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Assessment of the impact of climatic and environmental parameters on malaria transmission in the Greater Abidjan region using satellite imagery and Google Earth Engine

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RESUME: *Malaria in Côte d'Ivoire is strongly influenced by climatic and environmental conditions, constituting a major threat to public health.*
Previous studies have shown that global warming could alter the spread of malaria due to changes in temperature and precipitation that affect the distribution of mosquitoes and the parasite. These studies also highlighted that the risk of malaria could increase due to the influence of local environmental and climatic factors.
The present study combining remote sensing, GIS and data analysis was carried out to better understand the transmission dynamics and factors influencing mosquito proliferation. The spatial analysis revealed the influence of each climatic and environmental factor on transmission, and a map of the risks of mosquito proliferation in Greater Abidjan was created. This map shows that 19.80% of the area is very high risk, 21.40% is high risk, 33.10% is medium risk, and 25.7% is low risk. This tool is valuable for optimized allocation of resources and better effectiveness of malaria control programs.
Keywords: *Malaria, Environmental factors, climate change, spatial analysis, Google Earth Engine, satellite imagery*

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I. INTRODUCTION

In Côte d'Ivoire, climate change could significantly increase malaria transmission, leading to an increase of 16 to 29% in cases in the north of the country and 6 to 14% in the south by 2050 (Ebi et al., 2021). This is because climate change is altering the seasonality and transmission of the disease, thereby increasing its threat. Anopheles Gambiae, the main mosquito vector of malaria in Côte d'Ivoire, is now much more widespread in various Ivorian areas, particularly in coastal and peri-urban regions (Korenromp, 2005), (A. Gillespie, 2015).

The Ivorian government is fighting malaria through a multi-dimensional approach that includes enhanced surveillance and research, community initiatives, behavior modification, collaboration with other sectors, and implementation of innovative technologies (AK, 2015) (Anya, 2017).

Traditional environmental survey methods are expensive and can be limited, while Google Earth Engine can analyze large data sets. The present study aims to use geospatial technology to identify vulnerable areas and informed decision-making, leading to targeted interventions and optimized resource allocation.

II. METHODOLOGY

1.1 Presentation of the study area

Located in the south of Côte d'Ivoire, along the Gulf of Guinea, Greater Abidjan extends over 2,119 km² and includes the city of Abidjan and surrounding towns and villages (figure 1). Its diverse landscape includes the Ebrié lagoon, marshy plains, hills and picturesque beaches. Administratively, the district includes 13 municipalities, 10 of which constitute the city of Abidjan. The surrounding communes are Alépé, Azaguié, Bonoua, Dabou, Grand-Bassam and Jacqueville. Greater Abidjan benefits from abundant rainfall, with an annual average of around 1,750 mm, and constantly high temperatures throughout the year, with monthly averages above 18°C (AK. K., 2015).

The region is the main economic and demographic center of the country, with rapid population growth fueled by rural exodus and immigration. Despite its economic wealth, Greater Abidjan faces significant socio-economic disparities, with a large proportion of the population living in poverty and a significant informal economy (Martin, 2021). Rapid urbanization has led to uncontrolled spatial expansion, with the proliferation of informal neighborhoods and slums characterized by precarious housing, often built without respect for safety and hygiene standards (YAO, 2010) (Atta Koffi, 2015).

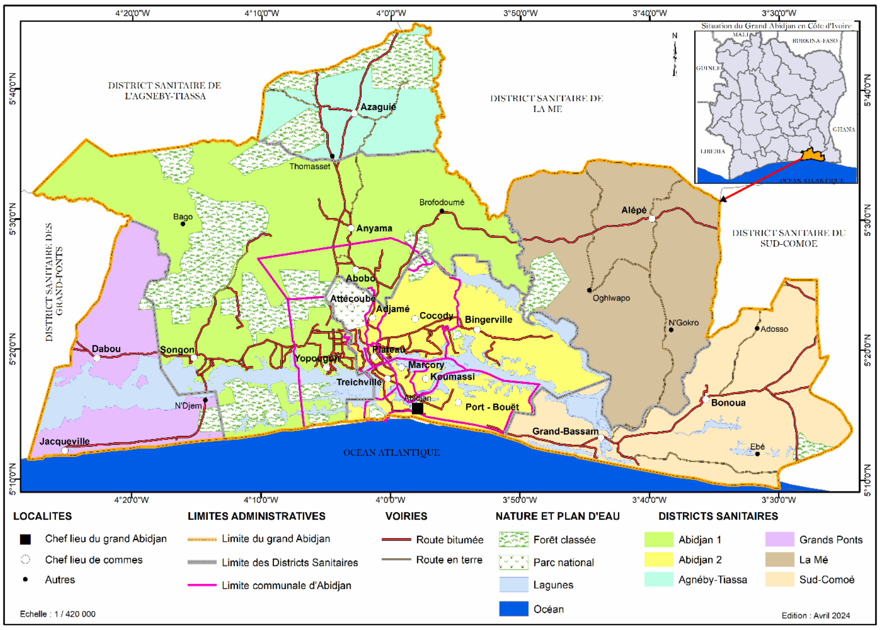

Figure 1: Location of the study area

2.1 Material and methods

2.1. Data

The use of satellite images and in-situ data is essential to understand the complex factors that influence the spread of the disease.

2.1.1. Satellite data

Satellite imagery, downloadable Google Earth Engine data, including multispectral optical images, synthetic aperture radar (SAR), and elevation data (DEM), provide information on surface temperature, soil moisture, and seasonal variations (Table 1). These data are used to map land cover types that influence the presence of disease vectors and human exposure, and to identify areas of standing water suitable for mosquito breeding. Such information can then be used to understand variation in malaria transmission and identify areas at risk of mosquito proliferation.

Table 1: data sources

Types	Data source	Spatial Resolution	Temporal resolution	Threshold

Temperature	Landsat-8	30 m	14 days	Min : 24° C Max : 35° C
NDVI	Landsat-8	30 m	14 days	Min : 0,73
Land use	SENTINEL 2	10 m	8 days	See table x
Precipitation	HydroSHEDS	5,5 km	.10 days	Min: 1700 mm; Max 2700 mm ;
Flow accumulation	THE ASTER	30 m		> 56
Water resource	Global Surface Water Mapping Layers	30 m		>0% water

2.1.2. In-situ data

Since local factors influence disease transmission, it is essential to use local data (entomological, epidemiological and census-related) when studying malaria transmission in a specific area.

2.1.2.1. Data from the census (RGPH 2021)

The RGPH (General Population and Housing Census) provides demographic, housing, socio-economic and geographic data (figure 2) which are essential for understanding malaria transmission. These data make it possible to identify risk factors, map areas of high prevalence, evaluate the effectiveness of interventions and plan malaria prevention and control strategies.

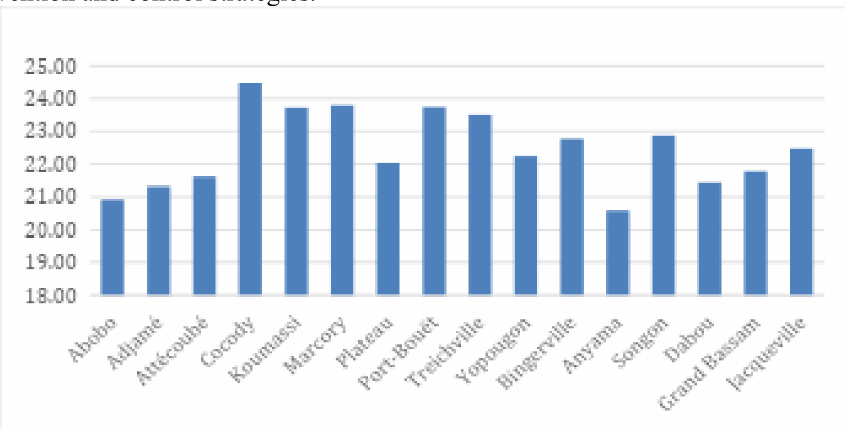

Figure 2: The distribution of the population in the Abidjan district according to the RGPH 2021

2.1.2.2. Entomology data

Key entomological data essential to understanding and controlling malaria transmission include identification of the disease vector species (Gambiae s.l.), its spatial distribution, abundance, density, infection rates and behavior (feeding preferences, endophagy[1] or exophagia[2], endophilie[3]).

The percentage of female Anopheles mosquitoes carrying the parasite (Plasmodium Falciparum sporozoite rate), a key indicator of the intensity of malaria transmission. 662 mosquitoes (An. Gambiae s.l.) were analyzed for sporozoite infection, based on data collection organized by PNLP in 2018 and 2019.

2.1.2.3. Epidemiological survey data

An epidemiological investigation into the transmission of malaria was carried out in certain localities of Greater Abidjan by the National Malaria Control Program in Côte d'Ivoire (tables 2 and 3). This survey required structured research, planned logistics, taking into account the specific environmental context of Greater Abidjan, and analysis and dissemination of the results to guide anti-malaria interventions.

Table 2: Number of confirmed malaria cases (from 2016 to 2020)

Health districts	2 016	2 017	2018	2019	2020

[1] *Behavior of certain hematophagous insects (which feed on blood) which bite their hosts inside their home*

[2] *Behavior of certain hematophagous arthropods (feeding on blood) which bite their hosts outside their living or resting places.*

[3] *Characteristic of a disease-carrying insect that has the ability to take refuge and rest inside human or animal habitations after biting their host*

Abobo Est	34 610	51 999	53 690	65 470	55 243
Abobo Ouestt	43 471	44 883	45 436	63 133	37 651
Anyama	31 969	32 275	34 103	52 478	43 503
Cocody-Bingerville	61 131	71 337	81 582	91 615	83 441
Koumassi-Port-Bouet-Vridi	61 190	70 040	77 553	83 591	74 307
Marcory-Treichville	20 331	20 184	38 519	41 424	31 104
Adjame-Plateau-Attecoube	23 847	43 601	42 200	46 683	83 441
Dabou	26 191	33 212	34 173	63 941	67 076
Grand Lahou	20 865	23 242	21 762	26 400	33 107
Jacqueville	24 829	22 867	22 485	26 318	27 009
Yopougon Est	18 168	38 382	37 009	50 138	54 845
Yopougon ouest-Songon	47 500	34 368	64 114	72 374	59 095
Health regions	2 016	2 017	2018	2019	2020
Abidjan 2	252 702	290 718	330 883	397 711	325 249
Abidjan 1-grands ponts	161 400	195 672	221 743	285 854	324 573

Table 3: Number of incident cases of malaria (from 2016 to 2020)

Health districts	2 017	2018	2019	2020
Abobo Est	58,18	72,27	107,41	88,47
Abobo Ouest	103,04	124,13	99,52	57,93
Anyama	228,79	192,81	275,24	222,73
Cocody-Bingerville	103,58	113,23	141,99	126,24
Koumassi-Port-Bouet-Vridi	63,78	69,67	81,27	70,70
Marcory-Treichville	50,52	48,54	97,38	71,38
Adjamé-Plateau-Attécoubé	37,31	57,62	60,3	47,94
Dabou	168,26	211,18	411,5	534,8
Grand Lahou	146,72	145,40	167,2	172, 3
Jacqueville	367,02	384,44	447,8	476,1
Yopougon Est	49,73	56,56	57,9	61,79
Yopougon Ouest-Songon	83,84	52,99	147,2	117,34
Health regions	2 017	2018	2019	2020
ABIDJAN 2	608	88,11	112,55	106,24
ABIDJAN 1-GRANDS PONTS	853	79,53	114,15	99,49

2.2. Computer hardware and software

To carry out a study combining classification of land use, analysis of the impact of climatic and environmental factors on the transmission of malaria and spatial analysis, it is essential to have efficient computer hardware and suitable software.

2.2.1. Software

- QGIS GIS software for spatial analysis and mapping.
- Google Cloud Platform for analyzing large-scale satellite images and environmental data, with access to vast data and complex analysis tools.

2.2.2. Method

Vector-borne diseases, such as malaria, are influenced by environmental and human factors, which can complicate the assessment of disease transmission risks. A multidisciplinary approach analyzing various data sets (Big Data) required the creation of a decision support tool to control vector-borne diseases. This process required the manual creation of training area polygons in the QGIS software, which offers high accuracy and flexibility, as well as rapid and objective automatic land cover classification on the Google Earth Engine cloud platform, the accuracy of which depends on the quality of the training points previously created in QGIS. For land use classification, we needed key climatic and environmental data (Thierry, Barbara, Mathieu, & Thibault, 2022; Belfali, Dalila, Cherik, & Kheira, 2023)

2.2.3. Process for developing the land cover classification model
2.2.3.1. Data preparation in QGIS: step 1

For creating training polygons, QGIS is preferable to Google Earth Engine due to its accuracy, flexibility, editing tools, and integration with other data. Google Earth Engine can be used for classification from these polygons, but its limitations in drawing, editing and processing very high resolution images make it less suitable for creating them (Figure 3).

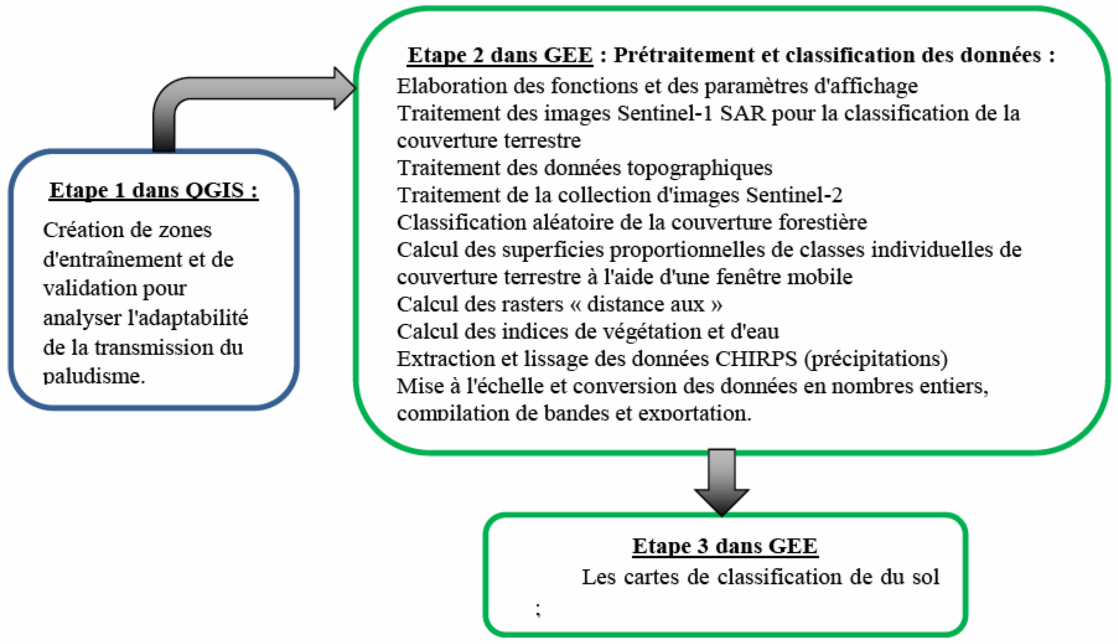

Figure 3: flowchart of the stages of the process of developing the land cover classification model

2.2.3.2. Land use classification: step 2

After creating the training area, the figure below (figure 4) presents the steps to follow to perform automatic land cover classification in Google Earth Engine (GEE) from training polygons created in QGIS.

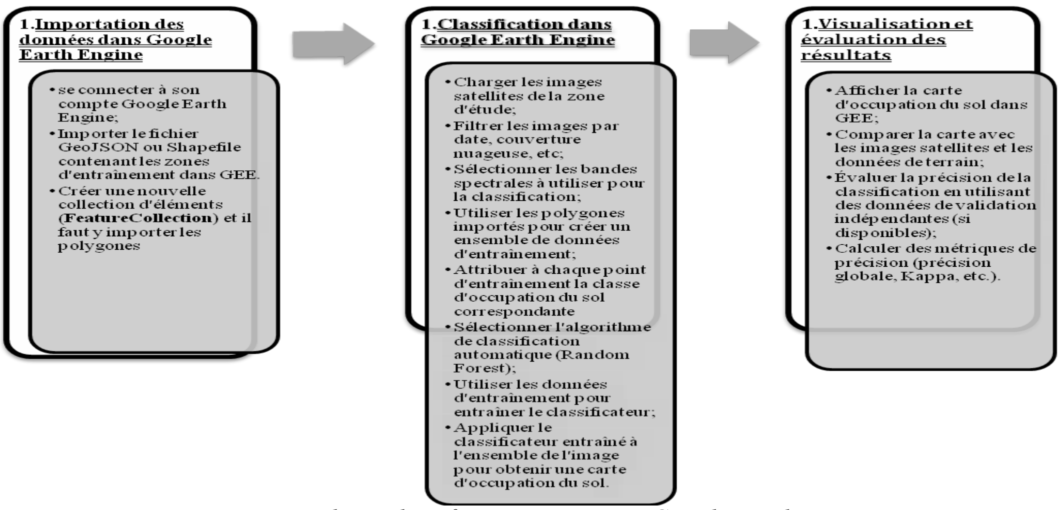

Figure 4: Land use classification process in Google Earth Engine

2.2.3.3. Boolean logic

Boolean logic is proving to be a valuable tool in classifying land use and identifying areas at risk of malaria transmission. By defining threshold values and combining various criteria using logical operators, it makes it possible to establish classification rules that assign a specific class to each pixel of an image based on its characteristics. The accuracy of this classification is then evaluated by comparison with field data or other reference sources (Regis & Claude, 2011).

Through the combination of environmental and climatic factors, Boolean logic facilitates the creation of detailed maps for targeted interventions by identifying discriminating characteristics for each class. In addition, its integration into decision trees makes it an effective decision support tool for classification and regression (figure 5).

$$\boxed{\text{Zone à risque} = (\text{présence de zones humides} > 60\%) + (\text{température} > 25°C) + (\text{NDVI} > 0{,}5)}$$

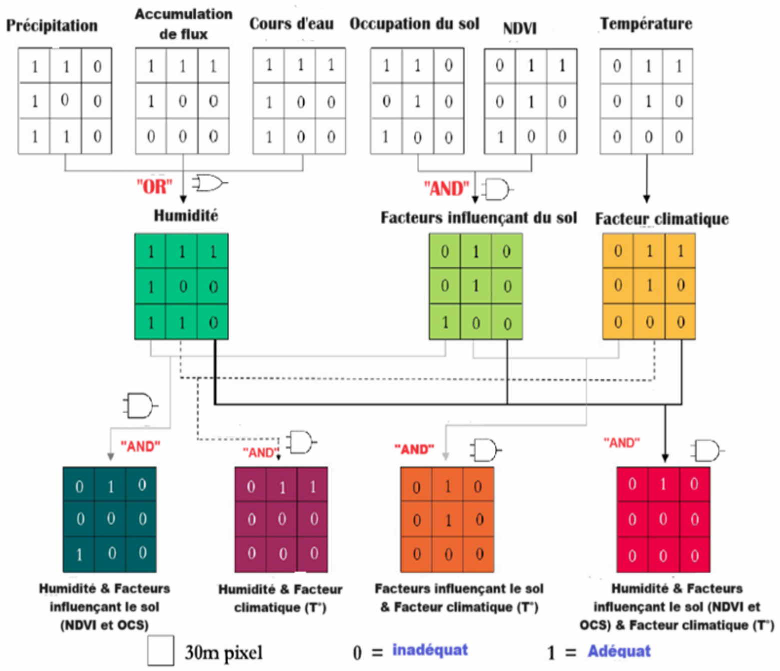

Figure 5: Diagram illustrating the integration of climatic and environmental variables using Boolean logic.

2.2.4. Decision tree

The Random Forest approach, used for land use classification, is based on the creation of several decision trees from a random sample of the data. Each decision tree predicts a class and the final class is decided by a majority vote. To assess whether a site is conducive to the spread of malaria, a decision tree is used to identify the determining factors and their risk thresholds (Unesco, 2020). Boolean logic is then applied to combine these factors and define classification rules. The “Random Forest” method, by combining several decision trees, is used to improve the precision and robustness of the risk assessment (figure 6).

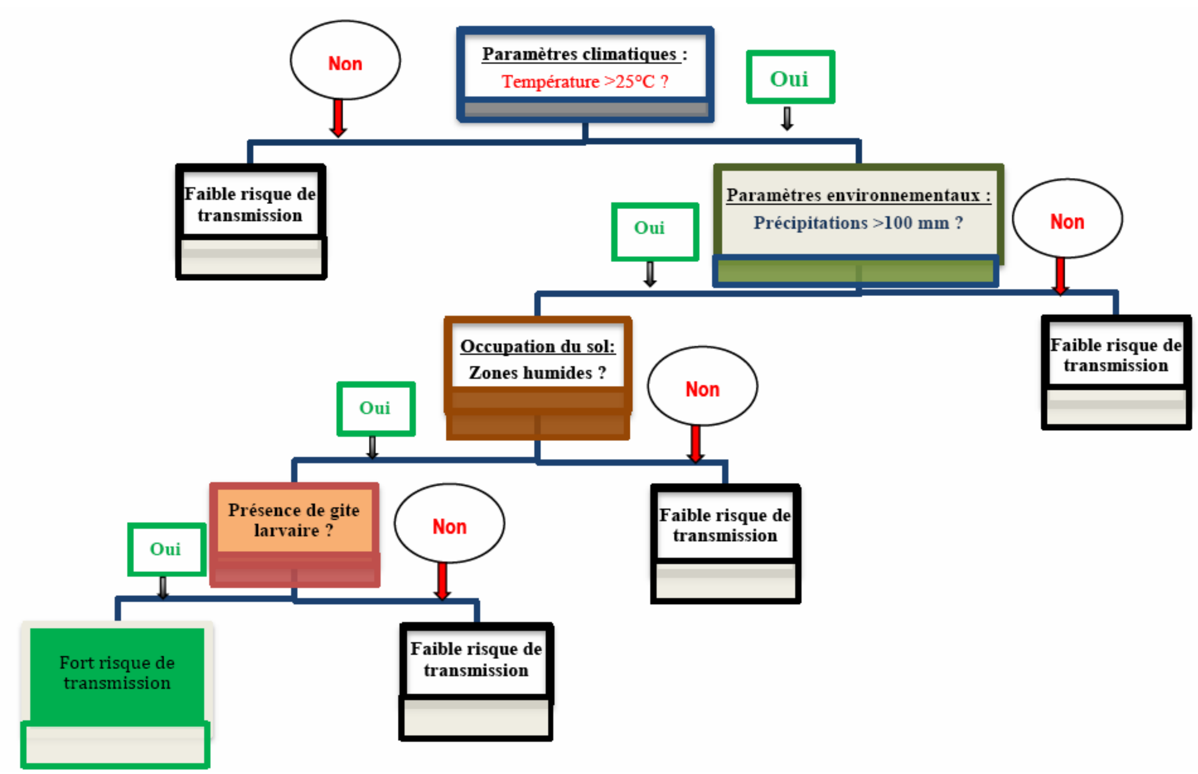

Figure 6: Land use decision tree (Random Forest

The identification of areas at high risk of malaria transmission was made possible by combining land use classification with logical operators, as well as cross-referencing information on land use, mosquito habitats and other environmental factors that favor mosquito proliferation and disease transmission. In order to accurately assess the risk of transmission in highly urbanized and dense areas like Greater Abidjan, it was essential to take into account a number of factors. Climatic factors such as the NDVI index, temperature and precipitation play a crucial role, as do the dynamics of the disease transmission reservoir (Philippe, Emmanuel, & Pierre, 2002).

III. RESULTS AND ANALYZES

3.1. Land use map

3.1.1. Temperature changes in 2015 and 2020

Previous studies, including one published in the Malaria Journal in 2018, have demonstrated a positive correlation between high temperatures and malaria incidence. An increase in temperature accelerates the development of mosquito larvae, increases their population and activity, and promotes the multiplication of the Plasmodium parasite and the frequency of bites. This 2018 study found that in Abidjan, an increase of just 1°C in average temperature corresponds to a 14% increase in malaria cases. This study, carried out between 2015 and 2020 and using satellite data from Sentinel 2 and Landsat 8, confirmed the significant influence of high temperatures on the transmission of malaria. The average temperature of Greater Abidjan during this period was 27.5°C, typical of a hot and humid tropical climate, conducive to the transmission of malaria. Of course, other environmental factors other than temperature can influence malaria transmission. Such as precipitation, NDVI, with high values observed in Greater Abidjan considerably increase the risk of transmission. This highlights the need for relevant and transversal analysis of data from various sources (Big Data) in order to strengthen prevention and control measures.

3.1.2. Changes in precipitation in 2015 and 2020

The Greater Abidjan region, characterized by a humid tropical climate with two dry and two rainy seasons, recorded an average annual rainfall of 1,800 mm between 2015 and 2020. The months of June and July 2017 and 2019 saw peaks in rainfall, which subsequently led to an increase in the population of malaria-carrying mosquitoes. Indeed, the warm and humid environment resulting from heavy rains is ideal for mosquito breeding because it increases the number of breeding sites (standing water), activity and survival of adult mosquitoes. Although precipitation and temperature are key factors in malaria transmission, other environmental factors such as vegetation growth (NDVI), which provides shelter for mosquitoes, are also stimulated.

3.1.3. Changes in NDVI (Normalized Difference Vegetation Index) in 2015 and 2020

The study on malaria transmission in Greater Abidjan between 2015 and 2020 highlighted the significant role of soil-related factors, notably the normalized difference vegetation index (NDVI) and land use. These factors are particularly important during two key periods: January to May and November to December. Despite rapid urbanization, vegetation remains significant, particularly in peri-urban areas like Anyama, Songon and Bingerville, with an average NDVI of 0.5.

Areas with high NDVI (> 0.2), such as the Banco Forest, the Bingerville botanical garden and the Vallée du Tir park, offer shade and humidity, conditions conducive to the rest of Anopheles mosquitoes. In contrast, areas with low NDVI (< 0.1), primarily in dense urban centers and expanding peri-urban areas, have reduced vegetation, increasing the availability of blood meals for these mosquitoes.

The peri-urban agricultural areas of Anyama, Songon, Bingerville and Abobo-Doumé, with the presence of stagnant water, constitute potential breeding grounds for mosquitoes, increasing the risk of malaria transmission. Although stagnant water is a major factor, other elements such as water quality, the presence of aquatic vegetation and temperature also influence the choice of breeding sites by mosquitoes.

3.1.4. Environmental changes linked to land use, watercourses and accumulation flows between 2015 and 2020

In addition, land use, hydrography and human behavior play an important role. Greater Abidjan, due to its rapid urbanization and population growth, is experiencing a change in land use which favors the transmission of malaria. Dense urban areas such as Abobo, Yopougon and Koumassi, as well as peri-urban agricultural areas, are particularly affected. The presence of stagnant water (from waste, inadequate habitats, irrigation), the accumulation of flows due to urbanization (increasing flooding and wetlands), and the hydrographic network with its waterways provide breeding habitats for mosquitoes. Analysis of hydrographic data, combined with other environmental and epidemiological factors, is essential to assess and prevent malaria transmission in the region.

The map, generated using the Random Forest model, identified different land use categories, including urban, agricultural, forest and wetlands (Figure 6). The high accuracy of this map is due to the ability of the Random Forest algorithm to handle complex data and non-linear relationships between variables. The results of the individual analysis of environmental parameters highlighted the significant influence of each of them on the transmission of malaria. The combination of these analyzes made it possible to create a risk map integrating all these factors. The PNLP aimed to reduce the incidence of malaria from 155‰ to 105‰ between 2016 and 2019. Instead, the incidence increased to 191‰ in the general population and to 582‰ among children under 5 years old, particularly in some localities like Anyama, Dabou, Grand Lahou and Jacqueville (see graph below). This increase may be due to several factors, including the scaling up of PECADOM/iCCM (Home Management of Illnesses/Integration of Community Consultations for Childhood Illnesses), the collection of data from the private sector, the strengthening of consultations in precarious neighborhoods and a possible double inventory of data. Malaria-related mortality decreased between 2016 and 2019. These data may not reflect all incidence cases due to the use of unconventional care structures or the lack of reporting of some cases.

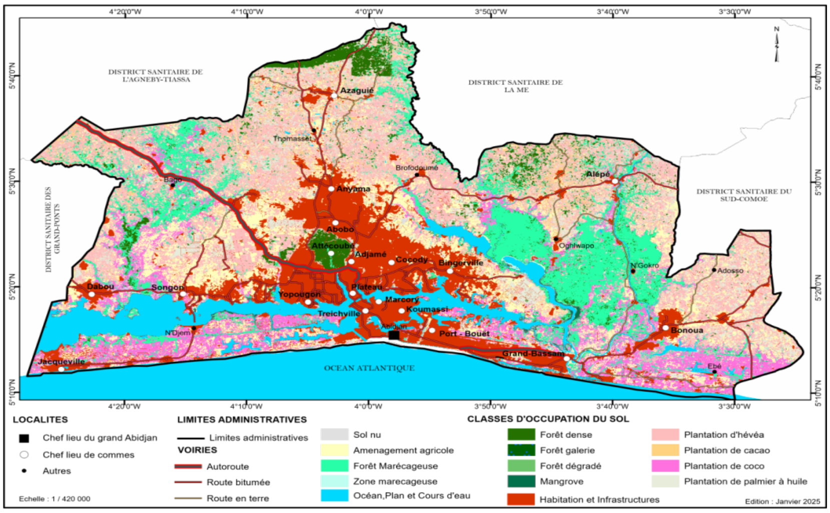

Figure 6: Land use map of Greater Abidjan

The different types of land use in Greater Abidjan are:

- **Dense urban areas**, with a high concentration of housing, buildings and roads, and little green space. This includes neighborhoods like Plateau, Cocody, Treichville, Marcory and Adjamé;

- **Peri-urban areas**, where there is a mix of housing, agriculture and natural spaces such as: Abobo, Yopougon, Koumassi and Port-Bouët;
- **Rural areas**, with scattered villages, agriculture, forests and wetlands, such as Dabou, Jacqueville, Anyama, Songon and Bingerville;
- **Industrial areas**, characterized by the presence of factories, warehouses and infrastructure, such as the Vridi Industrial Zone and that of Yopougon;
- **Wetlands**, such as lagoons and swamps, with stagnant water and dense vegetation. The Ebrié Lagoon and the Banco National Park are examples;
- **Forests**, with dense plant cover and significant biodiversity, such as the Banco Forest and the Téné Forest;
- **Urban green spaces**, including parks, gardens and recreational spaces, such as the Parc du Banco and the Bingerville Botanical Garden.

3.2. Impact of climatic and environmental parameters on malaria transmission

High-risk areas include peri-urban areas, due to their proximity to agriculture and wetlands, and rural areas, due to the presence of breeding sites and limited access to care (Figure 7). Wetlands also pose a high risk due to standing water. The risk in dense urban areas is moderate, while the risk in industrial and forest areas varies. Urban green spaces pose a low to moderate risk. Land cover classification to identify high-risk areas should take into account factors such as NDVI, temperature, precipitation, flow accumulation and watercourses, as the impact of land cover (OCS) on malaria transmission may vary depending on the local context and other environmental factors.

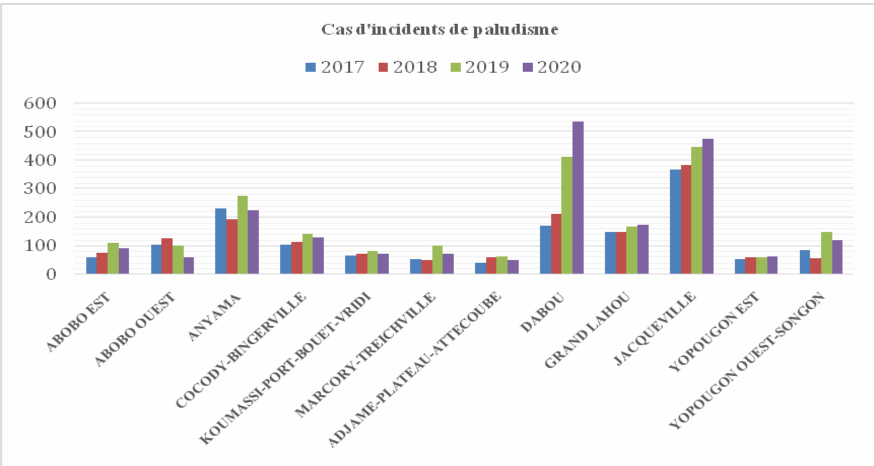

Figure 7: Cases of malaria incidents in Greater Abidjan from 2016 to 2019 (source: PNLP in 2024)

The health districts which were much more impacted by confirmed cases of malaria are: Koumassi-Port Bouët-Vridi (15%), Cocody-Bingerville (14%), Abobo Est (11%), Adjamé-Attécoubé-Plateau (9%), Abobo Ouest (9%), Yopougon Est (8%), Yopougon Ouest-Songon (7%), Dabou (7%), Anyama (7%), Jacqueville (5%), Grand-Lahou (5%) and Treichville-Marcory (4%) (figures 8 and 9). Although the environmental data approach is a valuable tool, it must be complemented with other data for a complete understanding of transmission and effective planning of interventions. Understanding the relationship between rainfall, female Anopheles and malaria transmission is crucial for implementing effective prevention and control strategies. Both spatial statistical analysis techniques contribute to a better understanding of risk factors and make it possible to standardize, compare and combine different environmental and socio-economic variables, which facilitates the analysis of the complex network of factors that influence malaria transmission.

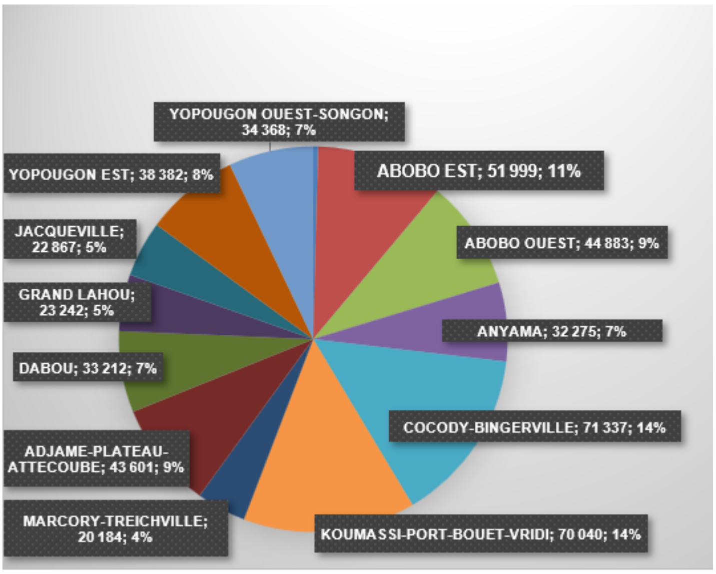

Figure 8: Confirmed cases of malaria in Greater Abidjan from 2016 to 2019 (source: PNLP in 2024)

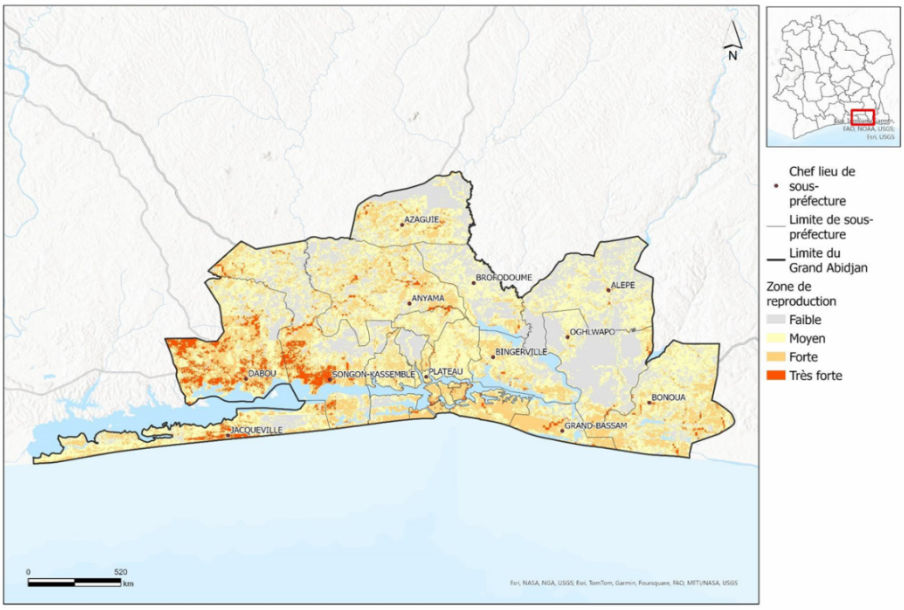

Figure 9: Mapping of areas at risk of exposure to malaria transmission

3.3. Discussion

Unlike previous studies, which were often limited by sectoral analysis and a limited number of environmental and climate factors, this study demonstrated that analyzing environmental and climate data using tools such as Google Earth Engine (GEE) can improve understanding of malaria transmission.

This innovative approach enables a more in-depth and comprehensive analysis, revealing correlations between key environmental and climatic factors (temperature, NDVI, precipitation, rivers, land use and flow accumulation) and areas at risk of malaria transmission. The study found that the interaction of these factors, such as high temperatures, dense vegetation, heavy rainfall, poor urban planning, inadequate sanitation and accumulation of waste, play an important role in the spread of the disease. By integrating several environmental parameters into a single model, the study made it possible to more precisely identify areas at risk and provided an exposure risk map to guide targeted vector control interventions (Sylvie, Carnevale, & Jean, 2008).

The results highlight the need for an integrated approach to malaria prevention and control that takes into account all environmental and climatic factors. This approach could include measures such as improving surface water management, promoting sanitation and waste management, raising public awareness of environmental risks and integrating climate and environmental data into epidemiological surveillance systems. The use of Google Earth Engine represents a major change, as it makes it possible to exploit high-resolution satellite data over large geographic areas, and to analyze temporal variations in environmental and climatic factors, paving the way for the development of predictive models of malaria transmission.

Although our study did not consider the reservoir of disease transmission, it is important to recognize that transmission dynamics are influenced by the prevalence of asymptomatic infections, the duration of infection, and the effectiveness of control measures (treated bed nets, spraying, and treatment). Previous research has demonstrated that several factors have contributed to making humans the main reservoir of malaria: high population density, frequent travel, urban expansion, deforestation, proximity to rivers, certain agricultural practices and resistance to antimalarial drugs (Tran, 2004; Ahmed, Chaitanya, Kanak, Quoc, & Singh, 2023). Therefore, a comprehensive malaria risk assessment should include not only climatic and environmental factors, but also socio-economic factors and the transmission reservoir. This holistic approach would make it possible to better understand the dynamics of the disease and to design more effective and targeted prevention strategies. Accurate land use data from satellite and/or field images are essential for this assessment.

IV. CONCLUSION

A multifactorial approach that integrates climatic, environmental and socio-economic parameters will allow a better understanding of the dynamics of the disease and the development of more targeted and effective prevention and control strategies. Analyzing environmental data in Google Earth Engine is proving to be a powerful tool for understanding and predicting malaria transmission.

REFERENCES

[1]. Gillespie, e. a. (2015). The complex role of vegetation in malaria transmission: a review. Parasites & Vectors.

[2]. Ahmed, E., Chaitanya, B. P., Kanak, N. M., Quoc, B. P., & Singh, S. K. (2023). Climate Change Impacts on Natural Resources, Ecosystems and Agricultural Systems. Springer Climate.

[3]. AK, K. &. (2015). Urban malaria risk in Abidjan: case study on environmental and socio-economic factors. Journal of Urban Health, 67-78.

[4]. A.K. K., &. has. (2015). Urban malaria risk in Abidjan: case study on environmental and socio-economic factors. Journal of Urban Health, 67-78.

[5]. Anya, S. E. (2017). Socioeconomic determinants of malaria in Africa: a systematic review. Malaria Journal, 145.

[6]. Atta Koffi, K. M. (2015). New housing configuration in the precarious neighborhoods of Abidjan: case of Jean Folly, Zoe Bruno and Sagbe. European Scientific Journal.

[7]. Belfali, Dalila, M., Cherik, & Kheira, B. (2023). Mapping agricultural capabilities in the Tiaret region using remote sensing and machine learning. Tunis: Ibn Khaldoun University.

[8]. Korenromp, E. L. (2005). The association between poverty and malaria in sub-Saharan Africa. . The American Journal of Tropical Medicine and Hygiene.

[9]. Martin, D.K. (2021). Urban poverty and the emergence of informal economic survival initiatives in Abobo, a commune in the northern peripheral area of Abidjan in the Ivory Coast. Canadian journal of tropical cartography (cangeotrop.ca journal).

[10]. Philippe, L. D., Emmanuel, G., & Pierre, J. (2002). Society and nature in the Sahel. London: Taylor and Francis.

[11]. Regis, C., & Claude, C. (2011). Spatial analysis and geographic information: Model and life cycle of geographic information. EPFL Press.

[12]. Sylvie, M., Carnevale, P., & Jean, M. (2008). Biodiversity of maliaria in the world. Paris: John Libbey Eurotext.

[13]. Thierry, B., Barbara, B., Mathieu, C., & Thibault, C. (2022). Remote sensing and spatial modeling: applications to the surveillance and control of mosquito-related diseases. Versailles: Éditions Quæ (Update Sciences & Technologies Collection).

[14]. Tran, A. (2004). Remote sensing and epidemiology: Modeling the dynamics of insect populations and application to the control of vector-borne diseases. AbeBooks.

[15]. Unesco. (2020). United Nations World Water Development Report 2020: Water and climate change. Unesco.

[16]. YAO, K.P. (2010). Urban development and proliferation of precarious neighborhoods in Abidjan: the case of the Banco 1 neighborhood (municipality of Attécoubé). Yamoussoukro: National Polytechnic Institute Houphouët Boigny.