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Geographic modeling of weighted regression of self-reported malaria cases associated with environmental risk factors in Benin during the rainy season

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Abstract

Background: Geographically Weighted Regression (GWR) is a technique applied to capture variation by calibrating a multiple regression model, which allows different relationships to exist at different points in space. With malaria elimination at the top of the health agenda, integrated action on all elements of the malaria system that contributes to improved knowledge and local capacity building for positive effects on the health of the local population is needed.

Methods: Several variables were collected for 192 sampling points in 12 communes in Benin, one per department. A questionnaire was sent to the head of the household to analyze the impact of environmental factors on reported malaria cases. Numerous GIS classification software for spatial analysis, remote sensing, data analysis/modeling and GPS management, R and MGWR software were used for geographic modeling.

Results: An abundance of malaria cases reported in crop areas than in non-crop areas and in rural areas than in urban areas. The Hot Spot Analysis shows the localities of South Benin and Malanville as priority issue areas with a remarkable increase in crop diversity favorable to malaria vector proliferation. The spatial autocorrelation z-score of 4.83653470763 shows that there is less than a 1% probability that this clustered pattern is the result of chance.

Conclusion: The observed non-stationarity means that the relationship between the variables studied varies from location to location depending on the physical factors of the environment that are spatially autocorrelated. Environmental factors therefore influence the intensity of transmission, seasonality, and geographic distribution of malaria. With minimal funding, we plan to correlate these data with parasitological and entomological da.

Keywords: GWR, malaria elimination, entomological da, environmental risk factors, Benin

1. Introduction

In Benin, malaria remains a serious public health problem. In 2020, 2,289,948 people contracted malaria resulting in 2,450 deaths (MOH, 2022). It is and remains the number one disease that worries and bothers health workers in the country's health facilities and is, in turn, the leading cause of death among children under five. Malaria is now a major health problem in sub-Saharan Africa [1].

Malaria transmission is multifactorial with vector-related factors. In addition, Environmental factors influence the intensity of transmission, seasonality and geographical distribution of malaria, together with the vector, human and parasite, they constitute the malaria system. They are: land use, number of people in the household, characteristics, number of rooms in the household, type of house in hard or precarious material, presence of lodging around the houses, number of rainfall recorded in the month, ambient temperature in the area, elevation, presence of watercourses, presence of crops, type of soil, climate in the area, month of abundance of mosquitoes, means of control, vegetation cover (bushes, shaded areas). Understanding the influence of local environmental factors on malaria cases is an important element to better predict and control this disease [2].

Geographically Weighted Regression (GWR) is a spatial statistical technique that, like local aspatial regression, recognizes that traditional "global" regression models may be limited when processes vary with context. GWR captures spatial process heterogeneity (i.e., process variation with spatial context) via an operationalization of Tobler's first law of geography: "Everything is related to everything else, but things that are close are more related than things that are far away" [3]. A set of local linear models is calibrated to any number of locations by "borrowing" nearby data. The result is a surface of location-specific parameter estimates for each relationship in the model that can vary spatially, as well as a single bandwidth parameter that provides intuition about the geographic scale of the processes. In addition, GWR generally provides better model fit and reduced residual spatial autocorrelation compared to traditional "global" regression that assumes relationships are constant in space [4].

The significant sociodemographic, behavioral, and environmental changes observed in the region prompt consideration of the possibility of a resurgence in the number of cases, associated in particular with the development of resistance to insecticides and therapeutic treatments [5]. In the Guyanese transmission foci, environmental risk factors have been shown to be of primary importance [6, 7]. Indeed, these factors partly determine the presence, density and spatial distribution of the vectors of parasites, the female mosquitoes of the genus Anopheles. Among these environmental factors, land use and land cover play an important role in directly influencing the distribution and density of Anopheles, which can be used as an indicator of malaria transmission risk [8, 9, 10].

The phytosanitary practices of vegetable farmers are a growing threat to human health and the environment. Consistent with the results of other studies, malaria is generally higher in the oldest age group. Shwartz *et al.* reported that individuals over 40 years of age were more likely to be infected with malaria than those under 40 [11]. This was observed in both malaria-immune and non-immune patients, suggesting that increasing age may contribute to a higher risk of malaria [12]. This is of particular concern, especially for the farmers in this study, who are constantly exposed to malaria due to their outdoor agricultural activities during times when mosquitoes bite the most. Some have shown the use of high doses of unregistered insecticides (generally from cotton) and with high frequency, but also the non-respect of pre-harvest treatment periods [13]. Overall, Anopheles gambiae s.l. was the major vector complex, followed by Anopheles funestus and Anopheles nili, as previously reported in other regions of Benin [14, 15, 16]. At a time when malaria elimination/eradication is high on the health agenda, there is a strong need for integrated action that addresses all components of the malaria system, contributes to improved knowledge and local capacity building, and results in positive health outcomes for the local population.

This paper aims to model the knowledge on environmental factors related to the spatial distribution of malaria.

2. Materials and Methodologies

2.1 Study sites

The study was conducted from mid-June to July 2022, the peak malaria transmission season and the highly active agricultural [17], in 12 districts in Benin, one commune per department, and two sites were selected per commune. Data on cases of malaria are collected on the basis of a simple declaration by a survey sent to the head of the household about its members.

In addition, it should be noted that in each commune, two villages were selected: one peripheral and one urban. In each village, eight households were selected, four of which were at high altitude and four at low altitude, for a total of 16 households per commune, i.e. 192 households for the 12 communes surveyed (Figure 1).

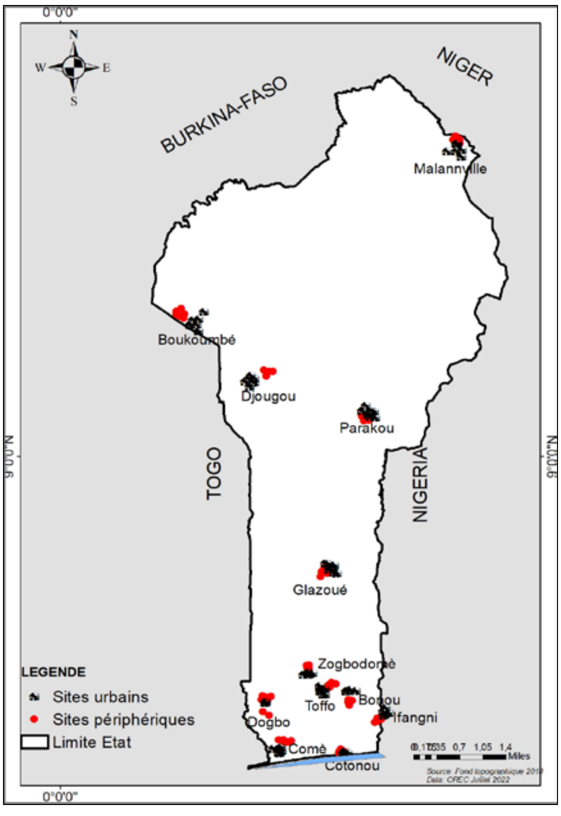

Fig 1: Map of Benin showing surveyed households

2.2 Data collected in the field
A total of 21 variables were evaluated (described below) for 192 houses in 12 districts of Benin, one per department to test the association with malaria cases. A questionnaire was administered with the head of the household to test if there is an association between the environmental factors and malaria cases on reported malaria cases. Further details on the variables and the dataset contain missing values (Table 1).

Table 1: Variables collected, their unit and description (Source: Data CREC)

Variables	Units	Description
Department	No	Administrative districts or territorial authority of the State
nb Cases Malaria Month In House	Malaria	The number of people in the household who contracted the disease during the month
Type House	No	Houses made of hard or precarious materials
Nearby Health Center	No	Knowledge of the nearest health center
Age	An	The respondent, a household member who knows the household well and is at least 18 years old before continuing with the questionnaire.
Gender	No	Male or female
nb Persons In Household	No	Household size
Built-upurbanland	No	Built-up urban land
Grasslands	No	A type of land use or biophysical cover of the land surface
Savannah	No	A type of land use or biophysical cover of the land surface
Presence_lodgings_Around	No	Presence of positive larval deposits of Anopheles spp. and/or. larvae of Aedes spp., the presence of other insects
Presence of LLINs	No	Presence of impregnated mosquito nets in the household
Sleep Under LLIN	No	Sleep under impregnated mosquito nets to protect yourself from mosquito bites
nb Rainfall Month	No	Number of rains in the area during the month
Ambient Temperature In Area	°C	Ambient temperature in the area
Elevation	meter	Elevation of the earth's surface
Presence Watercourse	No	Presence of overland flow of liquid water between a source and a mouth
Type Water Course	No	Types of watercourses: the gully, the lake, the stream, the torrent, the river, the stream.
Presence Culture	No	Presence of agricultural crops (rice plantations, banana plantations, market gardening.)
Type SoilIn Zone	No	Soil types in the area (hydromorphic, lateritic, clayey, sandy.)
Climate In Zone	No	The microclimate felt in the environment

Data processing was made possible by the use of some classification software: GIS and spatial analysis, remote sensing, data analysis/modeling, and GPS management software, R and MGWR.

GWR performs geographically weighted regression, a local form of linear regression used to model relationships of environmental elements on spatially varying malaria cases.

From a set of weighted features, we identified statistically significant hot spots, cold spots, and spatial outliers of environmental factors on malaria cases using the statistical tool Hot Spot Analysis (Getis-Ord Gi*).

Multiple Ring Buffer creates multiple buffers at specified distances around household malaria cases based on environmental characteristics. These buffers can eventually be merged and dissolved using the buffer distance values to create non-overlapping buffers. The Buffer tool, a geoprocessing tool in ArcToolbox's Analysis toolbox, generates buffer polygons, or offsets, around the input features at a specified distance. The buffers show the area that is within a certain distance of the input features, i.e., the edge cases with the vectors. This tool is popular because the concept of a buffer is easy to understand and buffering plays an important role in many geoprocessing workflows involving proximity or distance analysis (i.e., how far away are these features? or which features are at a certain distance from other features).

In the spatial autocorrelation framework, z-scores are standard deviations. If, for example, a tool returns a z-score of +2.5, this means that the result is a standard deviation of 2.5. Both z-scores and p-values are associated with the standard normal distribution.

Using R software, we performed the Likelihood ratio test, which assesses the goodness of fit of this distribution of observed malaria cases and then tests for differences in mean and/or count aggregation between treatments. Inferences about the differences in means between treatments as well as about dispersion more specifically a model found by maximizing over the entire parameter study space and another found after imposing a certain constraint. If the constraint (i.e. the null hypothesis) is supported by the observed data.

Negative binomial regression allowed us to model count variables, typically for overdispersed count outcome variables. This model allowed us to describe the distribution of count data, such as the number of parasites in blood samples, when that distribution is aggregated or contagious.

3. Results
3.1 Departmental distribution of malaria cases
We surveyed a total of 791 self-reported cases malaria cases in the 192 sites surveyed during the month of July, broken down by sex and department as shown in Table 2. The number of self-reported cases in sites or households varies from site to site, from household to household, or by sex.

Table 2 presents the number of cases malaria cases by department. It is broken down by sex. The analysis of this table shows that both sexes are affected by malaria. However, women are more infected than men. Self-reported women are most infected in the department of Ouémé, followed by the plateau, while in Couffo (followed by Zou) it is men who are most infected. This condition affects self-reported women less in Couffo and self-reported men in Mono. This could be explained by the fact that fewer women sleep under a mosquito net (or are more exposed because of their activities) and more men sleep under a mosquito net in general.

Table 2: Number of Self-reported malaria cases by department

Departments	Female	Male	General total
Alibori	32	29	61
Atacora	49	11	60
Atlantique	45	18	63
Borgou	9	38	47
Collines	34	20	54
Couffo	8	67	75
Donga	18	18	36
Littoral	10	54	64
Mono	41	8	49
Oueme	81	20	101
Plateau	65	40	105
Zou	15	61	76
General total	407	384	791

3.2 Evaluation of the influence of environmental parameters on self-reported malaria cases with the negative binomial model

3.2.1 Likelihood ratio tests of Negative Binomial Models

The evaluated negative binomial distribution shape parameter of the model is theta 126644.2.

The results of the model analysis of the variables show that the model is statistically significant (Table 3). The model: Negative Binomial (126644.2).

The significant p-values in both self-reported malaria cases suggest that malaria cases are more abundant in crop areas than in non-crop areas and more abundant in rural areas than in urban areas.

Table 3: Résultat du test de Likelihood ratio.

	theta	Resid. df	2 x log-lik.	Test	df	LR stat.	Pr(Chi)
1	24.96607	179	-637.9008				
2	126644.24402	112	-524.2992	1 vs 2	67	113.6016	0.0003304931

The table 4 shows that the main factors that directly influence the number of malaria cases are: age, type of land use and presence of agricultural crops, number of people in the room (p-value <0.05).

Table 4: Analysis of Deviance with the number of reported malaria cases as the dependent variable. Terms added sequentially (first to last); Df = degrees of freedom, Resid. Df. = residual degrees of freedom, Resid. Dev. = residual deviance.

	Df	Deviance	Resid. Df	Resid. Dev	Pr(>Chi)	Significant
NULL			179	173.283		
Department	7	30.039	172	143.245	9.342e-05	***
TypeHouse	1	3.252	171	139.993	0.071340	.
NearbyHealthCenter	1	0.009	170	139.984	0.924891	
Age	1	5.676	169	134.308	0.017203	*
Gender	1	0.088	168	134.221	0.767309	
nbPersonsInHousehold	1	35.402	167	98.819	2.682e-09	***
Built-upurbanland	1	7.635	166	91.184	0.005725	**
Grasslands	1	0.031	165	91.153	0.861238	
Savannah	1	0.146	164	91.008	0.702701	
Presence_lodgings_Around	1	0.310	163	90.698	0.577825	
Presence of LLINs	1	1.443	162	89.255	0.229633	
SleepUnderLLIN	1	0.224	161	89.031	0.635907	
nbRainfallMonth	1	0.645	160	88.386	0.421963	
Ambient Temperature In Area	3	5.171	157	83.215	0.159722	
Elevation	2	0.351	155	82.864	0.839001	
Presence Watercourse	1	2.918	154	79.946	0.087606	.
TypeWaterCourse	4	4.921	150	75.025	0.295448	
PresenceCulture	1	3.845	149	71.179	0.049884	*
TypeSoilInZone	36	11.428	113	59.751	0.999969	
Climate In Zone	1	1.089	112	58.662	0.296666	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

3.3 Malaria transmission risk area au Benin

With respect to malaria cases, the study confirmed that not only were the majority of these residents located near the river margin, lowlands, and food crops, but that they were also located within 200-1000 meters of the river. Figure 2 shows that all the characteristics favorable to malaria vector proliferation were found in the vicinity of the surveyed households. This map shows that the study area is split from 2 to 9 zones at risk of malaria transmission when the prediction goes from 200 to 1000 meters of buffer zone. Figure 2 presents the buffer zone of malaria cases in the 12 districts of our study area.

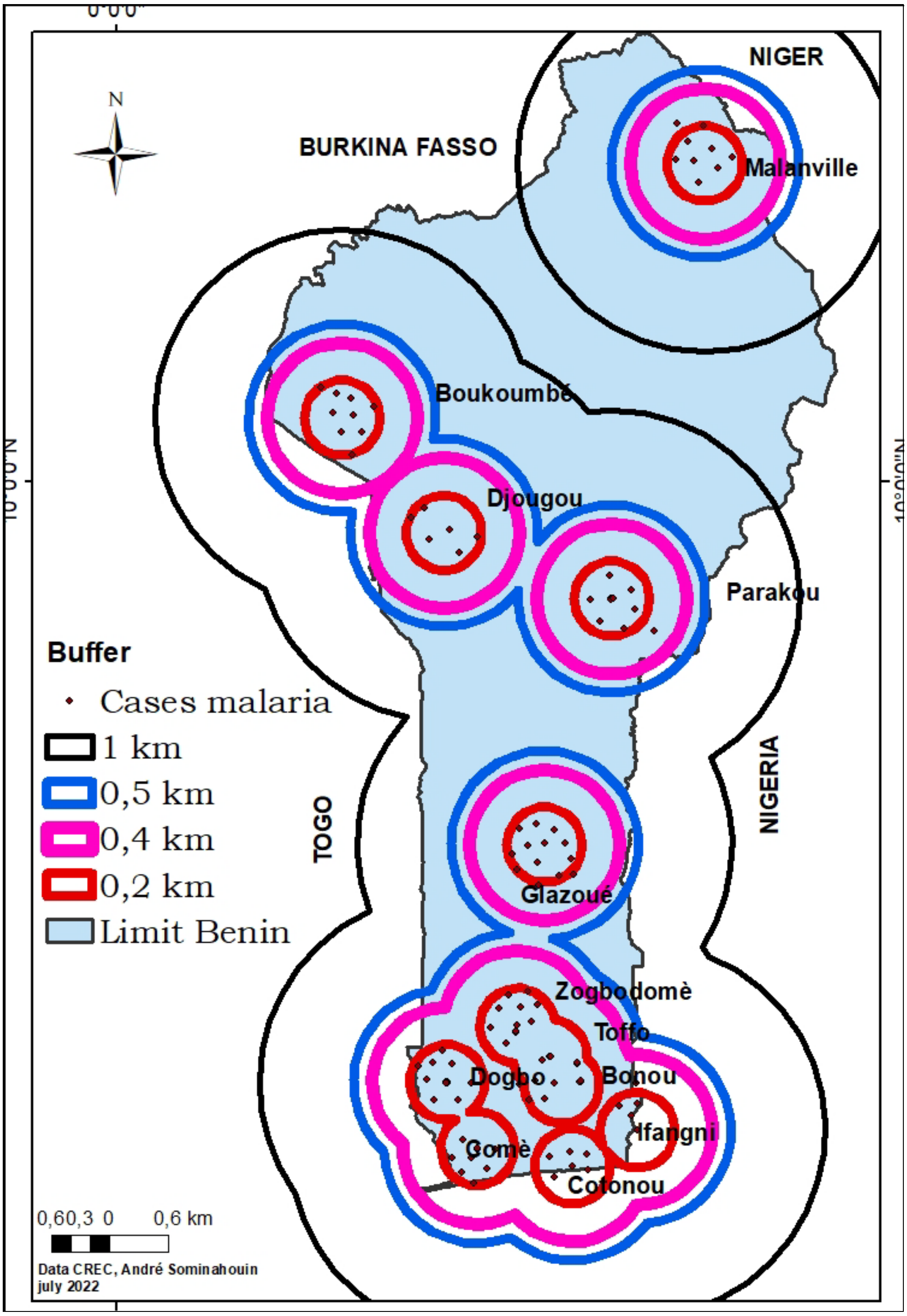

Fig 2: Buffer zone from 100 to 1000m of malaria cases in the urban/rural study area according to environmental parameters during July 2022

3.4 Modeling the determinants of malaria cases via GWR and Analysis Hotspot

As shown in Figure 3 (a), the adjusted R2 measure of the geographically weighted regression model is estimated to be 0.4895, which means that nearly 48% of the variation in agricultural practices is explained by the variation in malaria and stream cases. Bandwidth, a key parameter of geographically weighted regression (GWR) models, is closely related to the spatial scale at which the underlying spatially heterogeneous processes under consideration take place. It is estimated to be 4.788641. There is almost universal dispersion growth in the regression model of these statically significant factors that support the increase in malaria cases in Benin. Figure 3 shows non-stationarity, meaning that the relationship between the variables studied and varies from place to place as a function of physical environmental factors that are spatially auto correlated.

In addition, Figure 3b shows that the localities of South Benin in particular stand out as priority issue areas with a remarkable increase in the diversity of crops favorable to the proliferation of malaria vectors, using the spatial Hot Spot Analysis method (Getis-Ord Gi*). This is due to the ecological originality of these localities and the diversity of species found there. The northern localities except Malanville, on the other hand, inform us that the test is statistically insignificant; in simple terms, this generally means that we have no statistical proof that the difference between the presence of culture is not due to chance.

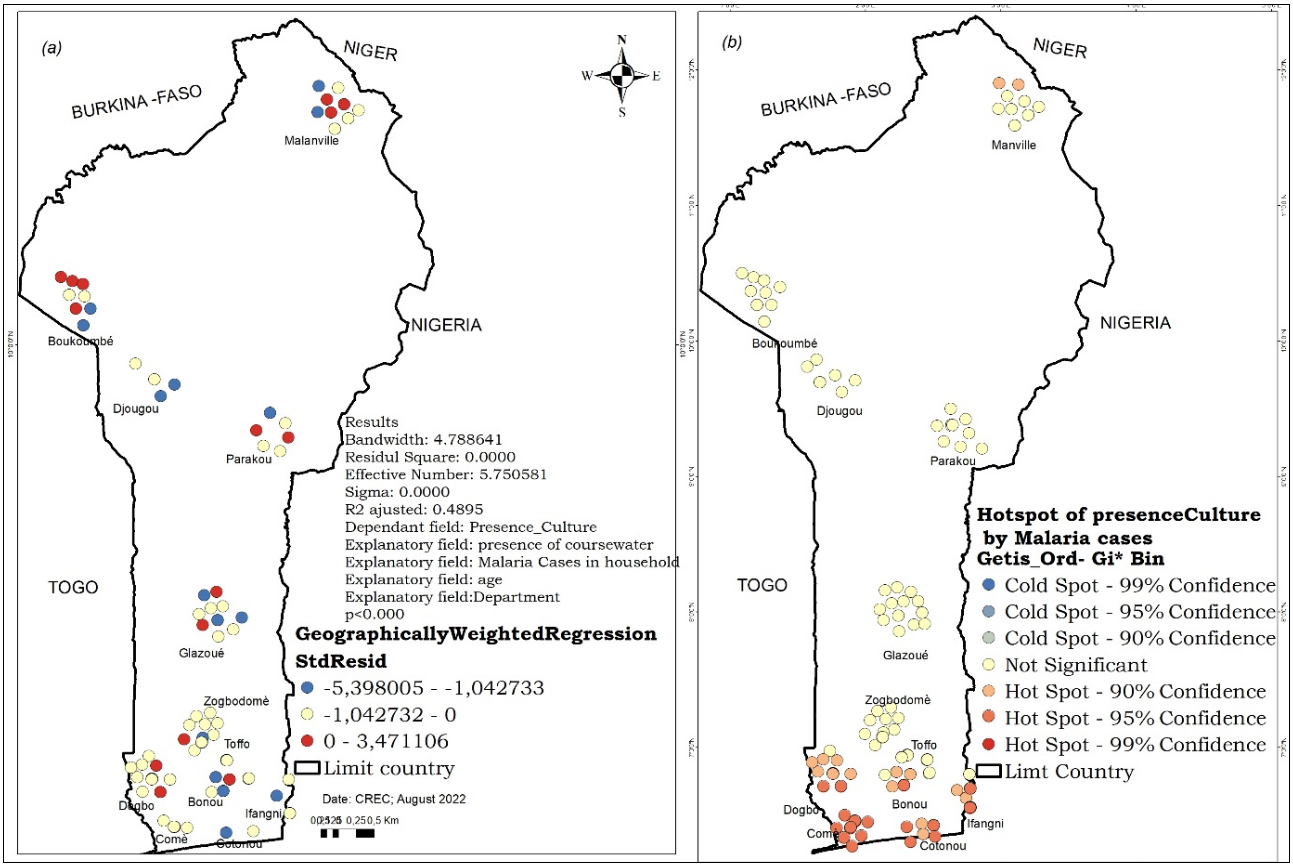

Fig 3: GWR (a) and Hotspot analysis of cultures via malaria case (b)

3.5 Spatial autocorrelation of malaria cases by household environmental factors

Running the model analysis tool produces low p-values and a very high z-score, indicating that the observed spatial pattern is unlikely to reflect the random pattern. It is urgent that the study be continuous to properly assess the level of contamination risk.

Given a z-score of 4.83653470763, there is less than a 1% probability that this clustered pattern is the result of random chance.

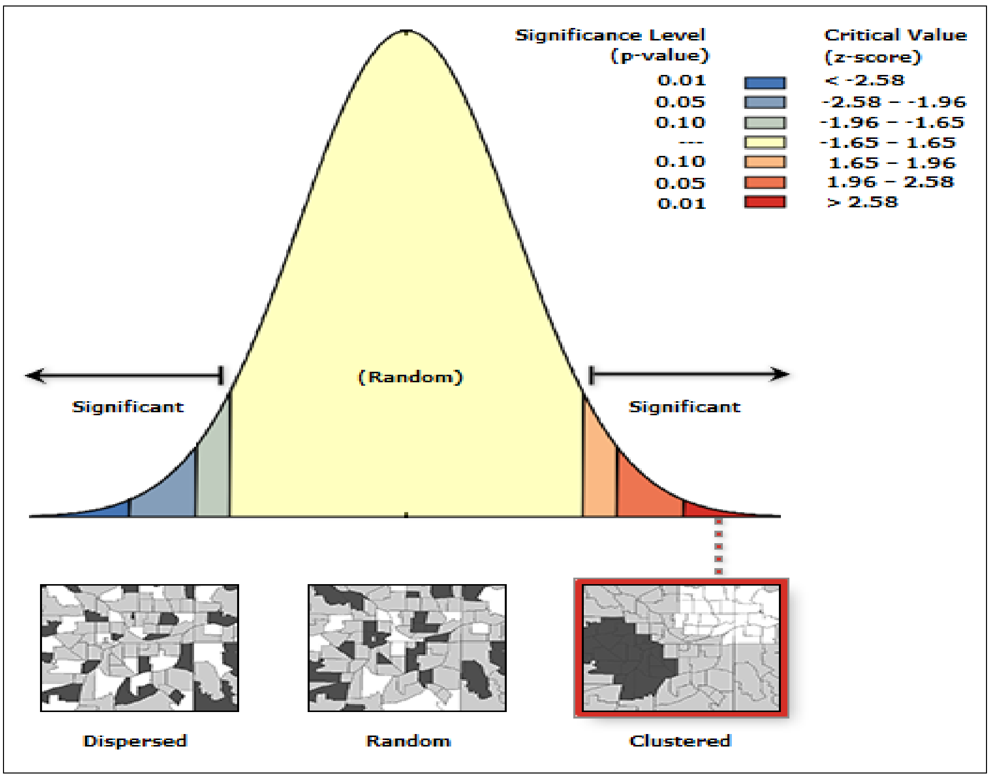

Fig 4: Rapport d’autocorrélation spatiale

4. Discussion
Our results show that both sexes are affected by malaria. But women are more infected than men. Women are most infected in the department of Ouémé followed by the plateau while in Couffo. These results are consistent with those of Quaresima *et al*. 2021 who showed that most malaria cases were women (62%), who were less educated and had more external risk factors associated with infection [18]. This study reported a tendency to prefer self-medication of malaria at home, which was practiced primarily by men (43%). These data suggest that women are more likely to be exposed to malaria infections than men, particularly because of their prolonged exposure to mosquito bites during the most dangerous hours. It would be better in the next study to highlight the need for future malaria control policies to be more socially and behaviorally oriented and to include a gender perspective [18].

Our results showed that both cases suggest an abundance of malaria cases in crop areas than in non-crop areas and more abundant in rural areas than in urban areas. Our results are contrary to those of Shah *et al*. (2022) who addressed the rural-urban context which was also found to be a major determinant of malaria: the risk of malaria infection was then shown to decrease from rural to urban core areas through peri-urban settlements [20, 21]. Given the importance of the rural-urban context, in addition to the primary analyses, they conducted an additional subgroup analysis to determine how the agriculture-malaria relationship may differ in rural versus urban landscapes. The work of Mboera *et al*., 2010 in Mvomero District, Tanzania, confirmed the evidence that malaria transmission risk varies even between neighboring villages and is influenced by agro-ecosystems. This study therefore demonstrates the need to generate spatial and temporal data on transmission intensity at smaller scales taking into account agro-ecosystems that will identify area-specific transmission intensity to guide targeted malaria control operations [22].

Our study is similar to Yu *et al*. (2009) who focused on the relationship between tobacco outlet density and demographics. According to them, the issue of non-stationarity and how the GWR method can be used to deal with these relationships was examined and verified [23, 24].

5. Conclusion
The issue of malaria transmission remains a major concern in Benin and will be of even greater concern by 2030. The non-stationarity observed with GWR means that the relationship between the variables studied varies from one place to another according to physical environmental factors that are spatially autocorrelated. The environmental factors that favor malaria vector proliferation are increasing exponentially and some key protective tools are declining in use in communities. The main factors that directly influence the number of malaria cases are: age, type of land use and presence of agricultural crops, and the number of people in the room.

At the same time, the malaria protection needs of the populations increase with the demographic dynamics in their degraded environment. Theoretically, the needs are met at the level of certain communes but remain unmet in the majority of their living environment. Analysis of spatially varying relationships using geographically weighted regression (GWR) has been the best method often used to address the non-stationarity problems that exist in data sets at different locations. Projects in the environment and malaria sector need to address the control needs of each locality for better spatial distribution of appropriate tools in relation to demand. In addition, training and discovery on effective malaria detection tools to avoid false positives. The provision of devices for the assessment of meteorological and environmental variables at the micro-scale should be a priority. The significant p-values in both cases suggest that malaria cases are more abundant in crop areas than in non-crop areas and more abundant in rural areas than in urban areas.

This work deserves to be deepened by other investigations taking into account the whole country, and it is for this reason that it would be necessary to consider continuing this research work during the other seasons of the year.

The outlook for malaria control is bleak and malaria control efforts have been increasingly unsuccessful because of the environment. Few now believe that global eradication of malaria will be possible in the foreseeable future. Environmental factors all play an important role in determining the intensity of malaria transmission, infected persons, illnesses, and deaths that need to be modeled to identify hot and cold spots. We objectively recommend that this study be better replicated with minimal funding from our loyal partners to combine entomology, parasitology, and the environment with adequate data collection tools and training.

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