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Spatiotemporal analysis of malaria incidence in Côte d'Ivoire from 2015 to 2019

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Background: The collection of malaria cases over time allows the identification of areas with the highest incidence. Our objective was to characterize the spatial distribution of malaria in Côte d'Ivoire from 2015 to 2019 at the health district level.

Methods: Data on the number of reported malaria cases confirmed by rapid diagnostic test (RDT) in the general population, the number of patients attending medical consultations and the total population by health district and year were collected from the National Malaria Control Program in Côte d'Ivoire. Crude and adjusted incidence rates were estimated for each health district and year. Adjusted incidence rates were used to perform global (Moran's index) and local indicators of spatial autocorrelation (LISA) analyses.

Results: Between 2015 and 2019, mean crude incidence rates increased from 155.5‰ to 229.8‰. We observed significant heterogeneity in malaria incidence rates across the study period and within a given year. The overall Moran index showed spatial autocorrelation for every year analysed except 2017. The LISA analysis showed that the health districts with high incidence rates were concentrated in the western zone of Côte d'Ivoire.

Conclusions: The use of spatial analyses to identify the areas with the highest malaria incidence rates is a relevant approach to optimize control measures in targeted areas.

Keywords: Côte d'Ivoire, malaria, spatiotemporal analysis

Introduction

A total of 241 million people worldwide were infected by malaria in 2020.[1] In the annual health report of Côte d'Ivoire, 5 935 178 malaria cases were declared during the same year.[2] One of the Millennium Development Goals (MDGs) established in 2000 by the United Nations was to reduce by 75% the global malaria burden in 2015. Between 2000 and 2015, the malaria incidence rate decreased from 146‰ to 91‰ worldwide. In sub-Saharan Africa, the area with the highest transmission, the incidence rate decreased from 408‰ to 235‰.[3] These results show a significant decline of the disease, even if the initial objectives are far from being reached.[4] In 2015, the United Nations launched new Sustainable Development Goals (SDGs). One of the goals is to eliminate malaria by 2030 by providing universal access to malaria prevention, diagnostics and treatment. To that end, disease surveillance is necessary to target interventions.[5]

In endemic countries, malaria cases are diagnosed and recorded daily in health structures to provide monthly and annual reports. These make it possible to evaluate the control efforts led by organizations and the authorities to fight the disease.[2] The systematic collection of data on malaria enables a retrospective analysis of the disease to follow its evolution.[6,7] Geographic information systems (GIS) are powerful tools for aggregating, storing and analysing massive data (epidemiological, demographic, entomological and others). In addition, they provide a decision-making tool by highlighting disparities in the spatial distribution of these data.[6,7]

In Côte d'Ivoire, malaria is the leading cause of medical consultation, with >5 million cases reported in 2019.[2] However, situational analysis survey results show a decreasing trend, as malaria accounted for 50.2% of the consultations in 2010, 43% in 2012 and 33% in 2014.[8]

According to the Malaria Strategic Plan 2021–2025,[9] the incidence of malaria is structured into five classes at the national level. Environmental factors as well as uneven use of malaria control and prevention measures justify this hierarchy of malaria incidence rates.

Many studies focused on malaria are conducted in Côte d'Ivoire but do not address the temporal and spatial evolution of the disease.[2,9] The objective of our study was to analyse malaria evolution from 2015 to 2019 in order to identify the health districts with the highest incidence rates that require better control efforts.

Methods

Study area

This study was conducted in Côte d'Ivoire. The country has 28 million inhabitants[10] distributed over an area of 322 463 km^2. In 2018, >81% of the population lived in areas where malaria incidence ranged between 300‰ and 500‰.[11] Three major mosquito species, *Anopheles gambiae*, *Anopheles funestus*, and *Anopheles nili* are responsible for transmission of the disease. However, the geographical distribution of the disease vectors varies. While *A. gambiae* is the main vector encountered, it is also accompanied by *A. nili* in the southwest region and by *A. funestus* in the centre and west regions.[12] *Plasmodium falciparum* species is responsible for 95% of malaria infections.[13]

Côte d'Ivoire is characterized by two main types of vegetation: forest and savannah.[14] In terms of the agro-climatic context, four zones can be defined. The Basse Côte d'Ivoire encompasses the south and southwest highlands, including that of Man, and is covered by dense humid forest (hyper- and umbrophilic sectors). The centre of Côte d'Ivoire is limited in the north by the two branches of the 'V Baoulé', in the west by the Sassandra region and in the east by Ghana. It is covered by semideciduous forest (mesophilic sector). The pre-forest area of Côte d'Ivoire is located with the 'V Baoulé' on one side and a central strip above the mesophilic forest on the other side. The northern region belongs to the Sudanian sector, subdivided from north to south into three zones: the Sudanian sector, the sub-Sudanese sector and the clear forest.

The health map was modified from 2015 to 2019.[2] From 82 health districts in 2015 and 2016, the country was divided into 83 health districts in 2017 and 86 health districts in 2018 and 2019. As long as the creation of a new health district corresponds to the splitting of an existing health district, we conserve the division into 82 health districts (Figure 1).

Data collection

The data used in this study were obtained from the National Malaria Control Program (NMCP) in Côte d'Ivoire after validation. These data correspond to the monthly malaria cases detected by public and private health facilities, as well as cases identified during home-based management. Data from hospitals and university hospital centres are excluded, as they are considered referral facilities.

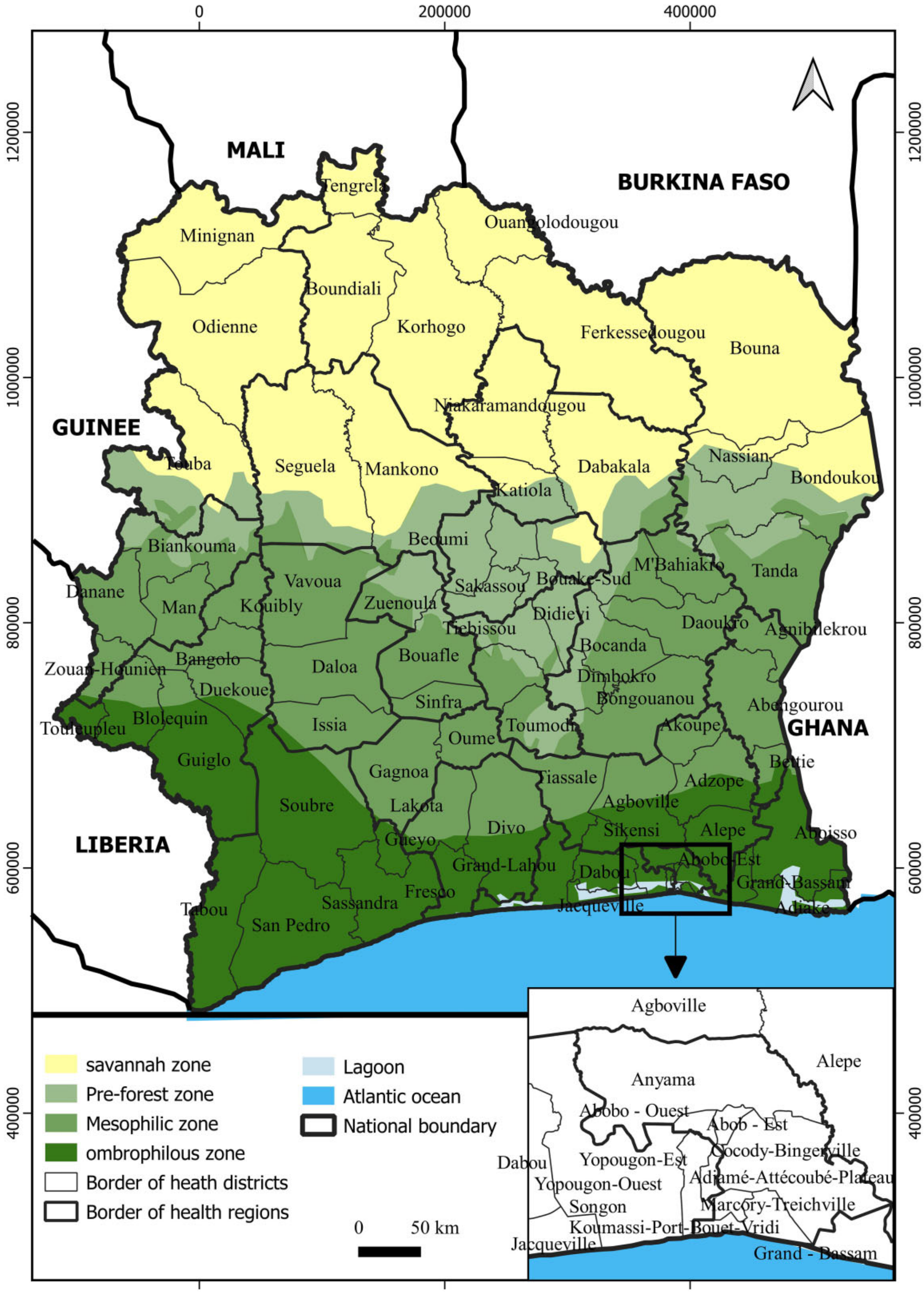
A malaria case is suspected if the axillary temperature is ≥37.5°C or if there is a fever history in the previous 48 h. A thick drop or a rapid diagnostic test (RDT) should then be performed to confirm the disease, depending on the health structure level. The patients are registered in the file of people who came for consultation, and if the result of the malaria test (RDT or thick drop) is positive, they are included in the batch of malaria cases registered for the current month.

In public and private health facilities with a laboratory, qualified personnel called 'medical biology technicians' perform the thick drop test. In remote health centres without a laboratory, patients are tested with an RDT by nurses. In the communities, community health workers (CHWs) carry out the RDT. These CHWs are trained by technicians recruited by the NMCP and its partners.

The Department of Informatics and Health Information (DIHI) is responsible for health data management in the country, including malaria data.[2] Each health facility reports monthly all the activities carried out, including the number of cases of all the diseases observed during the month and prevention and sensibilization activities. After working sessions at the health region level, the epidemiological surveillance officers use the District Health Information Software (DHIS), which is an open-source software platform for reporting, analysis and dissemination of data for all health programs. The data are then approved by the DIHI after several workshops in which the NMCP officers participate. Finally, these validated data are published by the DIHI in the annual health report. Partners such as the NMCP have the ability to retrieve these data on the platform for analysis. Data management has moved forward in the second part of 2016 with the implementation of the DHIS 2 platform in pilot sites such as San Pedro, Abengourou and other health districts. The DHIS 2 platform was successfully expanded throughout the country in 2017.[15]

Data provided by the NMCP were classified according to two age groups: the general population and children ages 0–4 y, regardless of gender. The number of people attending a medical consultation in healthcare structures and the population size of each district were also collected from these institutions. These data are used to calculate the crude incidence rate and the adjusted incidence rate of malaria in the country per district and per year.

The crude incidence rate corresponds to the number of new malaria cases observed over a specified period and in a designated area, divided by the total population in the area and multiplied by 1000.[2,7] As the attendance rate of health structures differs from one health district to the next, the crude incidence rate is adjusted according to the attendance rate. To calculate the adjusted incidence rate, we first calculate the adjusted number of malaria cases. The number of confirmed malaria cases is divided by the attendance rate and multiplied by 100 for a specific health district. The adjusted incidence rate is obtained by dividing the adjusted number of malaria cases by the total population of each study site and multiplying the number by 1000.[16,17]



Source : DIIS / RASS , 2015-2016

Cartography by Mardoché Azongnibo , 2022

Figure 1. Distribution of the 82 health districts in Côte d'Ivoire in 2015.

Data analysis

In order to analyse the evolution of malaria in Côte d'Ivoire from 2015 to 2019, we first calculated the crude annual incidence rates, then the adjusted annual incidence rates for each health district. The results were mapped according to the division of the NMCP.[13] Next we calculated Moran's global spatial autocorrelation index (Moran's I) for the adjusted incidence rates. Moran's I indicates if the spatial distribution of the adjusted incidence rates is clustered, dispersed or random. A positive Moran's I indicates the presence of a cluster of similar incidence rates, which is not however locatable.[17,18] When Moran's I was positive, we undertook further analyses by using local indicators of spatial association (LISA). The LISA method makes it possible to locate spatial aggregations of high or low values.

Moran's I is an inferential statistic, meaning that the results of the analysis are always interpreted in the context of the null hypothesis. In the case of our study, it supposes that the health districts with adjusted incidence rates are distributed randomly among the entities of the studied area:[17,18]

$$I_{Moran} = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_j - \bar{x})^2},$$

where i, j is the spatial unit, n is the number of spatial units, xi is the value of the variable in the unit i, x is the average of x and w_{ij} are the elements of the spatial interaction matrix to define spatial contiguity, distances or shared borders.

If the p-value is not statistically significant, the null hypothesis cannot be rejected, as the spatial distribution of health districts according to the adjusted incidence rates may be the result of random spatial processes.[17] When the p-value is significant (<0.05), the null hypothesis is rejected, meaning that the adjusted incidence rates are not randomly distributed.

When the p-value is statistically significant and the z-score is positive, the null hypothesis can be rejected. In this case, the spatial distribution of the health districts according to the high and/or low adjusted incidence rates is subject to a spatial aggregation that is more important than would be expected if underlying spatial processes were random. If the p-value is statistically significant and the z-score is negative, the null hypothesis can also be rejected. The spatial distribution of the high and/or low adjusted incidence rates is subject to a spatial dispersion that is more important than would be expected if underlying spatial processes were random.

Proposed by Anselin,[18] the LISA and Moran's local index were designed in order to decompose global indicators, namely Moran's I. The LISA must meet two requirements. First, the LISA for each observation indicates the significant spatial clustering of similar values around that observation. Second, the sum of the LISA for all observations is proportional to Moran's I of spatial association:

$$I_i = \frac{\sum_j w_{ij}(p_i - \bar{p})(p_j - \bar{p})}{\sum_i (p_j - \bar{p})^2},$$

where p_i and p_j are the values of spatial units i and j such as i and j are considered neighbouring values given their degree of proximity, p_i is the mean value of spatial units and w_{ij} is the proximity measurement of spatial units i and j.

Moran's I is the most widely used to describe spatial clusters of observations with high or low values. Unlike Moran's I, which only provides one statistic, Moran's local index is calculated for each individual observation.

The statistical significance of Moran's local index can be determined through several approaches. A basic approach consists of calculating the z-scores of Moran's local index for each observation i. A significant positive z-score (e.g. $z > +1.96$) indicates that observation i and its neighbour values have similar significant values (spatial clusters with high or low values). A significant negative z-score (e.g. $z < -1.96$) indicates that the value of observation i is significantly different from the neighbour values (spatial clustering with aberrations).

Moran's local index can be visualized in both the Moran scatter plot and on a map. Moran's scatter plot shows the relationship between the value of the observation variable and the mean value of the variable in the neighbouring locations. It is organized into four quadrants: high–high, high–low, low–low and low–high. Calculations of Moran's scatter plot are detailed in the global measures of spatial clustering. Local results of Moran's index can then be represented by colour, according to the scatter plot quadrant, on a map showing spatial clusters (high–high, low–low) and spatial aberrations (high–low, low–high).[18]

In this study, statistical analyses were performed with R version 4.1.2 (R Foundation for Statistical Computing, Vienna, Austria). Moran's index and LISA analyses were carried out with GeoDA version 1.20. We used QGIS version 3.16 for mapping.

Results

Descriptive analysis

The average crude annual incidence rates ranged from 155.5‰ in 2015 to 229.8‰ in 2019. The adjusted incidence rates ranged from 354.4‰ (2017) to 548.2‰ (2019) (Figure 2).

In 2015, only two health districts, Jacqueville in the south and Sakassou in the centre of the country, had high crude incidence rates (ranging between 400‰ and 499‰) (Figure 3). For 2016 and 2017, none of the health districts had a crude incidence rate >400‰. In 2018, five health districts had high crude incidence rates and one (Sakassou) had a very high incidence rate (≥500‰). In 2019, 11 health districts had high incidence rates.

In 2015, 18 health districts had a very high adjusted incidence rate (≥499‰) (Figure 4). This number rose to 23 in 2016. In 2017, we observed a heterogeneous pattern of malaria incidence, as health districts had very low to very high incidence rates of malaria. We also observed a decrease in the number of health districts with a very high incidence rate (n=9). In 2018 and 2019, the number of health districts with a very high incidence rate increased from 44 to 55. During that period, only the health districts in the city of Abidjan showed very low to low adjusted incidence rates (<299‰).

Spatial analysis

The spatial analysis of the adjusted incidence rate of malaria highlighted a positive spatial correlation between the different health districts every year, except for the year 2017 (Table 1). Therefore we conducted LISA analyses for 2015, 2016, 2018 and

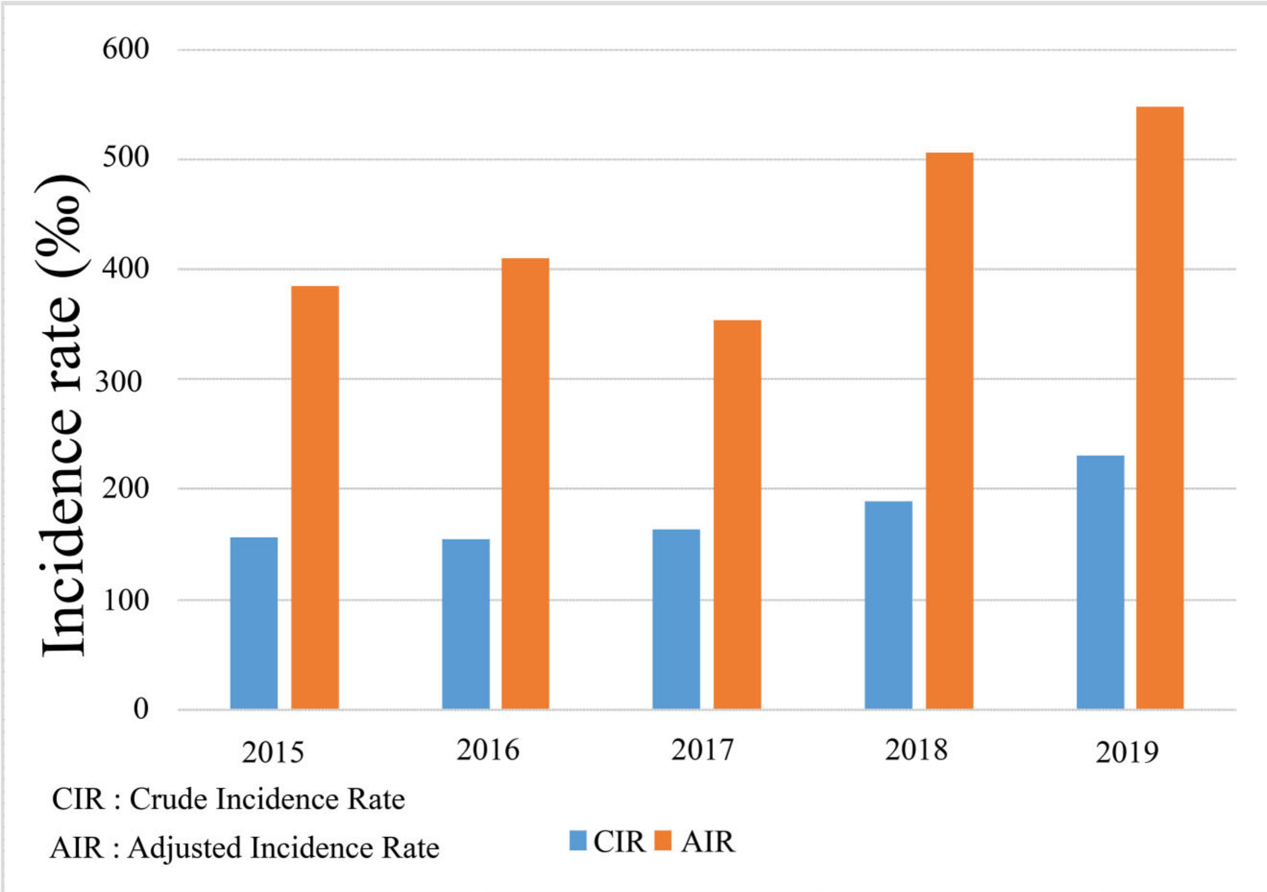


Figure 2. Annual incidence rates of malaria between 2015 and 2019.

2019 to highlight clusters of health districts with similar adjusted incidence rates.

We observed a cluster of health districts with high malaria incidence rates in the western part of Côte d'Ivoire (Figure 4). In the southern part of the country we observed a cluster of health districts with low malaria incidence rates. From 2015 to 2016, the health districts of the northeast showed lower incidence rates of malaria, although they were located near the Nassian district, which has a very high incidence rate. In 2018 and 2019, the malaria incidence rate of the health districts near the city of Abidjan progressively increased from a very low to a low incidence rate.

Discussion

This study shows that between 2015 and 2019, the annual crude and annual adjusted incidence rates of malaria increased in Côte d'Ivoire. This evolution could be explained by several factors.

First, the integration of community and private for-profit data into DHIS 2 began in May 2018 with the agreement of all stakeholders on indicators and collection tools.[11] Furthermore, in 2018, the country implemented a home-based care strategy for malaria cases (*Prise En charge des CAs de paludisme à DOMicile* [PECADOM]) and extended consultations in the most vulnerable areas in major cities. In addition, all of the health sectors, including the for-profit private sector, are now sending consultation data to the Ministry of Health.[11] Finally, a greater use of RDTs from 70% to 84% between 2016 and 2018 and the inclusion of suspected malaria cases can also explain the increase of declared malaria cases.[9]

Furthermore, the spatial analyses highlight a significant heterogeneity of incidence according to the health districts and a non-random distribution, except during the year 2017. This result can hardly be attributed to the quality of the data that were validated. However, it could be explained by a change in data management that began in the second half of 2016 with the implementation of the DHIS 2 platform tested in some health districts and then generalized in 2017 throughout the country. The decline in malaria incidence recorded in 2017 can be linked to this new system, as the national reporting completeness rate was at its lowest in that year, at 95.4% (compared with 99.3% in 2019). However, it is unclear whether this poor score applies to all activities, including malaria case reporting. In addition, not all of the stakeholders were yet providing their data, as consensus on data supports and indicators was only reached in May 2018.

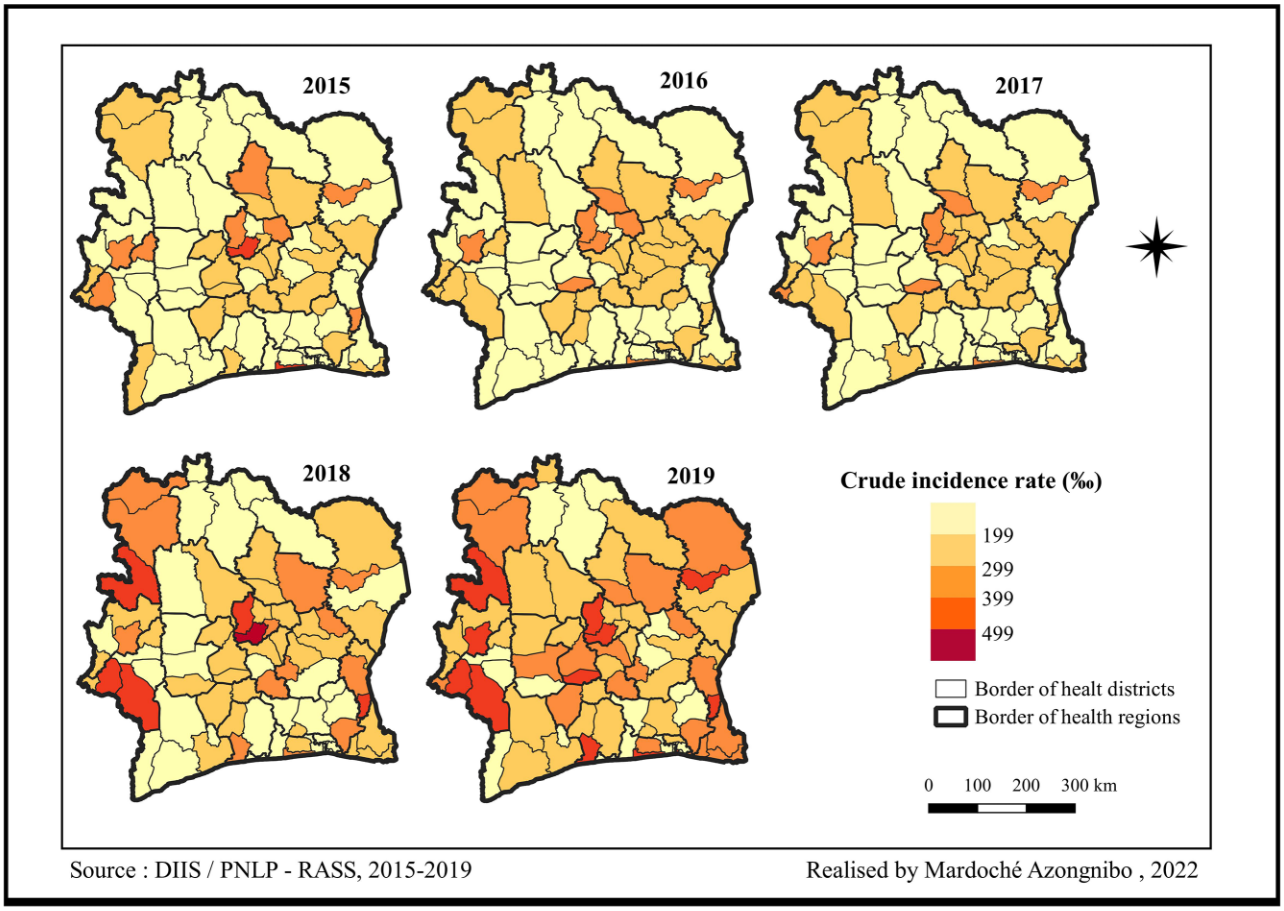


Figure 3. Crude incidence rates of malaria in the general population from 2015 to 2019 according to health districts in Côte d'Ivoire.

The LISA analyses made it possible to locate clusters of health districts with a high malaria incidence in the western part of Côte d'Ivoire. Moreover, clusters of health districts with a low malaria incidence have been found in the south, especially around Abidjan. Significant heterogeneity in malaria prevalence had already been observed in children ages 6–59 months[19,20] and 6–11 y.[21] Raso et al.[22] used collected prevalence data between 2007 and 2012 to show that the western part of Côte d'Ivoire was a high-risk area for malaria transmission. Similarly, entomological studies identified this part of the country,[23] especially the Man health district, as a high-risk area for malaria transmission.[12,13,23] More than 20 y ago, Nzeyimana et al.[24] attributed the high level of transmission and the high prevalence of the disease in the region to ongoing deforestation.

This is the most elevated region in the country, with many valleys and a climate characterized by a long rainy season, which explains the permanent occurrence of vectors. Studies conducted in 2015 and 2019 by the NMCP highlighted the very high entomological transmission with 348.6 bites/person/y in rural areas and 166.6 bites/person/y in urban areas in the health district of Man (unpublished data by the National Malaria Control Program).

In broad terms, it can be seen that the high-incidence health districts are located in bioclimatic zones favourable to permanent and high transmission, although this might not be the only reason for clustering in the western part of the country.

Our study identified clusters of health districts with high incidence rates in the central part of Côte d'Ivoire. These findings are consistent with observations of previous studies conducted in Taabo[25] and the rural area of Bouaké.[26]

Our approach makes it possible to locate areas with high malaria incidence. This method can be used in the fight against malaria by identifying the areas in need of better control efforts, as was previously demonstrated in the Comoro Islands[27] and in Madagascar.[7] It has also been used in West Africa, notably in Bandiagara (Mali), but on a different scale.[28] In Bandiagara, the household was the reference spatial unit, while our study used the health district as the reference spatial unit. However, other surveys in China[6] and Madagascar[7] based on the district health scale have demonstrated its relevance.

Although clusters of health districts with high incidence rates were successfully identified for 2015–2019, our study has limitations. The data used were collected through the healthcare system and are therefore strongly related to the attendance rates in

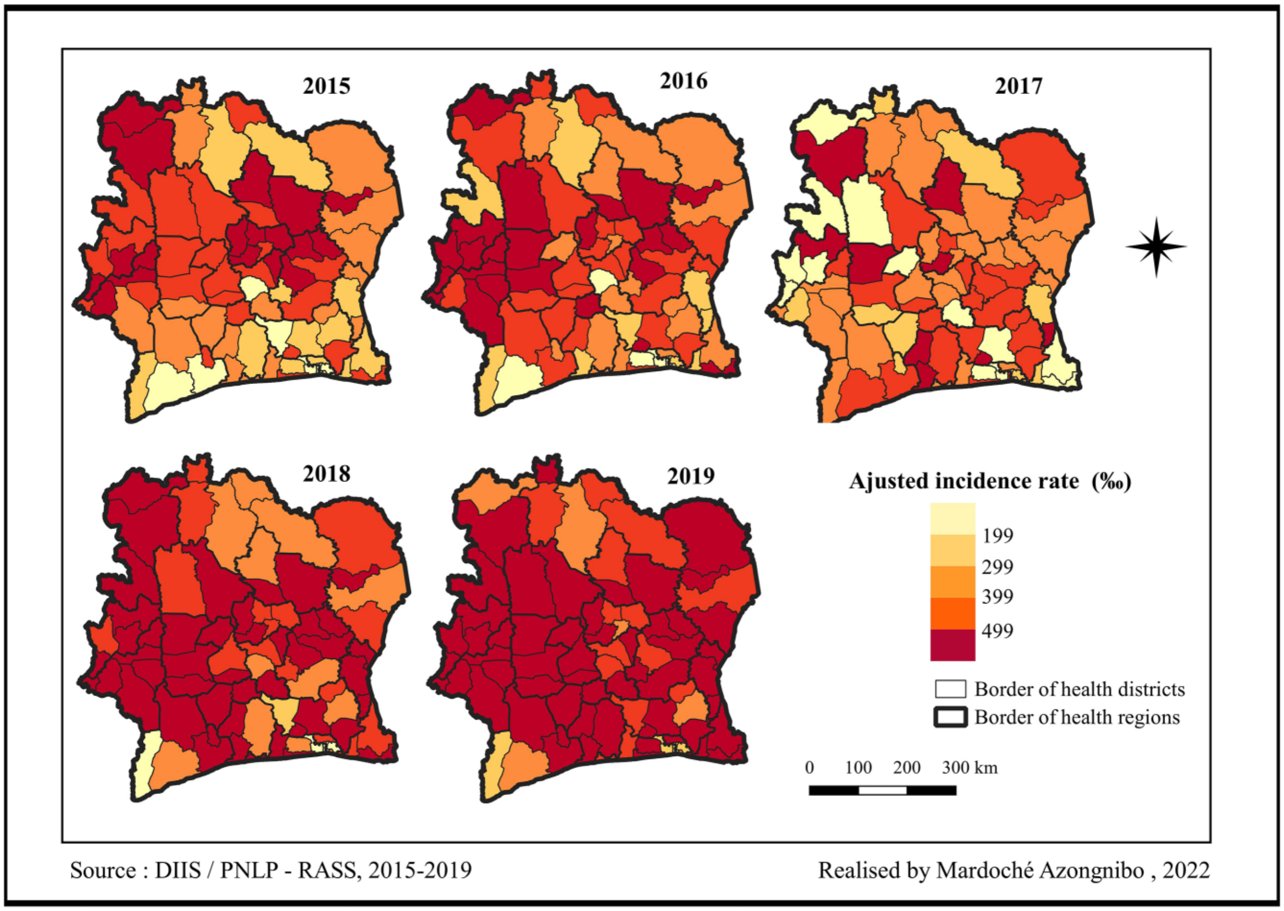


Figure 4. Adjusted incidence rates of malaria in the general population from 2015 to 2019 according to health districts in Côte d'Ivoire.

Table 1. Results of the spatial analyses conducted on the adjusted incidence rates of malaria from 2015 to 2019

Year	I	z-Score	p-Value	Decision
2015	1.334	16.279	0	Clustered
2016	1.247	15.165	0	Clustered
2017	0.033	0.551	0.581	Random
2018	1.190	14.523	0	Clustered
2019	1.378	16.833	0	Clustered

health facilities. The use of adjusted incidence rates based on the attendance rate of medical facilities makes it possible to correct the biases due to the use of data collected in a hospital environment.[29] However, this correction remains limited, especially since the attendance rate of healthcare structures remains relatively low in Côte d'Ivoire (52.7%), especially in rural areas.

In conclusion, our study showed that the spatiotemporal distribution of malaria in Côte d'Ivoire was very heterogeneous in space and time. Spatial analyses made it possible to identify clusters of health districts with high incidence rates. These areas require close attention, and actors in the fight against malaria could use these findings to optimize control strategies in targeted areas.

Authors' contributions: KRMA, FF, NGC and AMA designed the study protocol. The data were retrieved from the NMCP by KRMA, FF, SBA and PKA. The analysis, interpretation and writing were carried out by KRMA, EB and FF. NGC, MNWKD, KFA, MGN and PKA critically reviewed the manuscript for intellectual content. All authors have read and approved the final manuscript. KRMA and FF are the guarantors of the paper.

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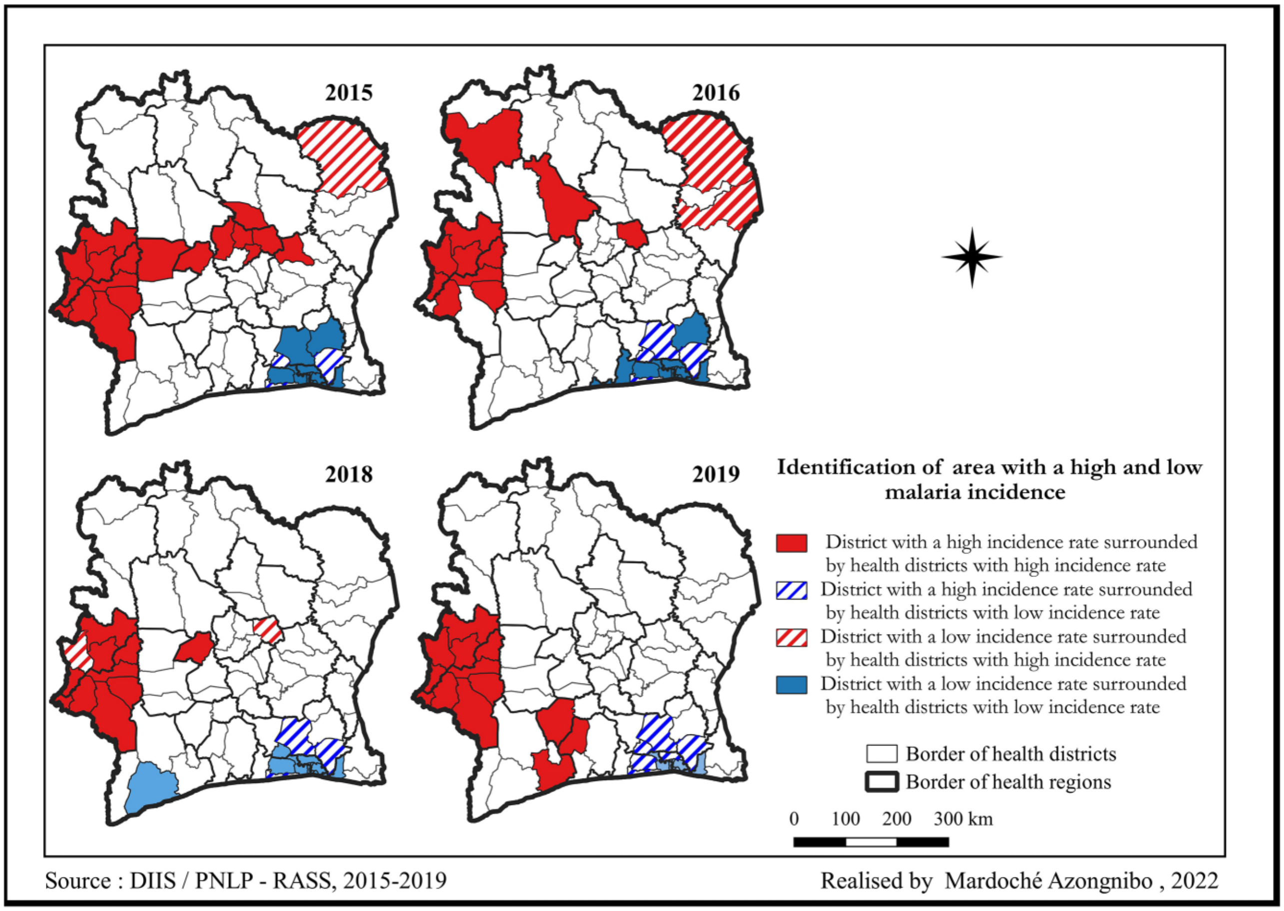

Figure 5. Identification of clusters of health districts with high and low malaria incidence rates from 2015 to 2019 according to the health districts in Côte d'Ivoire.

Ethical approval: Not required.

Data availability: The data underlying this article will be shared upon reasonable request to the corresponding author.

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