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Unleashing the power of intelligence: revolutionizing malaria outbreak preparedness with an advanced warning system in Benin, West Africa

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Abstract

Background Malaria is a significant vector-borne disease that exhibits high sensitivity to climatic variations within the West African region. In Benin, the effective prevention and mitigation of malaria pose considerable challenges, primarily due to the prevailing conditions of poverty and environmental adversities. This study endeavours to devise an advanced system for early detection and warning of malaria outbreaks in the northern part of Benin, employing monthly time series data pertaining to climatic variables.

Methods Monthly climate data were sourced from Meteorological Agency of Benin (METEO-Benin), alongside malaria incidence data procured from the database of the Benin Ministry of Health, that covered the timeframe of 2009–2021. To ascertain the influence of climatic variables on malaria incidence, principal component analysis was applied. Subsequently, an intelligent model for forecasting malaria outbreaks was developed using support vector machine (SVM) algorithm. The developed model for malaria outbreaks was then employed to establish an intelligent system for warning and forecasting malaria incidence on a monthly basis, utilising the Meteostat platform, an online weather data service provider, in conjunction with the Streamlit framework. This application exhibits responsiveness and compatibility across all web browsers.

Results Relative humidity and maximal temperature significantly influence malaria incidence in the northern region of Benin. SVM regression algorithm forecasts 80% prediction rate for malaria incidence. Consequently, the intelligent malaria outbreak warning system was successfully devised, enabling the automatic and manual prediction of monthly malaria incidence rates within the districts of northern Benin.

Conclusions This system serves as a valuable tool for stakeholders and policymakers, facilitating proactive measures to curtail malaria transmission in Benin.

Keywords Climate change, Malaria, Early warning system, Benin

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Text box 1. Contributions to the literature

• Comprehensive analytical approach using PCA and SVM to provide a holistic understanding of the climatic-malaria relationship.

• Targeted focus on northern Benin, offering nuanced insights into local malaria transmission patterns.

• Development of a user-friendly, web-based malaria outbreak alert system to facilitate proactive, evidence-based interventions.

• Practical implications for malaria control through targeted preparatory activities and resource allocation. Context-specific insights to inform effective, locally-tailored strategies for tackling climate-malaria dynamics in West Africa.

Introduction

Climate change's effects on human well-being have received increasing focus these decades. There is mounting evidence that climate change is wreaking havoc on world health, both directly and indirectly through disruptions in ecological and socioeconomic systems. The change in climate has affected human health and increased the susceptibility of poor communities. Malaria constitutes the most harmful infectious disease in West Africa. Transmissible via vector, malaria is transmitted to humans by the Anopheles mosquito bite. Plasmodium falciparum is the primary cause of malaria in West Africa. The burden of malaria-related mortality and morbidity is particularly severe in impoverished countries and among the most disadvantaged populations within these countries [1, 2]. Climatic factors such as temperature, humidity, and rainfall influence the transmission of malaria by affecting the duration of mosquitoes and modifying the parasite life cycles or the biting behaviour of the parasites [3–7]. Socioeconomic factors also contribute to the occurrence of malaria, both in rural and urban areas [8].

Benin, a low-income country in West Africa, faces severe malaria challenges [9]. The country is significantly impacted by the prevalence of malaria due to environmental challenges and climate change.

In Benin, malaria is the leading cause of both mortality and morbidity. A total of 3.163.648 malaria cases were observed in 2021, with a slight increase of 1.4% between 2020 and 2021 and 2,956 deaths [10]. Despite decades of efforts made by the Benin government, malaria continues to impose a significant burden, causing 95% of deaths [11]. The northern part of Benin is one of the most prevalent regions of malaria. Borgou, Atacora, and Donga are the provinces with the highest burden of malaria transmission in this region [12].

In Benin, there are limited studies assessing the association between malaria incidence and climatic variables. The study of [13] conducted a literature review on the effect of climate change on public health. In addition [14, 15], mapped the breeding sites of mosquitos in Cotonou and assessed the impact of climatic factors on the aggression and infectivity of anopheles in Northern Benin. Understanding these dynamics is of paramount importance, as it enables the forecasting of seasonal malaria prevalence, thereby providing valuable insights for policymakers to develop targeted interventions for malaria control planning. Early warning systems, when based on skillful forecasts and accompanied by timely responses, can serve as valuable tools for adapting to climate-related risks associated with infectious diseases [16]. Advanced seasonal weather forecasting allows for the early detection, months in advance, of situations that can lead to disease epidemics. This gives adequate time to implement effective population health interventions.

An outbreak is defined as a situation in which the number of malaria cases in a region exceeds the threshold established by the typical seasonal pattern of the disease. This threshold is generally determined using historical data collected at the district level over a minimum period of five years [17]. Typically, historical routine data at the district level spanning at least five years is used to determine this criteria [18]. Various methods including constant case counts, the 75th percentile, cumulative sum (C-SUM), and mean ± 2 standard deviations (SD) were recommended by the World Health Organisation (WHO) to compute the threshold. The optimal threshold calculation approach is contingent upon the severity of malaria transmission in a particular region [17]. The World Health Organization classifies malaria transmission intensity using the Annual Parasite Index (API). High transmission is prevalent, with 450 cases per 1,000 people. Medium transmission is less widespread, with 251–450 cases per 1,000. Low transmission is present but at lower levels, with 101–250 cases per 1,000. Very low transmission is rare, with 100 cases per 1,000 or fewer [17, 18].

Support Vector Machine (SVM) is a powerful supervised machine learning algorithm for handling small datasets, high-dimensional data, and simulating nonlinear decision boundaries. It may be used for a range of classification and regression issues, performs well in generalisation, and is robust to noise. SVM is effective and less prone to overfit since it offers sparse solutions. Because tit may be regularised to avoid overfitting, it is suitable for a variety of applications [19]. In this study, SVM will be used to model and predict the incidence of malaria.

Study area, climate, and population

The research area in northern Benin comprises the provinces of Atacora, Donga, and Borgou (Fig. 1). Borgou province encompasses approximately 23% of the national territory and is subdivided into eight districts. Atacora, on the other hand, ranks as the third-largest province and has an estimated population of 772,262 inhabitants. This population exhibited a growth rate of 3.04% between the

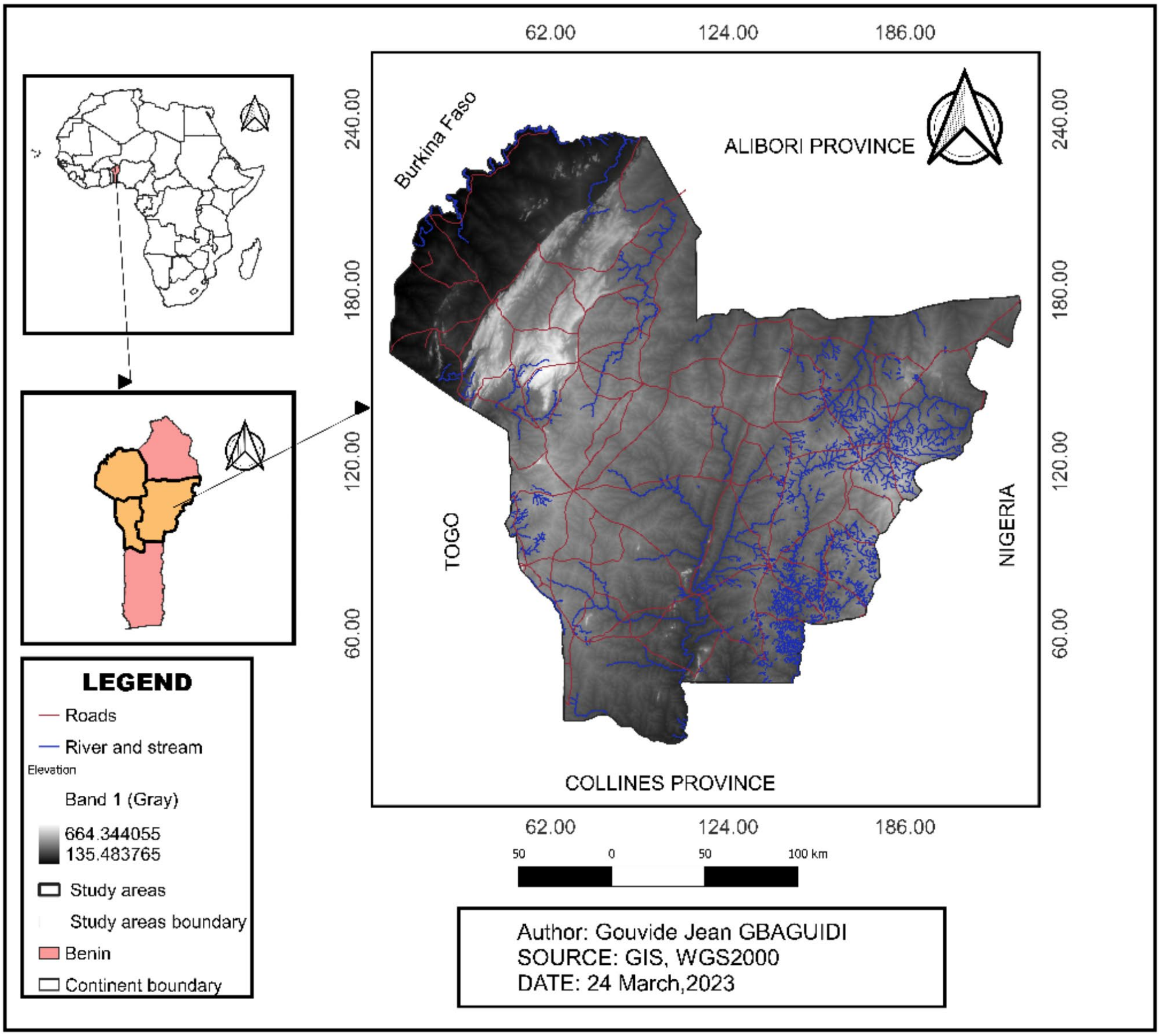

Fig. 1 Map of the research region of interest

years 2002 and 2013. Lastly, Donga province, with a population of 543,130, is divided into four districts. In northern Benin, the rainy season occurs from May to October, with an average monthly rainfall ranging between 200 and 300 mm. Specifically, the highest precipitation (253.61 mm) is observed in August, while January has the lowest amount (1.90 mm) [20]. The region also experiences distinct dry and wet seasons. From November to April, the region experiences the dry season, characterised by the arrival of the "Harmattan" winds originating from the northeast. These winds carry air from the Sahara Desert, contributing to the prevailing arid conditions during this period [21].

Data collection

Exogenous variables

Throughout the period from 2009 to 2021, we collected monthly climatic data encompassing wind speed, temperature, and relative humidity. These data were sourced from the meteorological stations located at Natitingou and Parakou Airport, which are administered by the National Meteorological Agency of Benin. Furthermore, we obtained monthly precipitation data for the same period from seventeen different rain gauge stations located in Northern Benin. K-Nearest Neighbors (KNN) imputation method was used to fill in missing values in a dataset based on the values of neighboring data points. The missing of the climatic data represent 3% of the data [22].

Endogenous variables

From January 2009 to December 2021, we collected monthly data on the incidences of malaria cases in each district of the three provinces of the study areas (Atacora, Donga and Borgou). The Benin Ministry of Health provided these monthly data, which encompass the total population that has been officially diagnosed with malaria. The data was retrieved from the DHIS2 system. A patient is classified as having malaria when the disease is confirmed through laboratory testing using microscopy or rapid diagnostic methods [23].The missing value of each month were replaced by the mean of the available data for that month.The missing value is estimated to 1%.

Data processing

Climatic factors controlling the transmission of malaria

To identifying the climatic variables that exert the greatest influence on the incidence of malaria, we employed principal component analysis (PCA) method. PCA facilitates the reduction of factors while retaining substantial information. The implementation of PCA involves several steps. Firstly, we constructed a matrix X, in which the rows corresponded to regions (M) and the columns represented indicators (K). Consequently, the dimensions of the matrix Y were M × K. Furthermore, we computed the mean for each variable across all observations and subtracted this mean from each individual observation. This process yielded a new matrix, denoted as $Y - \bar{Y}$, in which the sum of elements in each column equaled zero. Next, we computed the covariance matrix (ω) using the formula: $\omega = (Y - \bar{Y})^T(Y - \bar{Y})/m$. Within this covariance matrix, the diagonal elements corresponded to the variances of the respective variables, while the off-diagonal elements reflected the covariances between variables.

To assess the significance of each eigenvalue, we arranged them in ascending order ($\mu_1 \leq \mu_2 \leq \ldots \leq \mu_n$), enabling the identification of the most crucial principal components (Table 1). PCA, the Taylor diagram and outliers were computed using the packages FactoMineR, factoextra and car in R software version 4.3.2 respectively. The outliers in the data were identified using the Bonferroni t-test method provided by the car package in R. This method tests for outliers based on standardized residuals, allowing for the identification of observations that significantly deviate from the fitted model. For a sensitivity analysis, the imputed and complete data were used.

In our study, we followed the TRIPOD + AI statement, which is an updated guideline for reporting prediction models that use regression or machine learning methods(https://www.tripod-statement.org/).

Malaria early warning model

Support Vector Machine (SVM) was applied to create the malaria outbreak warning model. Random sampling method was utilised to create separate training and test sets (Refer to supplement). The training data set served to train the model, the test data was used to evaluate its estimated accuracy and the calibration data was used to calibrate the validated model to adjust the predicted values. The model was trained using 75% of the data, tested with 15%. The validated model was calibrated with the remaining 15% of the data. The performance of the model to forecast malaria occurrence in northern Benin was evaluated by computing different metrics such as Root Mean Square Error (RMSE), Mean Squared error (MSE) and Mean Absolute Error (MAE). RMSE is the square root of the MSE and represents the average magnitude of the prediction errors. MSE represents the average squared difference between the predicted values and the observed values and MAE represents the average absolute difference between the predicted values and the observed values. A lower value of these metrics indicates a better fit of the model.

To validate the model, we compute the bias and the correlation between the observed malaria incidence and the predicted as well as the standard deviation of the predicted and the observed malaria incidence. Taylor diagram was represented to analyse the statistical relationship between observed and predicted values (Fig. 2). It is an invaluable tool for comparing predicted and observed values of malaria incidence, to validate the model. This diagram helps in evaluating the model's predictive and correlational performance [24].Simple regression was used to calibrate the model by computing slope and the intercept [25].

Malaria early warning system

When case counts rise over the threshold for the typical seasonal pattern of malaria in a region, it is referred to as an outbreak. In this study, we use *mean ± 2 standard deviations* method recommended by WHO to detect the monthly malaria outbreak in each district of the study areas [17] This method takes the mean number of malaria cases in the month by adding 2 *standard deviations* The average threshold for each district was used to classify each district threshold level according to their statistical significance. Low, Medium, High, and Very High were the different levels with the p-values 0.005, 0.01, 0.001, and 0.0001, respectively (Table 1). The detection of an outbreak helps policymakers to raise awareness and take strategic intervention to reduce the risk.

A web application was developed for the malaria outbreak warning. It uses the built malaria outbreak warning model (See supplement). The web application was built using the Streamlit framework and is responsive and compatible with all navigators. The weather forecasting data is powered by Meteostat, an online weather data service provider. Meteostat offers a Python library for

Table 1 Outbreak thresholds in each district of the study areas

Districts	Values	Status	Districts	Values	Status	Districts	Values	Status	Districts	Values	Status
Bassila	Predicted > 13.38	Low	Copargo	Predicted > 16.38	Low	Kouande	Predicted > 15.63	Low	Tanguieta	Predicted > 13.99	Low
Bassila	13.38 < Predicted < 17.59	Medium	Copargo	16.38 < Predicted < 21.53	Medium	Kouande	15.63 < Predicted < 20.54	Medium	Tanguieta	13.99 < Predicted < 18.39	Medium
Bassila	17.59 < Predicted < 22.47	High	Copargo	21.53 < Predicted < 27.50	High	Kouande	20.54 < Predicted < 26.25	High	Tanguieta	18.39 < Predicted < 23.50	High
Bassila	22.47 < Predicted < 26.56	Very High	Copargo	27.50 < Predicted < 32.51	Very High	Kouande	26.25 < Predicted < 31.03	Very High	Tanguieta	23.50 < Predicted < 27.78	Very High
Bembereke	Predicted > 17.87	Low	Djougou	Predicted > 14.13	Low	Materi	Predicted > 23.97	Low	Tchaourou	Predicted > 5.48	Low
Bembereke	17.87 < Predicted < 23.49	Medium	Djougou	14.13 < Predicted < 18.57	Medium	Materi	23.97 < Predicted < 31.51	Medium	Tchaourou	5.48 < Predicted < 7.21	Medium
Bembereke	23.49 < Predicted < 30.01	High	Djougou	18.57 < Predicted < 23.72	High	Materi	31.51 < Predicted < 40.25	High	Tchaourou	7.21 < Predicted < 9.21	High
Bembereke	30.01 < Predicted < 35.48	Very High	Djougou	23.72 < Predicted < 28.05	Very High	Materi	40.25 < Predicted < 47.59	Very High	Tchaourou	9.21 < Predicted < 10.88	Very High
Boukoumbe	Predicted > 26.15	Low	Kalale	Predicted > 9.42	Low	N'Dali	Predicted > 11.89	Low	Toucountouna	Predicted > 18.47	Low
Boukoumbe	26.15 < Predicted < 34.37	Medium	Kalale	9.42 < Predicted < 12.39	Medium	N'Dali	11.89 < Predicted < 15.63	Medium	Toucountouna	18.47 < Predicted < 24.28	Medium
Boukoumbe	34.37 < Predicted < 43.91	High	Kalale	12.39 < Predicted < 15.82	High	N'Dali	15.63 < Predicted < 19.97	High	Toucountouna	24.28 < Predicted < 31.02	High
Boukoumbe	43.91 < Predicted < 51.928	Very High	Kalale	15.82 < Predicted < 18.71	Very High	N'Dali	19.97 < Predicted < 23.61	Very High	Toucountouna	31.02 < Predicted < 36.67	Very High
Cobli	Predicted > 14.68	Low	Kerou	Predicted > 20.52	Low	Natitingou	Predicted > 17.58	Low	Ouake	Predicted > 7.57	Low
Cobli	14.68 < Predicted < 19.30	Medium	Kerou	20.52 < Predicted < 26.97	Medium	Natitingou	17.58 < Predicted < 23.10	Medium	Ouake	7.57 < Predicted < 9.95	Medium
Cobli	19.30 < Predicted < 24.66	High	Kerou	26.97 < Predicted < 34.46	High	Natitingou	23.10 < Predicted < 29.52	High	Ouake	9.95 < Predicted < 12.71	High
Cobli	24.66 < Predicted < 29.15	Very High	Kerou	34.46 < Predicted < 40.74	Very High	Natitingou	29.52 < Predicted < 34.90	Very High	Ouake	12.71 < Predicted < 15.03	Very High
Nikki	Predicted > 8.18	Low	PARAKOU	Predicted > 5.99	Low	Pehonko	Predicted > 9.06	Low	PERERE	Predicted > 9.77	Low
Nikki	8.18 < Predicted < 10.75	Medium	PARAKOU	5.99 < Predicted < 7.87	Medium	Pehonko	9.06 < Predicted < 11.91	Medium	PERERE	9.77 < Predicted < 12.84	Medium
Nikki	10.75 < Predicted < 13.73	High	PARAKOU	7.87 < Predicted < 10.05	High	Pehonko	11.91 < Predicted < 15.22	High	PERERE	12.84 < Predicted < 16.40	High
Nikki	13.73 < Predicted < 16.24	Very High	PARAKOU	10.05 < Predicted < 11.88	Very High	Pehonko	15.22 < Predicted < 17.99	Very High	PERERE	16.40 < Predicted < 19.39	Very High
Sinende	Predicted < 25.68	Very Low	Sinende	Predicted > 25.68	Low	Sinende	25.68 < Predicted < 33.75	Medium	Sinende	33.75 < Predicted < 43.12	High
									Sinende	43.12 < Predicted < 50.98	Very High

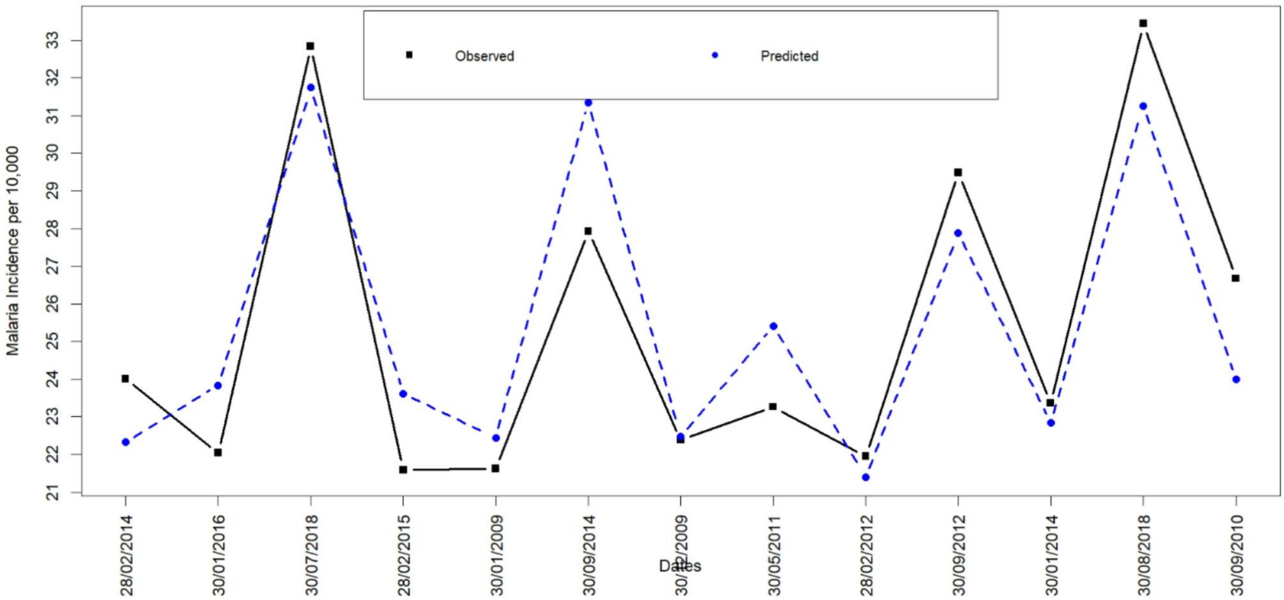

Fig. 2 Calibration of the malaria early warning model predicting one month in advance the incidence of malaria in northern Benin (refer to supplement)

Table 2 Eigenvalues and malaria incidence's variance explained by factors

Factors	Eigenvalues	percentage of variance	cumulative percentage of variance
F1	**4.28**	**47.52**	**47.52**
F2	**2.04**	**22.70**	**70.21**
F3	**1.09**	**12.12**	**82.34**
F4	0.87	9.70	92.04
F5	0.53	5.90	97.95
F6	0.13	1.49	99.44
F7	0.04	0.45	99.89
F8	0.01	0.11	100.00
F9	0.00	0.00	100.00

querying forecasting data using coordinates. This interface reduces complexity for users, as it does not require knowledge about the available weather stations. Instead, data can be retrieved directly. The front-end of the application uses HyperText Markup Language (HTML) and Cascading Style Sheets (CSS). These technologies are employed to structure and style the user interface of the application(See supplement).

This application works in three steps: The weather forecasting data provided by Meteostat is preprocessed before being used in the web application.The prediction data is post-processed and presented on the app's UI front layer. The application supports both automatic and manual data input. When a city is selected, the tool predicts the likelihood of a malaria incidence outbreak based on the last month's data up to the current hour. The current outbreak predictions and matching status are displayed. Users can manually enter a set of climatic variables and get a prediction that shows up alongside the status. The PCA analysis is carried out using R software version 4.3.2 and Python software version 3.12 is used to develop the support vector machine algorithm. The packages car and VIN were used to removed the outliers and fill the climatic missing data respectively.

Results

Climatic factors associated the transmission of malaria

Table 2 presents the loading factors from eigenvalues for each principal component. A thorough examination of this table reveals that factors F1, F2, and F3 have eigenvalues exceeding unity (Table 1). The number of factors influencing malaria incidence corresponds to the number of eigenvalues greater than unity in the population correlation matrix [26]. The respective eigenvalues (4.28, 2.04, and 1.09) associated with Factors F1, F2, and F3 indicate the presence of three principal components that explain a significant amount of variance in the data related to malaria transmission in the northern region of Benin. Factor 1 consists of mean and maximal temperature, as well as minimal, mean, and maximal relative humidity. Factor 2 comprises mean and minimal temperature, while Factor 3 is associated with rainfall (Table 3). Factor 1, Factor 2, and Factor 3 explain 47.52%, 22.70%, and 12.12% of the variation in the incidence of malaria, respectively. Collectively, these three factors account for 82.34% of the total malaria incidence variation. Based on Table 3, which presents the weight of each variable, Factor 1 emerges as the most influential factor in controlling malaria incidence (Table 2). Analysis of Table 2, which displays the loading of each factor, demonstrates that Factor 1, characterized by the highest eigenvalues,

Table 3 Loadings for weather and malaria variables

Variables	Axis 1	Axis2	Axis 3
Rainfall	0.158	-0.096	**0.888**
Minimal temperature	0.068	**0.952**	0.130
Maximal temperature	**-0.916**	0.224	0.093
Mean Relative Humidity	**0.938**	0.284	0.056
Max Relative Humidity	**0.889**	0.353	0.021
Wind speed	-0.024	0.55	-0.457
Min Relative Humidity	**0.955**	0.231	0.071
Mean Temperature	**-0.692**	**0.647**	0.138
Malaria Incidence	**0.588**	-0.312	-0.201

Table 4 Pearson correlation between Climatic variables and the incidence of malaria

Variable	Correlation	*P*-value
Mean Precipitation	-0.04	0.659714
Mean Temperature	-0.47	1.95E-08
Minimal Temperature	-0.18	0.039729
Maximal Temperature	**-0.48**	**8.83E-09**
Mean Relative Humidity	0.42	7.10E-07
Minimal Relative Humidity	0.41	1.99E-06
Max Relative Humidity	**0.43**	**4.31E-07**
Mean Wind.Speed	-0.20	0.027801

explains 58.8% of the variation in malaria incidence (Table 2). This proportion is significant when considering the role of this factor in malaria incidence prediction.

Although Factor 2 and Factor 3 have eigenvalues exceeding unity, their effects on malaria incidence are not statistically significant and poorly explain the variation in malaria incidence (-0.312 and – 0.201, respectively, for F2 and F3). Among the components of Factor 1, maximal temperature and minimal relative humidity have the greatest influence (Table 3). Thus, maximal temperature and minimal relative humidity are the climatic variables that significantly impact malaria transmission in Northern Benin (Table 3). In addition, the Pearson correlation between the climatic variables and the incidence of malaria reveals that maximal temperature has the highest significant correlation among the different temperature variables (-0.48) Regarding the relative humidity variables, Maximal relative humidity is the most significant correlated with incidence of malaria (0.43) (Table 4) So maximal temperature and maximal relative humidity are the variables most associated with the incidence of malaria. These two variables can be used as predictors to develop an early warning model and system for malaria outbreak in the study area.

Malaria outbreak warning model

To set up a malaria outbreak alert model, we employed support vector machine (SVM) algorithm using the Eq. (1).

Table 5 Model performance evaluation and calibration

Metric	MAE	RMSE	MSE	*R*-squared
Basic Model	2.30	2.70	7.270335	0.68
Validated Model	2.13	2.72	7.42	0.80
Calibrated Model	1.58	1.82	3.33	0.80

$$Malaria_{incidence} = \mathrm{f(Maximal\ Teamperature\ ,\ Maximal\ Relative\ Humidity)} \tag{1}$$

where f represents the non-linear function determined by the SVM with the radial kernel.

The model developed was trained, tested and calibrated (Refer to supplement).

The RMSE for the model developed with the imputed data is 2.6964, which is slightly lower than the RMSE for the complete case data, which is 2.7020. This indicates that the model trained on the imputed dataset demonstrates marginally better predictive performance.

The examining of the different metrics calculated reveals that the validated model predicts 80% percent of the incidence of malaria. The calibrated model exhibits the lowest (MAE = 1.58, MSE = = 3.33, and RMSE = 1.82 and R-squared = 80%) (Table 5). The calibrated model's predictions are very close to the observed values(Fig. 2). Additionally, the R-squared value of 80% suggests that the model explains a substantial portion of the malaria incidence's variance.

The analysis of the Taylor diagram shows a bias value of 0 (Fig. 3). The lower value of 0.43 from the difference between the observed standard deviation value of 4.08 and the predicted standard deviation value of 3.65 allow us to conclude that the model predicts accurately the incidence of malaria and the predicted value is very close to the observed value (Fig. 3). This is confirmed by the null value of the bias and the strong correlation between the predicted and the observed incidence of malaria. The positive correlation value of 0.91 is very close to the unity. This value suggests a strong positive linear relationship, indicating that the predicted values are closely associated with the observed values (Fig. 4). Over all, the malaria early warning model built using support vector machine is very performant and accurate model that can be used to predict one month in advance the monthly incidence of malaria and develop a malaria early warning system in northern Benin.

An intelligent malaria outbreak warning system

To enhance the collaborative efforts of stakeholders and malaria programmes aimed at reducing malaria transmission in Benin, we developed a web-based application specifically designed for malaria outbreak warnings. This application utilises the support vector machine (SVM) model built to predict the monthly incidence of malaria in Benin.

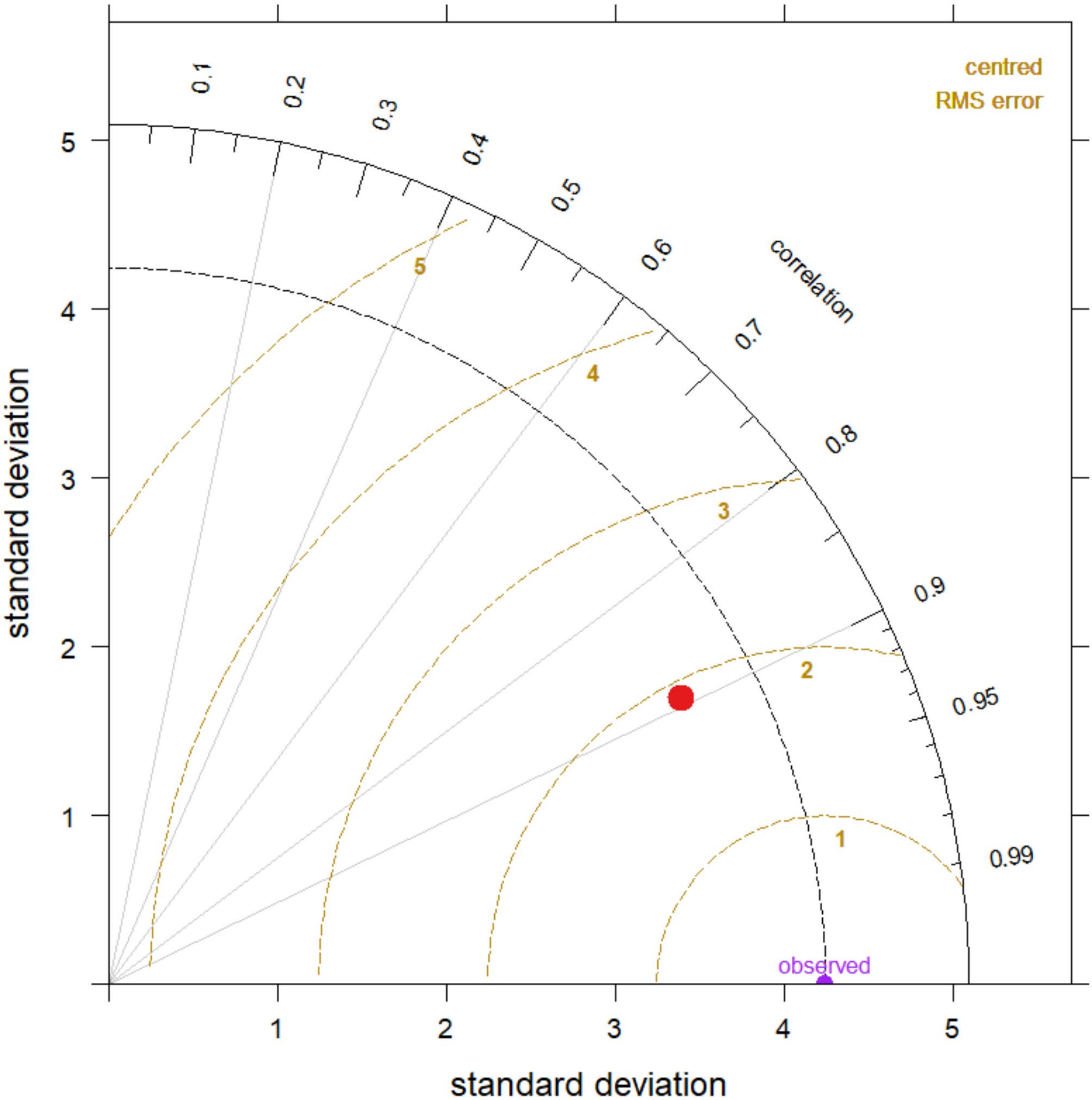

Fig. 3 Taylor diagram to assess the performance of the malaria early warning model

The application offers both automatic and manual data input. By selecting a specific city or district, the tool predicts the likelihood of a malaria outbreak based on the data from the previous month up to the current hour. The application displays the current outbreak predictions along with their corresponding status. Additionally, users have the option to manually input a set of weather measurements, which will generate a prediction accompanied by the corresponding status. It supports both English and French languages (Fig. 5).

The online accessibility of the application makes it easily available to users without any cost. This application proves to be a valuable tool for policymakers in Benin as well as local communities. It serves as an effective means of staying informed about the risk of malaria in any district within Benin. By providing accurate predictions and outbreak warnings, the application empowers users to make informed decisions and take proactive measures to mitigate the impact of malaria. Its availability and user-friendly nature contribute to its usefulness as a tool

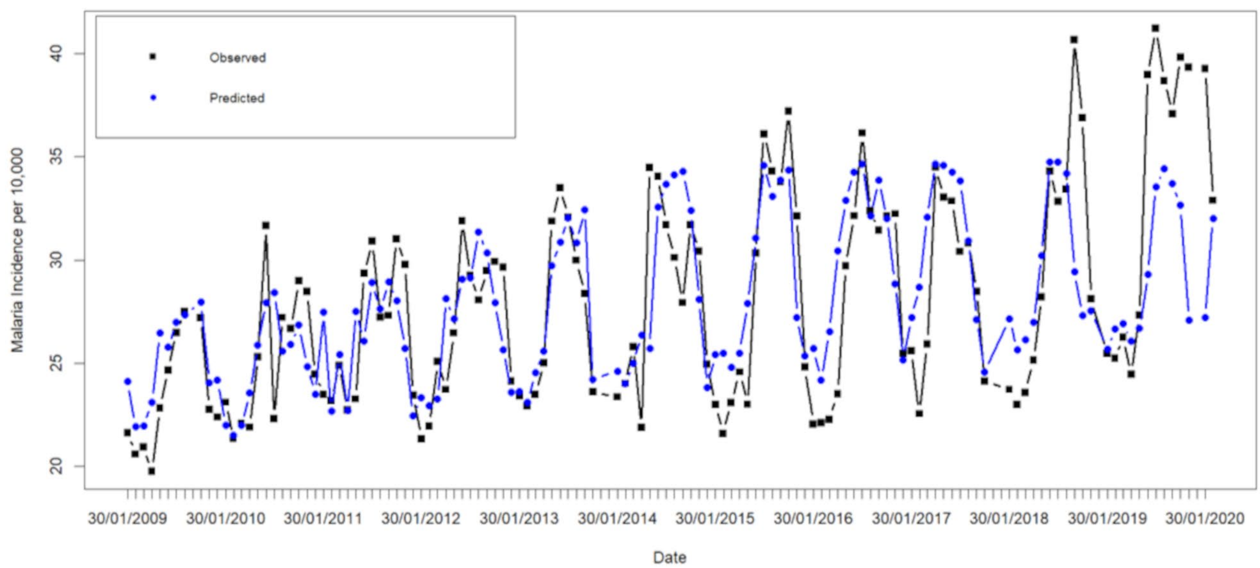

Fig. 4 Prediction of the monthly malaria incidence using 10% of the data

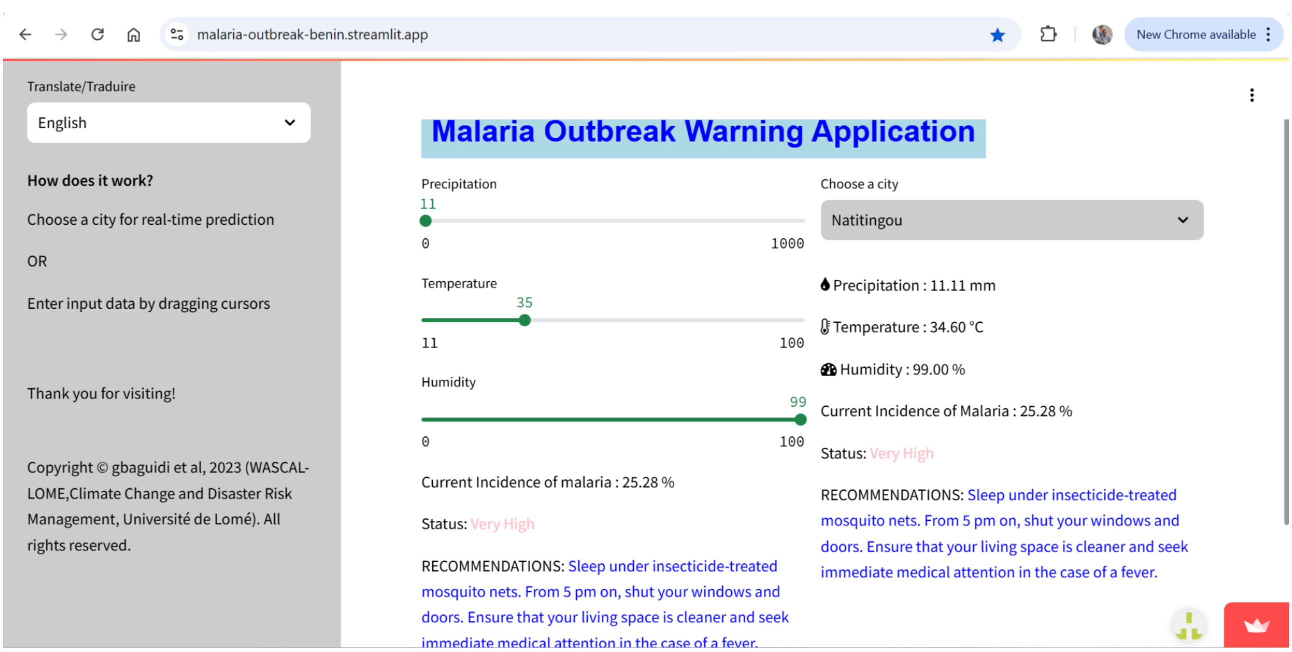

Fig. 5 Malaria outbreak warning application web in Benin

for enhancing malaria prevention and control efforts in Benin.

Discussion

Malaria early warning models can be effective tools for controlling malaria transmission. In northern Benin, the most important meteorological factors for malaria infection are relative humidity, and maximal temperature. Relative humidity affects positively malaria incidence while maximal temperature and mean temperature have negative effects on the occurrence of malaria. This result is consistent with the finding of [27], where malaria incidence is positively associated with relative humidity. The study of Gbaguidi in the same study areas ahas demonstrated that the incidence of malaria will increase over the 2021–2050 period [9]. This finding was supported by the IPCC AR6 report, which highlights the adverse effects of climate change on health, especially the transmission of malaria [28]. The findings of Gbaguidi in the same study areas agree with the negative impact of temperature on the transmission of malaria. Higher temperature decrease the incidence of malaria in northern

Benin [9].The use of climatic factors to predict the risk of malaria infection also agrees with the findings of [29], who developed a simple model of climate-related malaria transmission that provides insights into the sensitivity of disease transmission to changes in precipitation and temperature. To better anticipate prevalence uand outbreaks in the context of changing climate, weather factors must be included in surveillance programmes, as well as future climate forecasts included in epidemiological models [30, 31].

The early warning system developed can predict one month in advance the incidence of malaria in northern Benin and help policymakers and stakeholders to take preparedness actions. This tool is the first developed in Benin, and if developed at the national level, it can be effective in the decision-making process of malaria control.

Perpetual monitoring and assessment of existing and future malaria infection patterns in northern Benin are critical to ensure the efficacy of ongoing malaria control initiatives. By regularly assessing the transmission status, we can identify any changes or trends in malaria prevalence, which enables us to adapt and optimise control strategies accordingly. This proactive approach allows for timely interventions and the implementation of targeted measures to mitigate the impact of malaria in the region.

Limits of the study

One of the study's primary drawbacks is the absence of long-term availability of malaria data (number of cases). The accessible data ranges only from 2009 to 2021 and is presented at a monthly resolution. This constraint can have a major influence on the created malaria model and introduce bias, reducing its accuracy in forecasting malaria occurrences in the research locations.

Another barrier is the restricted number of meteorological stations. Donga province lacks its own meteorological station; hence, temperature, relative humidity, and wind speed data are obtained from neighbouring sites.

Furthermore, certain districts in the study regions lack rainfall gauge stations. This weakness may impair the model's efficacy in forecasting malaria incidence at the district level, potentially adding bias in districts where data were not included in the derivation of average values integrated into the model. As a result, forecast accuracy may be impaired in some districts, resulting in detectable mistakes. An early warning system developed predicting one month in advance the incidence of malaria in northern Benin could not be enough for policymakers to plan and put in place interventions.

Conclusion

In the findings of this study, climatic conditions influence malaria transmission in Northern Benin. Relative humidity and temperature may impact malaria transmission in the studied sites. A malaria early-warning model that was created using a support vector machine forecasts an 80% malaria incidence in the research locations. To estimate malaria risk in Benin, a web-based system particularly built for outbreak alerts was created. Its availability and user-friendliness make it an effective tool for improving malaria prevention and control efforts in Benin. The results of this study provide a strong tool for stakeholders to adopt targeted preparatory activities that decrease the consequences of climate change on human well-being by allocating resources where urgent actions are needed.

Abbreviations

API	Annual Parasite Index
SD	Standard deviations
C-SUM	Cumulative sum
CSS	Cascading Style Sheets
WHO	World Health Organisation
KNN	K-Nearest Neighbors
METEO-Benin	Meteorological Agency of Benin
PCA	Principal Component Analysis
RMSE	Root Mean Square Error
MSE	Mean Squared error
MAE	Mean Absolute Error
HTML	HyperText Markup Language
SVM	Support vector machine
WASCAL	West African Science Service Centre on Climate Change and Adapted Land Use

Supplementary Information

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Supplementary Material 1

Supplementary Material 2

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Author contributions

GBJ collected the data, analysed and interpreted the data, and wrote the manuscript. NK and GKK designed the study, verified the data collected, and validated the methods applied. WLF and KA reviewed the manuscript, accessed it, and validated the data processing methods. All authors had full access to all the data in the study, had the final responsibility for the decision to submit for publication, and approved the final version of this article to be published.

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Data availability

Data are available at the West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL), Université de Lomé. You should contact the corresponding author for the data request.

Declarations

Ethics approval and consent to participate
This study was approved by the Ethics Committee of the Ministry of Health of Benin. All methods were carried out in accordance with relevant guidelines and regulations and all experimental protocols were approved by the Ethics Committee. Informed Consent was obtained from all subjects and/or their legal guardian(s).
The data on malaria incidence are anonymised and were extracted from the Ministry of Health's platform. The Ministry had obtained authorisation to collect this routine data. Consequently, we were granted permission to use the data, but no ethics approval number was provided.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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