, 31, 33]
	•Deforestation area	2	[24, 25]
	•Annual accumulated deforestation	1	[22]
	•Forest coverage/Forest loss	2	[11, 26]
	•Land use: deforestation (mining, roads and population density)	1	[23]
Spatial scale	•Country level	4	[15, 18, 21, 38]
	•District level	8	[19, 20, 22–25, 28, 33]
	•Municipality level	12	[11, 16, 17, 26, 27, 29–32, 34–36]

highlighted that regions such as Brazil, French Guiana, and Ecuador did not show a clear link between climate and malaria, suggesting that non-climatic factors such as fumigation, availability of medicines, and population migration play a larger role [15].

Several studies have highlighted the correlation between the El Niño phenomenon and the incidence of malaria [15, 16, 20, 29, 32, 36, 38]. In Colombia, a study found that a 1 °C change in ENSO variables could result in a 17.7% to 9.3% change in expected malaria cases. In specific regions, such as the Pacific and Atlantic regions of Colombia, this change could reach 22.9% and 23.4%, respectively, for a 1 °C change in the ENSO variables [20]. This important statistical relationship highlights the profound impact of the El Niño phenomenon on the incidence of malaria in these areas of this country.

The authors of several papers were able to establish some seasonal patterns in malaria incidence, with peaks typically occurring in January–February and July–August. A study focused on French Guiana found that malaria incidence showed a clear seasonal pattern, with significant increases during these peak periods. Another study noted that intra-annual variability in malaria cases often coincides with rainy seasons, contributing to higher transmission rates during these months [16, 34, 35]. This seasonal influence is crucial for planning and implementing effective malaria control measures.

Studies that analysed the temperature variable found that temperature changes significantly affect the risk of malaria. One study shows that for every degree increase in temperature, the incidence rate of malaria could increase by between 10 and 80%, particularly in higher altitude regions where temperature fluctuations are more pronounced [18]. Additionally, it was found that warmer temperatures are positively associated with a higher incidence of malaria, especially during December and January, the warmest months in many malaria-endemic countries in Latin America and the Caribbean [15, 21, 22]. These findings highlight the fundamental role of temperature in malaria transmission dynamics.

Studies employing multivariate analysis explored the combined effects of various climatic and environmental factors on malaria incidence. One study used boosted regression tree (BRT) models to identify high malaria-risk areas and found significant variations between different areas in terms of malaria risk for *P. vivax* and *P. falciparum*. The highest risk areas identified included Zone II (Loreto) with 56.5% high risk for *P. vivax* and 27.8% for *P. falciparum*. Adiotionally, this study observed that precipitation had a stronger effect on *P. falciparum*, while higher soil temperatures decreased the incidence of *P. vivax* [29]. Table 5 shows the main results of the reviewed articles that evaluated the relationship between malaria incidence and climatic variables.

Relationship between climatic variables and/or deforestation and malaria incidence

Brazil was the country with the most articles on this subject (n = 8). One study, conducted between 1997 and 2000, found that deforestation increase the risk of malaria by 33%, RR = 1.33, for every 4.3% increase in deforestation. They observed the deforestation in 1997 and during 2000–2006. In 1997, deforestation was concentrated in and around Mâncio Lima, with significant changes observed between 1997 and 2006, while the deforestation between 2001–2006 did not show a significant association with malaria risk, highlighting the importance of historical deforestation patterns in predicting current malaria risk [28].

Achcar found that the deforestation rate in the Brazilian Amazon region had a behaviour similar to the pattern of malaria incidence, increasing from 1999 to 2004 and then decreasing. This temporal alignment highlights the complex interaction between environmental and epidemiological trends [33]. Terrazas found that during the study period, the crude rate in Amazonas was 4,142 cases per 100,000 inhabitants, with higher rates in Manaus and Río Negro compared to lower Amazonas. Additionally, 8% of malaria cases occurred in the indigenous population, where the highest incidence rates were observed. The multiple regression analysis showed a significant positive correlation between the average annual rate of deforestation and the incidence of malaria, explaining 35% of the variation in the incidence of malaria [31].

Research has shown that deforestation in one area can influence malaria rates in surrounding municipalities. Santos established that for every 100 km^2 of deforestation, 7.26 additional malaria cases are registered per thousand inhabitants in the municipalities of the Brazilian Amazon. Furthermore, deforestation in neighbouring municipalities generates an average increase of 4.52 malaria cases per thousand inhabitants. The total effect of deforestation, considering direct and indirect effects, is 11.78 malaria cases per thousand inhabitants per 100 km^2 of deforested forest [24]. Hanh in 2014 found that in timber-producing states, where 90% of deforestation has occurred, areas with a lower percentage of selectively logged had higher rates of malaria than areas with more selectively logged percent [30].

MacDonald explained that the annual loss of forests within a municipality leads to a significant increase in malaria incidence ($\beta = 0.327$, SE = 0.145, P = 0.024). Specifically, a 10% increase in deforestation would result in a 3.27% increase in malaria incidence, which translates to approximately 9,980 additional cases in 2008. The study

Table 5 Main finding between malaria incidence and climatic variables

Item	Year of publication	Study period	Country of study	Primary author
1	2002	1956–1998	Colombia, Ecuador, French Guiana, Guyana, Peru, Suriname and Venezuela	Gagnon [15]
	Key results •A significant positive relationship was found between El Niño and malaria epidemics in Colombia, Guyana, Peru, and Venezuela •Floods generate malaria epidemics in the coastal region of Peru and droughts favor the development of epidemics in Colombia and Guyana. In contrast in Venezuela, malaria epidemics are delayed by drought for 1 year •In Brazil, French Guiana, and Ecuador, non-climatic factors such as fumigation, variation in drug availability, and population migration are likely to play a larger role in malaria where they did not detect an ENSO/malaria signal			
2	2009	1960–2006	Colombia	Mantilla [20]
	Key results •The negative binomial regression model (NBRM) results showed a positive association between ENSO and the total number of malaria cases in Colombia. A 1 °C change in ENSO measuring variables (ENSO_Avg or ENSO_Dom) resulted in a 17.7% or 9.3% change in expected malaria cases, respectively •Regarding the five regions analysed in the study, the Pacific Region (R1) and the Atlantic Region (R2), showed that malaria cases are positively and significantly associated with the behaviour of ENSO (high during El Niño) for both the ENSO_Avg variables as ENSO_Dom and that a 1 °C change in these variables results in a change of 22.9% and 9.6% in expected malaria cases in R1 and, 23.4% and 19.4% in R2, respectively. In contrast, no significant relationship with malaria cases was evident during the study period in the Andean, Amazonian, and Orinoco regions (R3, R4, R5)			
3	2011	2003–2006	French Guiana	Girod [16]
	Key results •*Camopi*: Malaria incidence showed seasonality, with a peak in January–February (i.e., at the end of the short rainy season) and another in July–August (at the end of the long rainy season) • Correlation between human bite rates (HBR) by *An. darlingi* and precipitation 0.46 ($p < 0.01$) • Apatou: Malaria incidence showed two seasonal peaks, these occurred in January–February and July–August. There was no evidence between Correlation (HBR) and precipitation • Régina: In this health centre, no clear seasonal variation was observed in the incidence of malaria during the study period and no correlation was evident between (HBR) and precipitation			
4	2011	2001–2009	French Guiana	Stefani [37]
	Key results • When studying the intraannual variability, two peaks were observed for *P. vivax* (January and June). While only one peak was observed for *P. falciparum* (January) • Meteorological and hydrological characteristics are positively correlated with the incidence of malaria • Seasonality in Camopi was determined by rainfall, the incidence of malaria was significantly higher during the rainy period where greater precipitation and lower average minimum temperature are observed (December to June) than during the dry period (July to November) ($p < 0.001$) • Regarding *An. darlingi*, a significant correlation was observed between the incidence of malaria and the human bite rate (HBR) recorded a month before ($p = 0.03$), observing a peak in the month of May			
5	2011	2002–2007	French Guiana	Basurko [35]
	Key results •The study highlights a clear seasonal pattern in malaria incidence in Cacao, influenced by rainfall, river levels, and temperature variations, with significant correlations found between malaria cases and specific meteorological factors in the Cacao village between 2002–2007 •The highest malaria incidence was observed in 2005 and 2006 •Univariate ARIMA Model: Significant factors include mean minimum temperatures at time t and t-12 months and mean maximum temperatures at t-1, t-2, and t-9 months •Multivariate ARIMA Model: Incidence of malaria was inversely correlated with the minimum temperature at time t, and with maximum temperature at t-2 and t-9 months •The observed data suggests a complex relationship where both very high and low temperatures can impact malaria transmission dynamics differently •The temperature variations significantly influence malaria incidence, with lower minimum temperatures being positively associated with higher malaria cases and higher maximum temperatures inversely related to malaria incidence •Precipitation: •Positive Correlation: Higher precipitation levels create standing water, providing breeding sites for mosquitoes •Seasonality: Malaria incidence often peaks during or after rainy seasons			

Table 5 (continued)

Item	Year of publication	Study period	Country of study	Primary author
6	2012	1990–2000	Venezuela	Delgado [36]
	Key results •The moderate ENSO phases significantly influence malaria incidence, varying by municipality and year •The Cajigal municipality had the highest malaria incidence regardless of ENSO phase or year. However, Sucre municipality has shown high, variable malaria incidence tied to ENSO events •Regarding temperature variables, the spatial maps (1990–2000) show higher malaria cases during cold phases across municipalities. In contrast, the highest cases in 1999 were during La Niña (4,800), followed by El Niño (3,700), and neutral phases (2,000) •Sucre and Cajigal municipalities have the highest malaria during moderate ENSO events, and fewer during weak or strong events, while malaria in Sucre municipality varies with ENSO, while Cajigal remains endemic with up to 2,000 cases, unaffected by ENSO			
7	2013	2003–2009	Brazil	Filizola [29]
	Key results •It was observed that the distribution of malaria was heterogeneous in the four municipalities analysed (Coari, Codajás, Manacapuru, and Manaus) during the years studied •The incidence of malaria was influenced by the years in which extreme ENSO events (El Niño and La Niña) occurred, with 2003, 2005, and 2007 being the ones that had the highest number of malaria cases, while 2008 and 2009 showed a decrease •A significant correlation was observed between malaria incidence and temperature, especially during years with climatic extremes (2003, 2005, and 2009), because temperature increases are associated with an increase in mosquito abundance •Precipitation showed a strong correlation with malaria, being the best descriptor of malaria seasonality. It was observed that the greatest malaria transmission occurred from June to September (dry season), associated with the period after the rain •A marked relationship was also observed between water levels and malaria; this may be because the increase in water levels generates breeding sites for mosquitoes			
8	2014	1990–2005	Colombia and Etiopia	Siraj [18]
	Key results •For Colombia, only data from *P. falciparum* in Antioquia •Most cases were concentrated at altitudes of 1200 to 1300 m above sea level, with an average temperature of 17.6 to 18ºC •In Colombia and Ethiopia, changes in the altitudinal distribution of malaria cases were reported with average temperature over the years, a shift of the cumulative curve to the right was observed, indicating that more cases of malaria occur at altitudes. highest in a given year. This does not mean that the number of cases increased from 1994 to 1997, but rather that the distribution of the disease has moved toward a higher elevation •Scatterplots of mean altitude versus these temperatures demonstrate a movement of the distribution to higher altitudes in warmer years for the two mountain regions •The best statistical model showed a significant positive effect of mean temperature on the logarithm of malaria cases for both regions. In Colombia, this rate ranged between approximately 10 and 80% for every 1 °C increase in temperature from the highest to the lowest municipalities			
9	2014	1980–2013	Panama	Hurtado [21]
	Key results •95% of cases were caused by *P. vivax*. *An. albimanus* is the main vector in Panama •There were great differences in the seasonality of malaria during the two periods. From 1980 to 2002, epidemics were most common during December, January, and February; no differences were observed between the months. On the contrary, from 2003 to 2013 a clear seasonality was observed, with a peak of cases in February and a significant increase in the number of cases at the end of the wet season in November, the dry season (December-March) and the beginning of the rainy season in April •After a model selection process, malaria incidence for 1980–2002 was found to be a second-order autoregressive process and was also significantly associated with the El Niño 4 (SST4) index •The SST4 index was associated with interannual cycles of malaria for four-year periods ranging from 1980 to 1995 and eight-year periods between 1995 and 2006. In 1995, there was a correlation between four-year cycles in SST4 and rainfall, and a similar pattern was also observed for the Maximum Temperature. Additionally, Maximum and Minimum Temperatures were seasonally associated with SST4 for a period of one year			
10	2015	2014–2015	Brazil	Bauch [23]
	Key results •Conservation scenarios based on the estimated regression results suggest that the incidence of malaria, ARI, and diarrhea would be reduced by expanding strict protected areas, and malaria could be further reduced by restricting roads and mining • Strict protected areas (PAs) were negatively correlated with the three major diseases: malaria, diarrhea, and acute respiratory infection (ARI). This may have been due to the combined effects of reduced deforestation and exposure, meaning that strict PAs may serve as a barrier against disease. Sustainable use PAs, which allow human use and/or occupation, were positively correlated with malaria • Bioclimatic factors and natural water bodies were positively correlated with malaria. In contrast, altitude, higher temperature, and precipitation were negatively correlated with malaria • The author does not specify the species of *Plasmodium* causing the malaria cases, nor did he take into account entomological data			

Table 5 (continued)

Item	Year of publication	Study period	Country of study	Primary author
11	2018	1998–2016	Panama	Amarilis [38]
	Key results •The authors did not observe a clear seasonality in the distribution of malaria cases, however, the maximum points reached were observed in September and March Regarding climatic variables: precipitation showed strong seasonality with dry months (December–April) and a peak in July. A positive correlation with malaria was observed with a lag of 7 months. The temperature peaks occurred in April and no significant correlation with malaria was observed. An increase in malaria cases was evident during the warm phases of ENSO when the SST4 index reached its peak			
12	2018	2014–2015	Brazil	Coutinho [32]
	Key results •A strong trend was observed in malaria cases and seasonality is evident in river levels, precipitation, and temperature in the studied areas •PRQQ Area (Includes Lake Paraquequara, which is on the edge of the city limits): Showed a highly significant model (p < 2.2e-16), where the river level is the most significant factor and explains about 50% of the occurrence of the cases, additionally, moderate correlations were also observed for air temperature and precipitation •BARC Area (Barcelos): Moderate correlations were also found with river level, while air temperature had a weak correlation •In the SGC Area (Sao Gabriel da Cahoeria): No significant statistical relationships were found. However, he observed an inverse effect between malaria cases and river levels and a positive correlation with precipitation and air temperature •The river level variable had an immediate positive correlation with malaria incidence, while precipitation and temperature showed delayed effects •Temperature: Higher temperatures (> 28.5 °C) were observed to be associated with a reduction in malaria cases in BARC and PRQQ, but not in SGC •Precipitation: It was observed that PRQQ recorded the greatest increase in cases from December to January when there was constant rainfall and a slight drop in temperature and the river level went from dry to flooded			
13	2019	2010–2017	Peru	Solano [26]
	Key results •For the study period 2010–2017, 321,210 cases of malaria were reported in 2,766 (96.9%) georeferenced villages of Loreto •Cases increased from 10,994 in 2011 to 59,257 in 2014 and 58,679 in 2015, then in 2017 they decreased slightly to 51,663 •CAR (Cummulative annual rainfall) was the highest predictor, ranging from 17% to 48.4% for *P. vivax* and from 11.5% to 30.7% for *P. falciparum* •The highest risk areas identified for malaria using BRT models were: Zone I (Maynas): 42.9% high risk for *P. vivax* and 11.7% high risk for *P. falciparum* Zone II (Loreto): 56.5% high risk for *P. vivax*, and 27.8% high risk for *P. falciparum* Zone III (Datem del Marañón and Alto Amazonas): 34.5% high risk for *P. vivax* and 5.4% high risk for *P. falciparum* Zone IV (Requena and Ucayali): 3.9% high risk for *P. vivax* Zone V (Ramón Castilla): 45.3% high risk for *P. vivax*, a significant number of towns at risk			
14	2020	2006–2018	Ecuador	Gunderson [27]
	Key results •Between 2006–2018, 9,230 cases of *P. vivax* malaria and 499 cases of *P. falciparum* were reported in Ecuador •*P. vivax:* The incidence increased in 2008, decreased at the end of 2011, and increased again in 2014 •*P. falciparum:* maintained low levels until a peak in early 2016, then remained low •It was observed that the cantons bordering Loreto, Peru, had a higher incidence of malaria than the non-border cantons (3.1% increase for *P. vivax*, 3.0% for *P. falciparum* per increase of 1 case/1000/ month) •The Aguarico canton presented the highest rates, with peaks of 7.4 cases/1000/week (*P. vivax*) and 2.3 cases/1000/week (*P. falciparum*) •Precipitation had a stronger effect on *P. falciparum*, while higher soil temperatures decreased the incidence of *P. vivax*, similar effects on soil moisture were observed for both species			

found that in the "interior" regions of the Amazon, deforestation significantly increases the incidence of malaria, particularly for *P. falciparum* (β = 0.716, SE = 0.323, P = 0.027). However, no significant relationship was found in the "outer" regions where most of the forest has already been cleared.

Other studies point out that the relationship between deforestation and malaria is not always simple. Studies indicate that extreme levels of deforestation could reduce the incidence of malaria due to the degradation of mosquito habitats. For example, as deforestation exceeds 363 km^2, the incidence of malaria tends to decrease. Furthermore, each 10% increase in municipal forest cover is associated with 4.32 additional cases of malaria per thousand inhabitants of the municipality. Population density is negatively related to malaria cases, possibly due to increased urbanization and reduced mosquito exposure. Furthermore, a 0.1-degree increase in average annual temperature results in 7.7 additional malaria cases, although no significant statistical relationship was found between rainfall and malaria cases [24].

The impact of forest fragmentation on malaria incidence is also significant. Smaller and more numerous forest patches are correlated with increased malaria cases, particularly patches smaller than 5 km^2, which showed a correlation with malaria cases (0.81; $P < 0.005$). The regression analysis indicated that each km^2 of deforestation corresponded to an increase of 27 new malaria cases ($km^2 = 0.78$; $F1,10 = 35.81$; $P < 0.001$), while each km^2 of impacted forest corresponded to an increase of 16 new cases. The statistical correlation between average monthly malaria cases and the three levels of forest use considered in this study differed, with a positive correlation for malaria and deforestation ($r = 0.80$; $P = 0.002$) [25].

Feged-Rivadeneira (2018) explored the relationship between spatial clusters, ethnicity, and deforestation alerts reported in the Colombian Environmental Information System (SIAC). They found two patterns of infection: an endemic one produced by *P. vivax* mainly in the indigenous and Afro-descendant population, and another of occupational risk produced by *P. falciparum*. All *P. falciparum* groups were located along the Pacific or Lower Cauca basin, suggesting that moderate deforestation favors malaria transmission. Furthermore, they found a high correlation between gold exploitation and malaria in several departments of Colombia [19]. De Oliveira Padilha et al. (2019) studied malaria in Brazil between 2009 and 2015 their findings indicated that in Rondônia, higher levels of deforestation were associated with a reduction in malaria cases, while in Acre, increased deforestation in the Brazilian Amazon is correlated with a higher incidence of malaria, suggesting that landscape modification is a crucial factor in the spread of the disease [22].

Piedrahita analysed how environmental and climatic factors, such as precipitation and NDVI, correlate with malaria incidence in the Colombian Pacific region. Although he did not directly address deforestation, the author suggests that NDVI and precipitation are significant factors in malaria incidence, implying that changes in vegetation cover due to deforestation could influence disease patterns, proposing that less vegetation can lead to an increase in malaria cases, while in areas with more vegetation may have a lower incidence [17].

Table 6 Main findings between malaria incidence, climatic variables, and deforestation

Item	Year of publication	Study period	Country of study	Primary author
1	2010	2006	Brazil	Olson [28]
	Key results •The 54 health districts of Mâncio Lima reported 15,437 confirmed cases of malaria between 2006 and 2008, with a spatial distribution that reflects population settlements along two dominant river channels and in the urban area •The average incidence of malaria was 1.16 cases per person, varying between 0.4 and 12 cases per person in the different health districts •Initial deforestation in 1997 was concentrated in the city of Mâncio Lima and its surroundings, with significant changes in deforestation between 1997 and 2006, especially to the west and south of the city. Deforestation increased on average between 6.6% and 26% in health districts during this period •The univariate analysis showed that deforestation between 1997 and 2000 was the most predictive factor for malaria risk, with a relative risk (RR) of 1.33 (95% CI 1.12–1.58) for a 4.3% increase in deforestation •Deforestation in 1997 was not significant on its own, but cumulative deforestation between 1997 and 2002, 1997 and 2001, and 1997 and 2000 showed a significant positive correlation with malaria risk •Multivariate Analysis: Adjusting for access to care and the spatial area of health districts, deforestation between 1997 and 2000 was associated with a malaria risk of 1.48 (95% CI 1.26–1.75). The most recent deforestation (2001–2006) did not show a significant association with malaria risk			
2	2011	1999–2008	Brazil	Achcar [33]
	Key results •During the study period, the incidence of malaria decreased in most provinces from 1999 to 2002, from this year until 2005, there was an increase in malaria cases, which subsequently decreased •The deforestation rate in the Brazilian Amazon region followed a similar pattern: increasing from 1999 to 2004 and decreasing after 2004 •Deforestation between 1997 and 2000 is significantly correlated with an increase in malaria risk. A 4.3% increase in deforestation during this period was associated with a 1.33 to 1.48 times greater risk of malaria •The proposed Bayesian model suggests that the number of inhabitants per km^2 and the Human Development Index (HDI) have some association with the number of malaria cases			
3	2014	2003	Brazil	Hahn [30]
	Key results •To understand the impacts of deforestation, paved roads, fire zones, and controlled logging, the authors constructed a negative binomial model of malaria counts at the municipal level controlling for human population and social and environmental risk factors •Both paved and unpaved roads and fire zones in a municipality increase the risk of malaria •Within timber-producing states where 90% of deforestation has occurred, compared to areas without selective logging, municipalities, where between 0 and 7% of remaining forests were selectively logged, had the highest risk of malaria (1.72, 95% CI: 1.18–2.51), and areas with highest rates of selective logging had the lowest risk (0.39, 95% CI: 0.23–0.67) •They also found other factors that increase the risk of malaria significantly such as unpaved roads 51%-55% ($p < 0.0001$), forest fires 34–37%, and selective logging are risk factors for malaria not previously recognized in the Amazon. Brazilian and highlight the need to regulate and monitor the alteration of the forest below the canopy			

Table 6 (continued)

Item	Year of publication	Study period	Country of study	Primary author
4	2015	2003–2012	Brazil	Terrazas [31]
	Key results •For the study period, the crude rate in Amazonas was 4142 cases per 100,000 inhabitants, with higher rates in the Manaus and Río Negro regions compared to the lower Amazon. 8% of malaria cases occurred in the indigenous population, the highest incidence rates occurred in this population •Between 2003 -2012, the eastern and southern regions, Tabatinga and Guajará were the areas that presented the highest deforestation rates •Multiple regression analysis showed a significant positive correlation between the average annual rate of deforestation and malaria incidence. The model explained 35% of the variation in malaria incidence, that is, deforestation contributes to the variability in malaria incidence, explaining part of the variation in the observed cases			
5	2018	2003–2012	Brazil	Santos [24]
	Key results •This study found that for every 100 km^2 of deforestation, 7.26 additional cases of malaria are recorded per thousand inhabitants in the affected municipality. Additionally, deforestation in neighboring municipalities generates an average increase of 4.52 cases of malaria per thousand inhabitants in a municipality •The total effect of deforestation (considering direct and spillover effects) is 11.78 cases of malaria per thousand inhabitants per 100 km^2 of deforested forest •The relationship between deforestation and malaria is not linear. As deforestation exceeds 363 km^2, the incidence of malaria tends to decrease due to the extreme degradation of the forest environment •Each 10% increase in municipal forest cover is associated with 4.32 additional cases of malaria per thousand inhabitants in the municipality •Population density is negatively related to malaria cases, possibly due to increased urbanization and reduced exposure to mosquitoes •A 0.1-degree increase in average annual temperature results in 7.7 additional cases of malaria. No significant statistical relationship was found between precipitation and malaria cases			
6	2018	2009–2015	Brazil	Chaves [25]
	Key results •There is a high positive correlation between the number of patches from 5 km^2 to 0.25 km^2 and the number of malaria cases. However, when added to the number of patches less than 0.10 km^2, this correlation loses statistical significance ($r = 0.46$; $p = 0.12$) •Patches smaller than 5 km^2 were of particular relevance because this spatial resolution showed a significant correlation with malaria cases (0.81; $p < 0.005$) and deforestation (0.96; $p < 0.0001$), and this patch size may be biologically related to the preferred habitats of *An. darlingi* larvae •Simple linear regression analyses showed that each km^2 of deforestation corresponded to an increase of 27 new cases of malaria ($r^2 = 0.78$; $F_{1,10} = 35.81$; $p < 0.001$), while each km^2 of impacted forest corresponded to an increase of 16 new cases •In the simple linear regression analysis, the variables that were correlated with malaria cases were: deforestation, impact, accumulated rainfall, number of patches < 5 km^2, number of patches < 0.5 km^2, and number of patches < 0.25 km^2 •The statistical correlation between the monthly mean malaria cases and the three levels of forest use considered in this study differed: malaria and deforestation were positive ($r = 0.80$; $p = 0.002$); the impact of malaria and forests was moderate ($r = 0.56$; $p = 0.06$); and malaria and forest degradation were weak ($r = 0.25$; $p = 0.43$)			

Table 6 (continued)

Item	Year of publication	Study period	Country of study	Primary author
7	2018	2009–2010	Colombia	Feged [19]
	Key results •Two infection patterns were found, one endemic produced by *P. vivax* mainly in indigenous and Afro-descendant populations and the other being occupational risk caused by *P. falciparum* •The deforestation pattern of the Colombian Pacific was characterized by being widely spread and presenting low deforestation rates, where the presence of both parasites was observed *P. falciparum* and *P. vivax* •Moderate urbanization rate and places with moderate but sustained deforestation were associated with the reintroduction of *P. vivax* • Additionally, high correlation was observed in areas of medium and high gold exploitation and the occurrence of malaria			
8	2019	2009–2015	Brazil	de Oliveira [22]
	Key results •There was a high and positive correlation between the decrease in malaria and higher proportions of accumulated deforestation in Rondônia • Geographically weighted regression showed that the relationship between malaria incidence and cumulative deforestation is complex because it could be positive or negative depending on the amount of forest remaining • As deforestation increased, the incidence of malaria also increased in Acre, while as deforestation increased, the incidence of malaria decreased in Rondônia • The time series regression showed a positive association between malaria incidence, precipitation and cumulative deforestation, while the human development index in the western areas of Acre showed a negative relationship • Landscape modification caused by accumulated deforestation is an important factor in the incidence of malaria in the Brazilian Amazon. However, this relationship does not have a linear correlation because it depends on the total proportion of land covered by forests • Cruzeiro do Sul: An increase of 10 km^2 in deforestation meant ~400 more cases of malaria per 1000 inhabitants per month between 2009–2015 • In Mancio Lima, Rodrigues Alves, Tarauca and Oporto Walter, an increase of 10 km^2 in deforestation meant from 2 to 54 more cases of malaria per 1000 inhabitants per month between 2009–2015			
9	2019	2003–2015	Brazil	MacDonald [11]
	Key results •Annual forest loss within a municipality significantly increases malaria incidence ($\beta = 0.327$, $SE = 0.145$, $P = 0.024$) •A 10% increase in deforestation would result in a 3.27% increase in malaria incidence (approximately 9,980 additional cases in 2008 •In the "interior" regions of the Amazon (pre-frontier or active areas), deforestation significantly increases malaria incidence, especially for *P. falciparum* ($\beta = 0.716$, $SE = 0.323$, $P = 0.027$). While for the "outer" regions of the Amazon, where the majority of the forest has already been cleared, no significant relationship was found between deforestation and malaria incidence ($\beta = 0.020$, $SE = 0.014$, $P = 0.136$) •Two-way feedback: •A bidirectional feedback was found between deforestation and malaria: while deforestation increases malaria incidence, a high malaria incidence reduces annual forest loss ($\beta = -1.410$, $SE = 0.654$, $P = 0.031$) •A 1% increase in malaria incidence would reduce deforestation by 1.41%, approximately 219 km^2 less lost in 2008 •This negative effect of malaria on deforestation was consistent in the interior region of the Amazon but disappeared in the outer regions			

Table 6 (continued)

Item	Year of publication	Study period	Country of study	Primary author
10	2020	2013–2015	Colombia	Piedrahita [17]
	Key results •The municipality with the highest incidence was Novita in the department of Chocó, with the highest number of new cases of malaria between 2013 and 2015, with an average annual parasitic index (API) of 142.8, while the municipality with the lowest incidence was Pasto in the department of Nariño. showed the lowest API, with 0.003 •The Generalized Regression Model (GLM): showed that the environmental variables related to the incidence of malaria were precipitation and NDVI, with a statistically significant correlation (R^2 = 0.98, P < 0.05) • The Observed API Map, showed that the departments of Chocó and Nariño had the highest malaria incidence values •Estimated API Map: Based on the explanatory variables of incidence (precipitation and NDVI), it allowed the categorization of malaria risk at a finer spatial resolution. In the Pacific region, 69 out of 179 municipalities had moderate to high-risk areas •Additionally, a statistically significant relationship was found between the presence of *Anopheles darlingi* (X^2 = 21.022, p = 0.0002) and *Anopheles nuneztovari* (X^2 = 12.932, p = 0.0059) with the high-risk category; and *Anopheles albimanus* with the low-risk category (X^2 = 13.62, p = 0.004). It was also observed that the presence of a single species is related to a low risk, while the co-occurrence of two or more species increases the risk from moderate to high (X^2 = 88.008, P < 0.005)			

Table 6 shows the main results of the reviewed articles that evaluated the relationship between malaria incidence, climatic variables, and deforestation.

Discussion

The review highlights limited exploration of the relationship between deforestation and malaria in Latin American literature, with most studies conducted in Brazil and two in Colombia. Historical deforestation patterns and specific local conditions are crucial for understanding malaria risk, as highlighted by Olson and Achcar [28, 33].

Olson found that malaria risk increased by 33% for a 4.3% increase in deforestation, between 1997 and 2000, while deforestation from 2001 to 2006 did not correlate with malaria risk [28]. Similarly, Achcar observed a temporal alignment between deforestation rates and malaria incidence, increasing from 1999 to 2004 and then declining, underscoring the complex interactions between environmental and epidemiological trends [33]. Baeza et al. propose that malaria risk may follow different trajectories in the short term, showing an increase in malaria incidence in the early stages of deforestation, followed by a decrease as the vector reaches endemic levels [39].

The studies analysed showed that there are significant regional variations in the correlation between deforestation and malaria in the same country, as evidenced in the studies by Terrazas and Santos. Terrazas reported higher rates of malaria in Manaus and Río Negro, with a significant positive correlation between annual deforestation and malaria incidence, explaining 35% of the variation [31]. Santos further showed that for every 100 km^2 of deforestation, 7.26 additional cases of malaria were recorded per thousand inhabitants, and neighboring municipalities also experienced an increase in malaria cases due to deforestation, indicating the broad regional impact of deforestation on malaria incidence [24]. While, to Oliveira-Padilha (2019), the relationship between deforestation and malaria can differ even within the same country. In Acre, a positive association between malaria incidence and deforestation was observed, while in Rondônia the opposite behaviour was observed, suggesting that the implications of deforestation on malaria risk are heterogeneous and depend on the level of activity anthropogenic [22].

The interaction between environmental changes and malaria incidence is complex as shown by MacDonald and other authors. MacDonald found that a 10% increase in deforestation resulted in a 3.27% increase in malaria incidence, particularly in the interior regions of the Amazon [11]. However, extreme levels of deforestation could reduce the incidence of malaria due to habitat degradation, and each 10% increase in municipal forest cover is associated with 4.32 additional malaria cases per thousand inhabitants [24]. Additionally, Chaves (2018) noted that smaller and more numerous forest patches were correlated with an increase in malaria cases, further complicating the relationship between deforestation and malaria [25]. Stefani (2013) supports this finding and shows that deforestation is strongly associated with an increased risk of malaria soon after forest clearing, but the risk may decrease as deforestation intensifies due to urbanization or large cultivated areas [10].

However, some studies, such as those by Hahn and Oliveira-Padilha, present contradictory findings on the impact of deforestation on the incidence of malaria. Hahn (2014) found that in timber-producing states, municipalities with low percentages of selectively forest clearing had the highest risk of malaria, while areas with high rates of selective logging had the lowest risk, which suggests that different types of deforestation activities could influence malaria risk. differently [30]. Oliveira-Padilha reported that, in Rondônia, higher levels of deforestation were associated with a reduction in malaria cases, while, in Acre, increased deforestation was correlated with a higher incidence of malaria, which indicating that landscape modification plays a crucial role in the spread of the disease [22]. While, Feged-Rivadeneira (2018) found no relationship between the intense transmission of malaria in endemic areas of the Colombian Pacific and deforestation patterns, but noted a direct association in areas with high gold exploitation, promoting the endemicity of malaria in those regions [19].

Regarding climatic variables, the review of various articles indicates a positive seasonal effect linked to increased precipitation and average temperature in the malaria incidence in Colombia and LAC (Latin America and the Caribbean) between 2000 and 2020. This relationship is evidenced by several studies, highlighting the significant impact of climatic variables on malaria transmission [15, 16, 21, 23, 27, 34, 35].

In French Guiana, four studies conducted during different periods emphasize the region's unique climatic conditions. Known as one of the most humid regions globally, French Guiana experiences annual rainfall between 2,000 and 4,000 mm, with a wet season extending from December to July [40]. These climatic factors significantly influence malaria transmission dynamics in the region [15, 16, 34, 35].

Studies by Hurtado and Amarilis, spanning 1980–2013 and 1980–2002 respectively, reveal differing patterns of malaria epidemics in Panama. Hurtado observed distinct seasonal malaria patterns, with cases primarily occurring in December, January, and February from 1980 to 2002, and significant increases in November and the dry season from 2003 to 2013 [21]. In contrast, Amarilis found maximum malaria cases in September and March without clear seasonality [38].

Multiple studies highlight the correlation between the El Niño phenomenon and malaria incidence. In Colombia, a 1 °C change in ENSO variables could lead to a 17.7% to 9.3% change in expected malaria cases, with even higher impacts in specific regions such as the Pacific and Atlantic, reaching 22.9% and 23.4%, respectively, for a 1 °C change [20]. This significant relationship underscores the profound influence of El Niño on malaria incidence in these areas [15, 16, 20, 29, 32, 36, 38].

Conversely, studies in Brazil, French Guiana, and Ecuador did not show a clear link between climate and malaria, suggesting that non-climatic factors such as fumigation, medicine availability, and population migration play a more substantial role in these regions [15]. These findings highlight the complex interplay of factors influencing malaria transmission and the need for region-specific studies.

The variability in vector species and their seasonal abundance significantly impacts malaria behaviour in the region. Entomological studies reveal that the abundance of *Anopheles darlingi* mosquitoes increase one month before the rainy season, as observed in French Guyana, Brazil, and Colombia [17, 25, 34]. In Colombia, *Anopheles nuneztovari* and *Anopheles albimanus* are associated with high-risk and low-risk malaria categories, respectively [17].

A longitudinal survey in Urabá-Bajo Cauca and Alto Sinú found *An. nuneztovari* to be the most abundant species at the beginning of the rainy season, while *Anopheles pseudopunctipennis* was predominant during dry periods [41]. These findings indicate that the seasonal abundance and species diversity of malaria vectors can vary significantly, influencing malaria transmission patterns.

The reviewed articles predominantly used ecological studies (22) and cohort studies (2) [35, 37]. These studies employed various designs, including exploratory and analytical approaches, with time series analysis and multiple group studies being common.

Common statistical methods included negative binomial regression [18, 20, 30], Poisson regression [20, 27, 33], multivariate regression [25, 28, 32], the Spearman rank correlation coefficient [16, 25, 29], and linear regression [17, 25, 31]. Precipitation and temperature were the most studied covariates, followed by land cover and El Niño-Southern Oscillation (ENSO).

Notably, these ecological studies have presented further methodological development, such as the control of extreme values in time series, which reduces estimation bias [42, 43]. This is important for subsequent studies that include these variables in spatiotemporal analyses and propose optimal altitude and temperature ranges for disease transmission, helping suggest more specific control measures.

The ecological studies, the sources of information are mainly secondary sources, in which data validation must be carried out in order to build robust models that allow estimating the dynamics of different diseases transmitted by vectors such as malaria and their behaviour with other variables [44]. Strengthening national surveillance systems and standardizing data collection protocols are essential for accurate malaria risk estimation.

The studies reviewed were primarily conducted in Brazil (11), French Guiana (4), Colombia (4), Ecuador (2), Peru (2), Panama (2), Venezuela (2), Guyana (1), and Suriname (1). This regional distribution shows the need for more comprehensive studies across Latin America.

The studies reviewed indicate regional variations and complex interactions between environmental factors and malaria incidence. Tailored approaches to malaria management in deforested areas are needed, considering the diverse and sometimes contradictory deforestation effects on malaria transmission. Integrating satellite imagery and remote sensing data can improve understanding and management of the spread and intensity of malaria [3, 19, 23].

Deforestation influences malaria incidence, with impacts varying by region, period, and environmental factors. The complex interactions between deforestation and malaria underscore the need for targeted control measures and robust data analysis methodologies to effectively manage malaria risk in deforested areas.

Conclusions

This review of articles examined the relationship between climate variables, deforestation, and malaria incidence in Colombia, Latin America, and the Caribbean between 2000 and 2020, evidencing the following findings.

The relationship between climatic factors such as precipitation, temperature, and the El Niño phenomenon (ENSO) and malaria incidence is well documented in the region studied. Rainfall shows a positive correlation with malaria rates in countries such as Colombia, Ecuador, French Guiana, Guyana, Peru, Brazil, and Venezuela. Variations in climate, such as floods and droughts, significantly affect malaria transmission, highlighting the complex interplay between climate and malaria dynamics. Several studies highlight the strong influence of the El Niño phenomenon on malaria incidence.

Malaria incidence follows seasonal patterns, with peaks occurring during and after rainy seasons. This seasonal variability is crucial for planning and implementing effective malaria control measures. Temperature changes significantly affect the risk of malaria.

The relationship between deforestation and malaria is complex and region-specific. While some studies indicate that deforestation increases the risk of malaria by altering mosquito habitats, others suggest that extreme deforestation may reduce the incidence of malaria due to habitat degradation. There are important regional variations in how climatic factors and deforestation impact malaria incidence. In Brazil, for example, higher levels of deforestation are associated with different malaria risks depending on the region and period. Similarly, in Colombia, deforestation and gold exploitation are linked to malaria endemicity in certain areas.

The studies reviewed predominantly used ecological and cohort study designs, employing various statistical methods to analyse the data. Negative binomial regression, Poisson regression, multivariate regression, and linear regression were commonly used to explore the relationships between climate variables, deforestation, and malaria incidence.

The regional distribution of the studies indicates the need for more extensive research in Latin America. Integrating satellite imagery and remote sensing data can improve understanding and management of the spread and intensity of malaria.

Supplementary Information

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Supplementary material 1: PRISMA 2020 Checklist

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Author contributions

[CBC, NA, FDLH] contributed to the conceptualization and design. [CBC, ABVR] data analysis of this study. [CBC] drafted the manuscript. [NA, FDLH] contributed to reviewing and editing. All authors read and approved the final manuscript. The authors declare that they have no competing interests. CBC and ABVR: design of the work; analysis and interpretation data, prepared figures and wrote the main manuscript text. NA and FDLAHR: design of the work; supervision and editing.

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Availability of data and materials

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request. Data sharing is not applicable to this article as no datasets were generated or analyzed specifically for this manuscript beyond the results discussed.

Declarations

Ethics approval and consent to participate

Not applicable. This research does not involve human participants, human data, or animal studies.

Consent for publication

Not applicable. This manuscript does not contain any individual person's data.

Competing interests

The authors declare no competing interests.

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