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# Malaria Incidence Modeling Based on Climatic and Vegetation Factors in the Commune of Zogbodomey, Southern Benin

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**Abstract**

While it is true that climate affects human health, there are many reasons to believe that health also influences the epidemiology of malaria. Thus, in the current context of climate change, where we are witnessing an increase in the incidence of climate-dependent diseases, the implementation of operational tools such as early warning models appears to be of great use as a decision-making tool for controlling this disease.

The methodology adopted consisted of generating a linear regression model based on climatological and environmental parameters strongly correlated (at the 5% level) with the disease, after identifying the influence of these parameters on malaria. The model was then calibrated using backward elimination. Finally, validation was performed based on three statistical tests: the variance inflation factor test, the Durbin-Watson test, and the Goldef-Quandt test.

The results reveal that among the parameters most strongly correlated with malaria, only rainfall, vegetation index, maximum temperature, and minimum relative humidity proved to be the most relevant parameters of the model. The model itself proved quite reliable, with good predictive power and a fairly accurate reproduction of the disease's seasonality. Furthermore, it has a high correlation coefficient (r) of 87%, with a standardized standard deviation of 0.97, very close to the reference value of 1.

**Keywords:** Epidemiological model, climate-sensitive diseases, malaria, Zogbodomey commune, Benin.

## 1. Introduction

The idea that human health and disease are linked to climate dates back to antiquity. The Greek physician Hippocrates (400 BC) reported that epidemics are linked to the seasonal variability of the climate, and that anyone wishing to practice medicine properly must consider, in relation to the seasons of the year, the effects that each season can produce. In this way, they can predict, for each passing season and for the year as a whole, the diseases that will afflict the city in summer or winter (1). The study of the relationships between environmental factors and human health has therefore always been a major human concern.

A fundamental characteristic of equatorial regions, climate is considered one of the main factors in the occurrence and spread of infectious diseases. Its profound changes in recent years in Africa expose the continent to an increasing evolution of climate-sensitive diseases. This situation warrants particular attention, especially in terms of epidemiological monitoring. Thus, according to (2), there is no doubt that climate change can increase vulnerability to malaria. And, according to the IPCC (3), the health impacts of climate change will result, for example, in an increased probability of injuries and deaths due to more intense heat waves and fires, and in increased risks of foodborne and waterborne diseases. Furthermore, the risks of vector-borne diseases are expected to increase in general with warming due to the expansion of the area and the lengthening of the infection season. (4) showed in their work on the city of Pobè in Benin that the variation and interaction between climatic factors determine the resurgence of malaria, especially during the rainy season. (5) stated that the distribution and abundance of mosquito vectors depend on numerous climatic components. He adds that the same is true for the modulation of human-vector contact and the success of parasite development within the vector. Climate therefore considerably influences the geography and epidemiology of malaria.

Besides climate, vegetation cover, water resources, and poor environmental management promote the development of malaria-causing pathogens in the Collines department (6). Indeed, (7) believes that significant changes in vegetation cover and land use constitute both a cause and an aggravating factor in the spread of malaria. Malaria transmission therefore depends on numerous factors such as population and demographic trends, resistance to drugs and insecticides, human activities like deforestation, irrigation, and the drainage of marshy waters, etc., and their impact on the local ecology.

To eradicate malaria and protect public health, several actions are being undertaken at the national and international levels. Benin, in this fight, benefits from the effective contribution of international organizations, and local and foreign NGOs. For vector control to be effective, national surveillance systems must include entomological surveillance and monitoring of the coverage and impact of interventions in this area. Vector control should be based on local epidemiological and entomological data, including information on insecticide resistance and vector behavior. Countries should collect data in all settings, including in areas that are free of the disease but at risk of re-emergence (7).Unfortunately, this disease remains a constant concern not only for public health but also for the economic and social development of Benin. In order to

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strengthen existing actions and provide decision-makers with effective prediction tools, this paper proposes to develop an epidemiological forecasting model for diseases linked to climate and living conditions of populations in the northern region of Benin, based on climatic parameters favorable to their development.

*1.1 Nature and sources of the data used*

*1.2-Climatic Data*

The climatological data used in this study cover the period from 1990 to 2019 and specifically concern precipitation, temperature (maximum, minimum, and average), relative humidity (maximum, minimum, and average), and wind speed. These data originate from the synoptic station in Bohicon (Cana Meteorological Station) and are collected daily from the National Meteorological Directorate of Benin (METEO BENIN). The data were aggregated to obtain monthly averages (for temperature and humidity) and monthly totals (for precipitation).

1.2-1- Health or clinical data

For the purposes of this study, meteorological data collected daily will be converted to monthly timescales (monthly totals for precipitation and monthly averages for other climatic parameters). Studying the impacts of climate on health requires high-quality data. Given this, only the period from 2010 to 2020 will be considered for the subsequent analyses, as the available health data only covers this period. Furthermore, the health data for the 2010-2020 period are complete and contain no missing data. It should also be noted that the climatological data for the same period contain no missing data or outliers.

1.2.2 Vegetation index data by normalized difference

The normalized difference vegetation indexThe NDVI, or Near-Infrared Visible Light Index, is constructed from the red (R) and near-infrared (NIR) channels. It highlights the difference between the visible red and near-infrared bands. This index is sensitive to vegetation vigor and quantity. In this study, NDVI data covered the period from [date] to [date] in the municipality of Zogbodomey. The data were extracted from the NOAA website with a 1 km resolution and processed using the formula NDVI = (NIR - R) / (NIR + R).

1.2.3 Sampling

According to Lièvre (1998, p. 84): "a sample is a group of individuals extracted from a given population, under certain conditions, chosen in such a way that the conclusions of the study it undergoes can be generalized to the entire parent population." Regarding sampling methods, there are two (2) types:

- probabilistic methods and
- non-probabilistic methods
- The sample size per village is determined by the statistical protocol of Schwartz (1995):
- $\boldsymbol{X} = \frac{Z\alpha * Z\alpha * pq}{i * i}$
- **(Equation 1)**
- With: X = the sample size; Zα = 1.96 Reduced deviation corresponding to a risk α of 5%; p= n/N; p=proportion of villages to be visited (n) in relation to the number of households in the eleven (11) districts selected (N) in the Commune of Zogbodomey and q=1-p, and i= 5% (desired precision).
- In this specific case, p = 0.23, so q = (1 - 0.23) = 0.77= $\frac{n}{N}\frac{4571}{20070}$
- <u>Digital Application</u>:
- X = = X = 269,192 = 270 households$\frac{Z\alpha * Z\alpha * pq}{i * i}\frac{1{,}96 * 1{,}96 * 0.23 * 0.77}{0.05 * 0.05}$
- In each household, one person was interviewed, bringing the total number of people surveyed to 270. This number is proportionally distributed among the eleven (11) districts according to the population size of each district (Table I).

| Arrondissements | Nbre de ménages | Village | Nbre de ménages | Nbre de ménages interrogés | Taux (%) |
|---|---|---|---|---|---|
| AKIZA | 2120 | AKIZA | 188 | 11 | 4 |
| | | SEME | 155 | 9 | 3 |
| AVLAME | 1761 | ALLADAHO | 280 | 17 | 6 |
| | | AVLAME | 183 | 11 | 4 |
| CANA I | 1223 | DEGUELI | 130 | 8 | 3 |
| | | GBAME | 118 | 7 | 3 |
| CANA II | 1274 | AGOUNA | 128 | 8 | 3 |
| | | HADAGON | 185 | 11 | 4 |
| DOME | 2086 | BOLAME | 272 | 16 | 6 |
| | | GOHISSANOU | 101 | 6 | 2 |
| KOUSSOUKPA | 1444 | DEME | 439 | 26 | 10 |
| | | SAMIONTA | 468 | 28 | 10 |
| KPOKISSA | 1433 | AHOUANDJITOME | 269 | 16 | 6 |
| | | GBEDIN | 58 | 3 | 1 |
| MASSI | 2 680 | LONME | 244 | 14 | 5 |
| | | HLAGBA ZAKPO | 187 | 11 | 4 |
| TANWE-HESSOU | 2088 | ADJOGON | 248 | 15 | 5 |
| | | TANWE HESSOU | 158 | 9 | 3 |
| ZOUKOU | 1470 | AGRIMEY | 188 | 11 | 4 |
| | | KOTO AYIVEDJI | 177 | 10 | 4 |
| ZOGBODOMEY | 2 491 | DOVOGON | 156 | 9 | 3 |
| | | ZADO-GAGBE | 239 | 14 | 5 |
| 11 | 20070 | 22 | 4571 | 270 | 100 |

Source*:* INSAE, 2013; research work and calculations, July 2025

This table shows the sample structure. In each household, one person was interviewed, resulting in 270 households included in the survey. This number is proportionally distributed among the twenty-two (22) villages and districts according to the number of households in each district.

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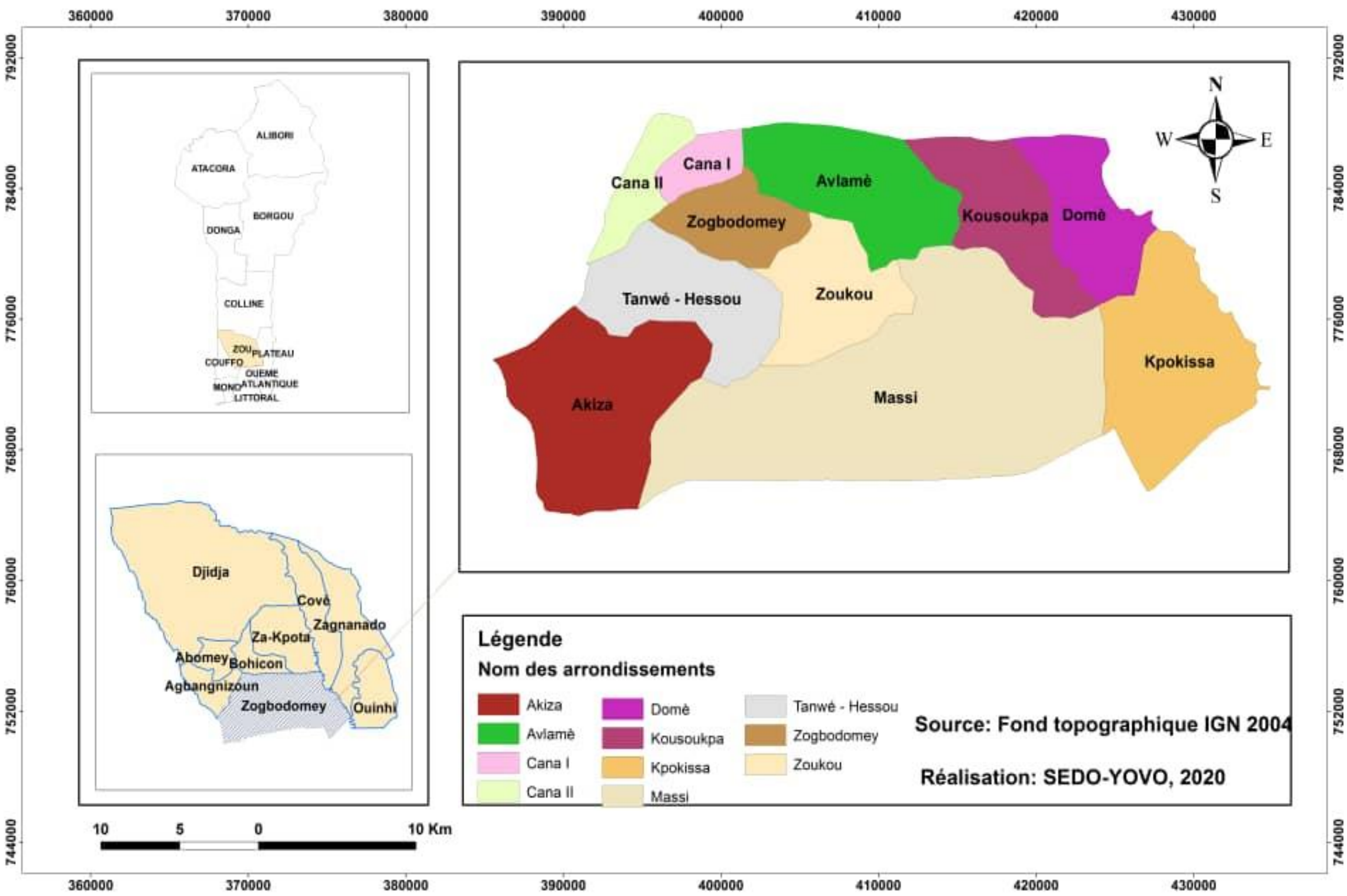
**2. Geographical location**

Located in the southern part of the Abomey Plateau, 150 km from Cotonou, the commune of Zogbodomey lies between 6°56' and 7°08' North latitude and 1°58' and 2°24' East longitude (see Figure 1). It is situated at the northern entrance to the Zou department. It comprises eleven (11) districts and is bordered by:

- To the North by the communes of Bohicon and Za-kpota;
- To the South by the departments of Atlantique and Couffo;
- To the East by the communes of Covè, Zagnanado and Ouinhi;
- To the West by the commune of Agbangnizoun.




*2.1. Climate and hydrographic network*

The climate is sub-equatorial with abundant rainfall throughout the year. There are four distinct seasons: two rainy seasons (March to July and August to October) and two dry seasons (October to November and December to March).

The hydrographic network is composed of several watercourses, the most important of which are: Zou, Ouémé, Hounto, Koto, Samion, Hlan, Da, and the Dohou. Lowlands are also found scattered throughout.

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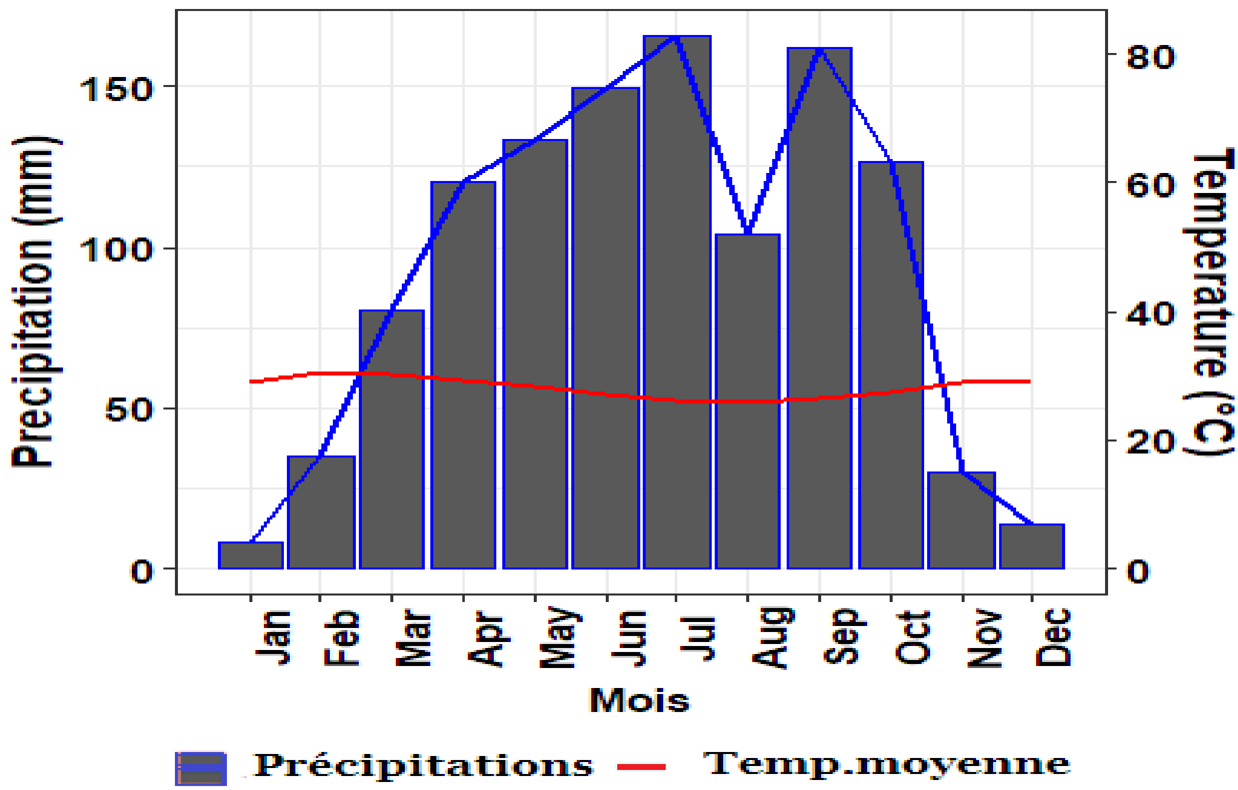


Figure 2: Ombrothermic curve of the zone
Source: Author, under R.

2.1.1 Vegetation

The vegetation consists mainly of:

- Compound savannas with several strata dominated by species such as Daniella Laxiflora and Parkia Biglobosa, Pericopus Laxiflora, Vitex Domania, Andropogon and Hyparenia etc…
- a classified forest located in Massi and Agrimey with a total area of 6500ha;
- a gallery forest along the waterways;
- an artificial forest planted with Tectoma grandis and Gmelina Arborea;
- a swampy forest in Lokoli.

2.1.2 Relief and type of habitat

The landscape of the Zogbodomey commune is characterized by the vast valleys of the Zou and Ouémé rivers, low-lying plateau areas, and the Lama depression. Traditional dwellings are the most common, with a few rare middle-class houses. Luxury homes are nonexistent in Zogbodomey. The majority of houses are made of adobe covered with corrugated iron or thatch. However, there are also some more permanent houses built with durable materials.

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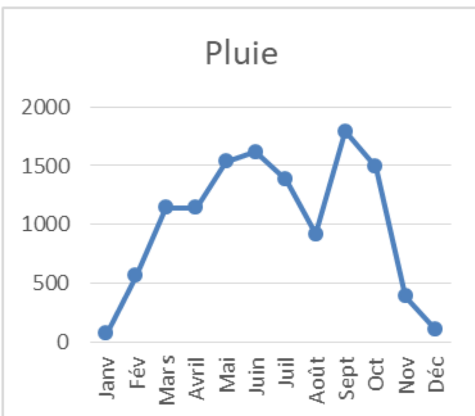
*2.2 Seasonal variability of parameters in the study area*

In order to establish the relationship between climate parameters, vegetation data and malaria pathology, climatological, NDVI and epidemiological data were correlated.

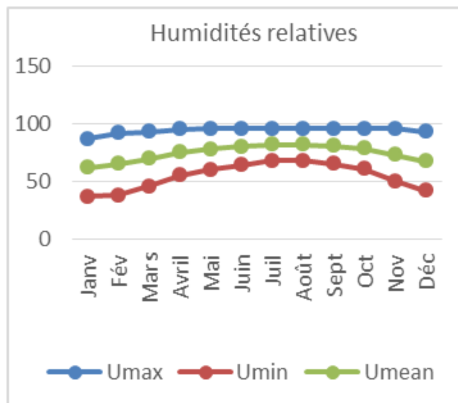
2.2.1 Seasonal variability of climatic parameters

The seasonal variability of climatological parameters was determined by a descriptive approach applied to data observed from 2009 to 2019. As such, the results below were obtained.

Figure **2:** Rainfall patterns in Zogbodomey, from 2010 to 2020 Figure 3: Hygrometric rhythms of Zogbodomey, from 2010 to 2020




**Source:** Benin Weather Agency, results in Excel, June 2020




Source : Benin Weather Agency, results in Excel, June 2020

Figure 2 shows that rainfall over the study period has two peaks, the first in June with a value of 1619.9 and the second in September with a value of 1793.5. The months of January and December had the lowest amounts of rain.

As for figure 3, it shows a variation between 37 and 96. The highest value in August-September and the lowest in January-December.

2.2.2 Seasonal variability of the vegetation index (NDVI)

The Normalized Difference Vegetation Index (NDVI), developed by JW Rouse et al. (1974), has become a benchmark index for dynamically monitoring vegetation cover. It is defined by the ratio: NDVI = (NIR-VIS) / (NIR+VIS), where NIR and VIS represent reflectances in the near-infrared (0.72 to 1.1 µm) and visible (0.58 to 0.68 µm) bands of the electromagnetic spectrum,

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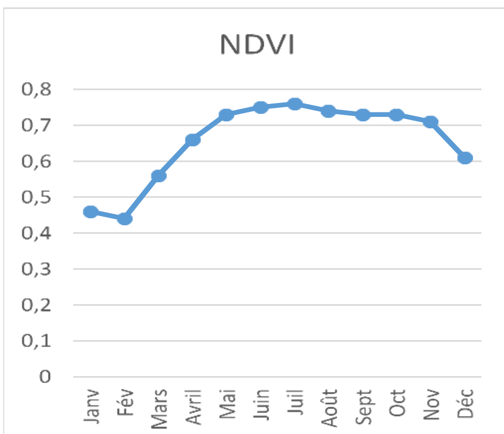
respectively. Vegetation reflectance is approximately 20% in the red (due to strong chlorophyll absorption) and 60% in the NIR (cellulose diffusion). The contrast in vegetation response across these two spectral bands allows for the quantification of energy absorbed by chlorophyll pigments. Consequently, the NDVI represents a measure of the canopy's photosynthetic capacity (Tucker and Sellers, 1986). It is also well correlated with the leaf area index and net primary production. The NDVI database used for this study comes from the processing of NOAA-AVHRR sensor data by NASA's GIMMS (Global Inventory Modeling and Mapping Studies) group. The variability of this index in the municipality of Zogbodomey over the study period (2010 to 2020) shows the following (see Figure 6).

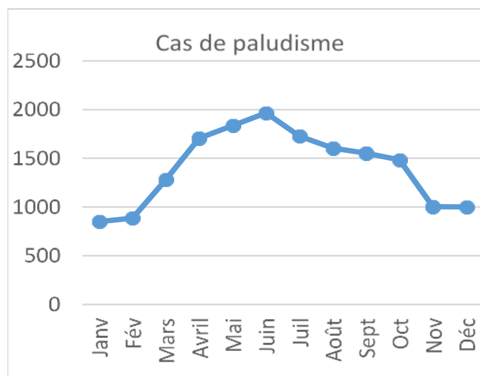
2.2.3 Seasonal variability in malaria cases

The seasonal variability of malaria cases is represented in graph number 4 below.

**Figure 4**Monthly cycles of NDVI data for Zogbodomey, 2010 to 2020 *Figure 5: Monthly patterns of malaria cases in Zobgodomey, 2010 to 2020*




Source: DDS Zou/Collines, résultat sous Excel, Juin 2020




Source: DDS Zou/Collines, résultat sous R, Juin 2020

The vegetation index (Figure 4) shows that the vegetation is strongly green during the months of May, June, July, October and November, periods favorable to the development of mosquitoes. Regarding malaria cases (Figure 5), the peak occurs in June with low contaminations in November, December, January and February.

*2.3 Statistical relationship between climatic, clinical and vegetation parameters*

Here, the aim was to investigate the correlations between the different parameters and the pathology under study. The results are recorded in the following table:

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**Table II:** Correlation matrix

| | NDVI | Rain | Umin | Umax | Tmin | Tmax | Palu |
|---|---|---|---|---|---|---|---|
| NDVI | 1,000 | | | | | | |
| Rain | 0.531 | **1** | | | | | |
| Umin | 0.157 | 0.696 | **1** | | | | |
| Umax | 0.551 | 0.570 | 0.577 | **1** | | | |
| Tmin | -0.334 | -0.568 | -0.551 | -0.406 | **1** | | |
| Tmax | -0.350 | -0.686 | -0.564 | -0.502 | 0.593 | **1** | |
| Palu | 0.853 | 0.504 | 0.341 | 0.661 | -0.353 | -0.518 | **1** |

**Source: Author**, result in R, December 2024

The correlation matrix shows a strong positive correlation between malaria and the explanatory variables Tmax, Umax, Umin, Rainfall, and NDVI. The Tmin variable shows a negative correlation of 0.353. We therefore conclude that the explanatory variables are correlated with each other in pairs and are well correlated with the explained variable.

*2.4 Malaria prevention measures by the populations of Zogbodomey*

2.4.1 Conditions favorable to mosquito proliferation

*The conditions favorable to the development and proliferation of mosquitoes are summarized in the following graph 1:*

**Figure 6:** Mosquito breeding seasons

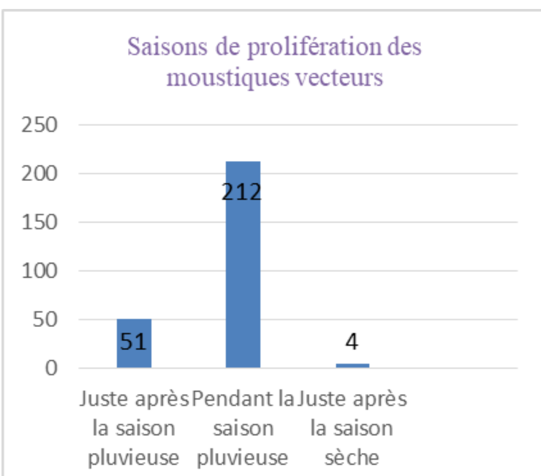
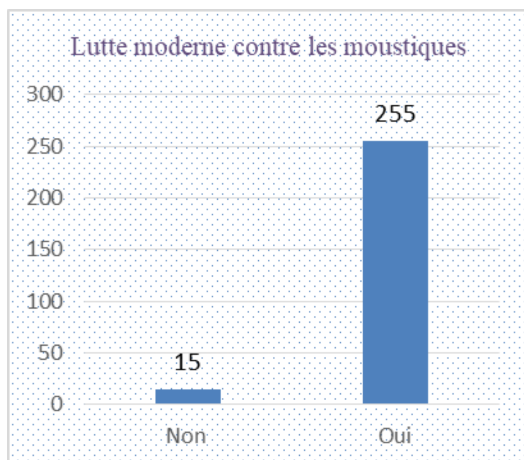


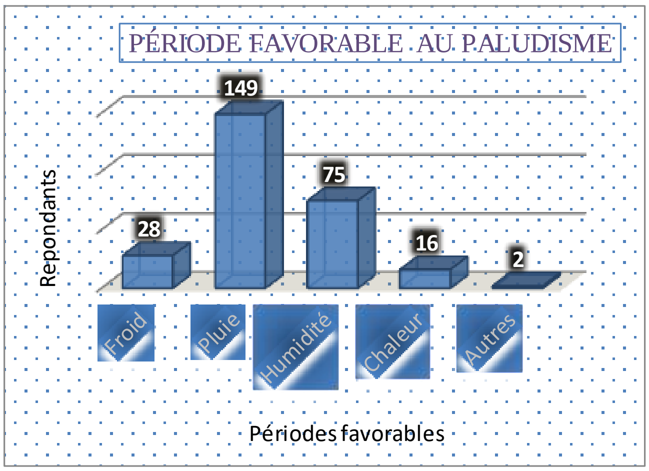

**Figure 7**modern mosquito control




**Source: Author**, survey data, results in Excel, August 2020. Source: Author, survey data, results in Excel, August 2020

By asking the question: "Have you ever tried to prevent malaria using traditional medicine? If so, how?', we obtained the responses translated by figure 10. Thus, we note that 94% of respondents admit to having used modern techniques to keep mosquitoes away.

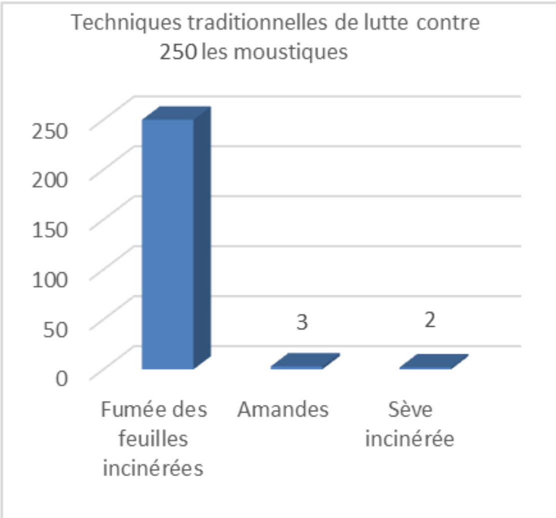
Indeed, traditional mosquito control techniques (and consequently malaria control) mainly involve the use of burned green or dry herbs and leaves. Through figure 12, we can easily see that the rainy season is the most favorable period for malaria, followed by periods of high humidity




**Source: Author**, survey data, August 2020

2.4.2 Endogenous measures for malaria prevention

By asking the question: "Have you ever tried to get rid of mosquitoes using traditional techniques and methods?", we obtained the following results:
Indeed, according to our respondents, some plants and herbs have insect-repellent effects.




**Picture**1: Leaf traditionally called "zansukpê-man" in FonPhoto taken on August 29, 2020 at 10:36 AM by the author

**Figure 9:** Traditional mosquito control techniques
**Source: Author**, survey data, results in Excel, August 2020

Most of our respondents use leaves that they burn or incinerate. The smoke from burning these leaves is said to have insecticidal or insect-repellent properties. The plants and The leaves commonly used are Eucalyptus camaldulensis, Azadirachta indica, Cyanotis lanata, Hyptis suaveolens, Eleusine indica, etc. A few of our interviewees admitted to having used dried sap from Boswellia dalzielii, burned in a container, as an insect repellent on several occasions. Others suggested they had used the shells of Vitellaria paradoxa almonds.

2.4.3 Modern malaria prevention measures

**Figure 10***:* Modern mosquito control products in Zogbodomey

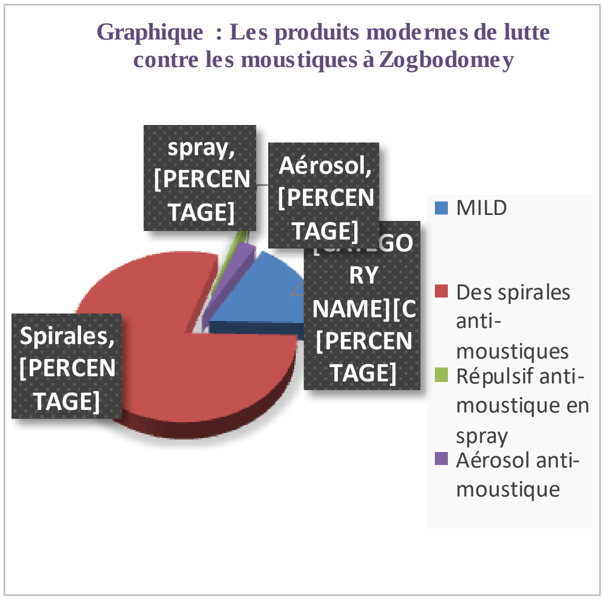



Figure 10 shows that the spiral mosquito nets traditionally called "zansukpê-hunu" are the most widely used by the people of Zogbodomey, due to their lower cost and therefore widespread availability. They are followed by Long-Lasting Insecticidal Nets (LLINs). It should be noted that the population uses fewer mosquito nets despite them being free; some use them to protect their crops from poultry.

Source: Author, survey data, results in Excel, August 2020

2.4.4 Resistance of vector insects to the insecticides used

Regarding public perception of insect resistance to the products used, 67% of our respondents said they were unaware of it, while 20% refuted this claim. Approximately 13% acknowledged the increasingly harmless effect of the products used.

Figure 11: perception of mosquito resistance to insecticides


**Source: Author**, survey data, results in Excel, August 2020

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## 3. Modeling

For the remainder of this study, the five (5) climatological parameters most strongly correlated with the incidence of the disease, namely rainfall, maximum temperatures (Tmax), minimum relative humidity (Umin) and maximum relative humidity (Umax) and the vegetation index (NDVI), were used to generate the linear regression model (E1) whose results reveal the following characteristics:

❖ **Equation of the generated model**

(E1): Palu = -1272.44+1272.09*NDVI-0.34*Rain+10.9*Umin+4.58*Umax+7.7*Tmin-16.47*Tmax (Equation 4)

❖ **Statistical parameters**

Coefficient of determination ($R^2$) = 0.852 Adjusted $R^2$ = 0.818 P-value = 0.045
The model coefficients are generally greater than 0.5, with a p-value of 0.045, which is below the threshold of 0.05.

### *3.1 Model Calibration*

The results obtained after backward elimination of all non-significant variables allowed us to derive the calibrated model. The variables maximum temperature, maximum relative humidity, vegetation index, and rainfall are included in the calibrated model.

❖ **Model equation after calibration**

(E2):Malaria = -809.7+1338.7*NDVI-0.36*Rain+12.1*Umin-15.27*Tmax (Equation 5)

❖ **Features of the calibrated model**

**Coefficient of determination $R^2$: 0.837; Adjusted $R^2$: 0.813; P-value: 0.019**

### *3.2 Model Validation*

Analysis of the test results confirms the validity of the generated model (E2). Indeed, the Goldef-Quandt test indicated homoscedasticity of the residuals when its associated p-value (p = 0.76) was greater than 0.05. Furthermore, the Dorbin-Waston statistic was satisfactory, with a value (DW = 1.73) between 1.5 and 2.5, revealing an absence of autocorrelation of the residuals. Finally, the VIF test revealed a lack of collinearity, indicated by a VIF value (3.705) less than 5.

Table III: Adjustment coefficients (Palu)

| Statistical | Learning sample | Validation sample |
|---|---|---|
| Observations | 33 | 11 |
| Sum of weights | 33 | 11 |
| DDL | 28 | 6 |
| **$R^2$** | **0.837** | 0.794 |
| **adjusted $R^2$** | **0.813** | 0.785 |
| MCE | 1193,581 | 3400,341 |
| RMCE | 34,548 | 58,312 |
| MAPE | 12,154 | 21,313 |
| **DW** | **1,730** | |
| CP | 5,000 | |
| AIC | 238,374 | |
| SBC | 245,856 | |
| PC | 0.222 | |

**Source** Author, using XLSTAT,

Table IV: Standardized coefficients (Palu)

| Source | Value | Standard error | T | Pr > \|t\| | Lower limit (95%) | Upper limit (95%) |
|---|---|---|---|---|---|---|
| NDVI | 0.912 | 0.096 | 9,472 | **<0.0001** | 0.714 | 1,109 |
| Rain | -0.397 | 0.144 | -2.749 | **0.010** | -0.692 | -0.101 |
| Umin | 0.305 | 0.115 | 2,650 | **0.013** | 0.069 | 0.541 |
| Tmax | -0.299 | 0.106 | -2.804 | **0.009** | -0.517 | -0.080 |

Source Author, Using Xlstat,

## 4. Discussion

The results obtained from this study have yielded significant findings that warrant further discussion. Indeed, the analysis of these results has, on the one hand, revealed that climate greatly influences the incidence of malaria. On the other hand, it has also revealed that the generated predictive model could be used to estimate the expected level of risk for a given region over a given period.

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*4.1 Predictive capacity of the model*

According to (2), the study of the relationships between certain climatic parameters and the occurrence of infectious diseases makes it possible to develop predictive models of future regions vulnerable to epidemics for control and management purposes. Thus, modeling depends, on the one hand, on the statistical performance of the tools used and, on the other hand, on a reasonable analysis of the facts and the interpretation of the links between the modeled variables (4).

In this regard, the multiple linear regression model generated in this study, based on climatic parameters, appears to reproduce the seasonality of malaria quite well. Furthermore, statistically, it also seems to have presented generally quite conclusive results.

Indeed, compared to actual observations, the malaria incidence periods from March/April to September (the month of peak incidence) were reproduced quite well by the model, with a correlation coefficient (r) of 0.94. (3) similarly stated that comparing a model's predictions with data from a real outbreak remains the ideal way to test the model's validity, which should demonstrate a certain level of agreement between the results obtained and the actual observations. Furthermore, a high r value would indicate a good fit between a model and the observed data (6).

The generated model was also validated by the fairly conclusive results of certain statistical tests, notably those of the VIF, Goldfeld-Quandt and Durbin Watson.

The VIF test, designed to determine the presence (if VIF > 5) or absence (if VIF < 5) of collinearity between variables, revealed a value of 4.51. This indicates an absence of collinearity, which is a necessary condition for model validation, especially since its presence reduces the precision and efficiency of the parameter estimators (1). Furthermore, (7) revealed that the existence of collinearity between explanatory variables leads to high standard deviations of the regression coefficients, which, in this case, are very sensitive to even small fluctuations in the predicate.

Similarly, the results of the Goldef-Quandt test, which determines the homoscedasticity of the model's residuals, were satisfactory, with a p-value of 0.522 exceeding the α threshold of 5%. Indeed, the homoscedasticity test determines the homogeneity of the variance of the residuals. This is a fundamental property of the linear regression model, and its principle states that if the p-value < α, there is heteroscedasticity of the residuals. Conversely, if the p-value > α, we speak of homoscedasticity of the residuals (8).

Regarding the Durbin-Watson test, the relevance of a model is limited by the presence of autocorrelated errors. Therefore, the results of the Durbin-Watson test, which detects the presence or absence of autocorrelation of residuals in a linear regression model, revealed an absence of autocorrelation of residual errors (DW = 1.73). This demonstrates the significance of

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the model since, according to the principle, the absence of autocorrelation of errors is accepted when the value of this statistic (DW) is close to two (9).

*4.2 Verification of the seasonality of the forecasting model*

The results of the analysis of the seasonal cycle of the model reveal that the latter has a good seasonal representation of the incidence of malaria in Zogbodomey (2).

Indeed, May appears, both for the model and for observation, to mark the beginning of an exponential increase in the number of malaria cases, which continues to peak in June. It then begins to decline and ends in November. Aside from the beginning, peak, and end of the disease's progression, the model also seems to simulate the specific malaria cases observed in December quite well, with a slight underestimation.

## 5. Conclusion

Given that living beings are constantly influenced by the environmental and climatic factors of their habitat, we have reason to believe that the epidemiology of malaria in our study area depends on the local climate and environment. The health sector remains a priority because the right to life is fundamental. However, the manifestations of climate variability, poor living conditions, unsanitary conditions around dwellings, and dense vegetation cover present a harsh reality that contributes to the development and proliferation of malaria-carrying insects in the Zogbodomey commune. This situation undermines the well-being of the population, the development of the health sector, and consequently, the national economy.

Aware of these threats, the development of tools to predict and anticipate climate-related disease risks is becoming essential. In this context, the present study, whose objective is to contribute to a better understanding of the relationship between climate and health in order to improve the surveillance and management of malaria, attempted to design a disease prediction model based on climatological and environmental parameters correlated with the disease, such as rainfall, maximum temperature, minimum relative humidity, and vegetation index.

The results revealed that the parameters most significantly correlated with the disease were rainfall, with a correlation coefficient (r) of 0.504 and a VIF of 3.567; maximum temperature, with an r of 0.518 and a VIF of 1.943; minimum humidity, with an r of 0.341 and a VIF of 2.274; and the vegetation index, with an r of 0.853 and a VIF of 1.587. Subsequently, rainfall, maximum temperature, minimum relative humidity, and the vegetation index (NDVI), after calibration, were identified as the most relevant parameters in the developed linear regression model. This model demonstrated fairly good representation of the seasonal behavior of disease incidence, with a strong correlation coefficient (r) of 0.837.

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