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Projection of future malaria prevalence in the upper river region of The Gambia

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Abstract

Background This work investigated the future (2021–2050) impact of Climate Change on Malaria Prevalence in the Upper River Region of The Gambia under two representative concentration pathways, RCP4.5 and RCP8.5, comparing it with the observed evaluation period of 2011–2022.

Methods The observed climatic variable data used was obtained from the Department of Water Resources and the corresponding malaria cases from the archive of the primary Health database, Banjul, The Gambia. Projected monthly temperature, precipitation, and relative humidity were downloaded from the coordinated Regional downscaling experiment (CORDEX) stimulation of the Rossby Centre Regional Atmospheric regional climate (RCA4). The dataset spans the decades from 2021 to 2050, providing insight into future climatic and epidemiological trends. Gradient Boost Machine Learning algorithm was utilized for the malaria projection both in the population below 5 and above five years.

Results The result revealed an increase in malaria incidence under RCP4.5 and RCP8.5 climatic scenarios for both age categories with a clear indication in the population above five years.

Discussion and conclusion The result pictures how climate change will impact malaria under RCP4.5 and RCP8.5 emission scenarios in the region and also clearly reveals that the upper river region of the Gambia population is at risk of malaria infection, thus, a strategic and robust intervention scheme is highly solicited.

Keywords Malaria prevalence, Climate change, Machine learning, RCP scenarios, Gambia

Background

The change in climatic conditions that occurred during the end of the Ice Age, leading to the era of global warming around 100,000 years ago, led to the acquisition of *Plasmodium falciparum* from gorillas in Africa, the spread of humans as well as parasites [1]. After the period known as the Ice Age, temperatures began to increase, and the period saw an increasing introduction of agriculture and the adaptation of the *Anopheles* mosquito, particularly in sub-Saharan Africa (SSA) due to the population density of human settlements. In this modern era of anthropogenic global warming driven by the burning of fossil fuel and secondary deforestation [2], there is a threat to expand the potential range and overall burden of malaria [3]. The parasite and the vector life cycles are temperature and rainfall-dependent and thus can be restricted by climate to the globe's warmer latitude and altitude ranges [1]. An increasingly warmer and humid environment has encouraged malaria, presently one of

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the most dangerous infectious diseases in SSA [4], along with climatic variation having a direct impact on the epidemiology of many vector diseases [5]. Thus, many attempts have been made to understand the historical development and transmission of the *Anopheles* parasite and its associated risk to humans [6, 7], as the discovery of avian malaria transmission by Ronald Ross and the human malaria parasite by Alphonse Laveran, and Battista Grassi [8], respectively, paved the way.

Climate change has already played a vital role in malaria dynamics and distribution, but the association pattern depends on the form of climate change and the pathogen-host system [9]. According to the IPCC WGII Sixth Assessment Report, the distribution and prevalence of malaria are influenced by rising temperatures and changing rainfall patterns (high confidence) [4, 10], and SSA has an ideal climatic condition for endemic malaria transmission [11]. Central Africa, some of the Southern Coast of West Africa, and the East of the African coast have the right climatic conditions for malaria transmission [11]. Projection on the influence of climate change on malaria estimated an increase in the population at risk of 1.6 million by 2030 and 1.8 million by 2050 [12]. Under RCP4.5 (moderate) and RCP8.5 (worst) climatic scenarios malaria is projected to increase in most West African countries [13–15] if an effective and adequate intervention scheme is not put in place as poor health care and health infrastructure is rarely climate-resilient could further increased malaria risk in SSA, in addition to the resistance of malaria vectors to insecticides [4].

Some elementary modeling has also proven that the increase in climatic conditions will accelerate the transmission rates of mosquito-borne disease [16–19] and widen its geographical distribution, leading to an increase in malaria prevalence even in current endemic areas [20–22]. Changes in climatic variables, most especially changes in average temperature, will most likely cause a proliferation of the malaria vector at higher altitudes, thereby resulting in an increase in malaria transmission in areas previously unaffected [4, 23]. At lower altitudes where malaria is already a problem, warmer temperatures will change the parasitic life cycle in a mosquito, enabling it to develop more quickly and increase transmission, thus having implications on the disease burden [4, 23–25].

Malaria remains endemic in the Upper River Region of The Gambia despite the combined efforts by the governmental and non-governmental health parastatals in the region, The Gambian population is still at risk of all-around malaria transmission, and malaria cases have progressively increased from 52,767 in 2019 to 72,301 in 2020, 74,089 in 2021, and 108,506 in 2022 [26], simultaneously with reported death from 41 in 2015 to 62 in 2022 [26]. The upper river region has the highest disease burden than any other region in the country [27, 28], with children under five being more vulnerable to the disease condition [29, 30]. The actual malaria cases are mostly higher than the reported cases since the private health facilities and home treatment of the infection with the use of both orthodox and traditional medicine are not recorded.

Climatic conditions, with other environmental and socioeconomic factors, may have contributed to maintaining residual transmission in the Region. Extreme temperatures, as the yearly average temperature of the region (31.85 °C) is 2.27% higher than other regions in the Gambia [31]. Improper drainage systems, rice production, flooding, increased outdoor biting in response to weather conditions [30], a limited number of community health workers, a weak health system, poverty, and increased insecticide resistance [29].

The objective of this study is to predict future malaria prevalence in the URR of The Gambia under the RCP4.5 and RCP8.5 climate scenarios using machine learning models because of its peculiarity in modeling complex and non-linear relationships between climate variables and health outcomes, offering significant advantages over traditional statistical methods. Similar studies have adopted one or more of these machine learning algorithms: Gradient Bosting, Linear Regression, Random Forest, and Support Vector [2, 15, 32–34], as they are mostly used in solving regression problems in supervised machine learning to predict a desirable outcome.

Methods

Study area

Upper River Region of The Gambia

The study was conducted in the Upper River Region (URR) of The Gambia (URR). The region is the second largest town among the six regions in The Gambia, with a land mass of about 2000 sq km and a population density of 116/km^2 [35] and geographical coordinates of 13° 19′ 0″ N and 14° 13′ 0″ N [36]. Most regions in The Gambia, including the URR, lie in the Tropical wet and dry or savanna climate zone, which has a distinct long dry season and a short rainy season [36, 37]. The estimated annual rainfall is between 800 and 1200 mm, and the average number of rainy days ranges from 54 days in Banjul to 31 days in URR [36]. In the dry season, the highest average temperature is between 33.22 °C and 42.42 °C, while in the wet season, the lowest average is between 19.48 °C and 27.99 °C, a conducive temperature that supports most of the life cycle of malaria vector and parasite transmission [5, 21] (Fig. 1).

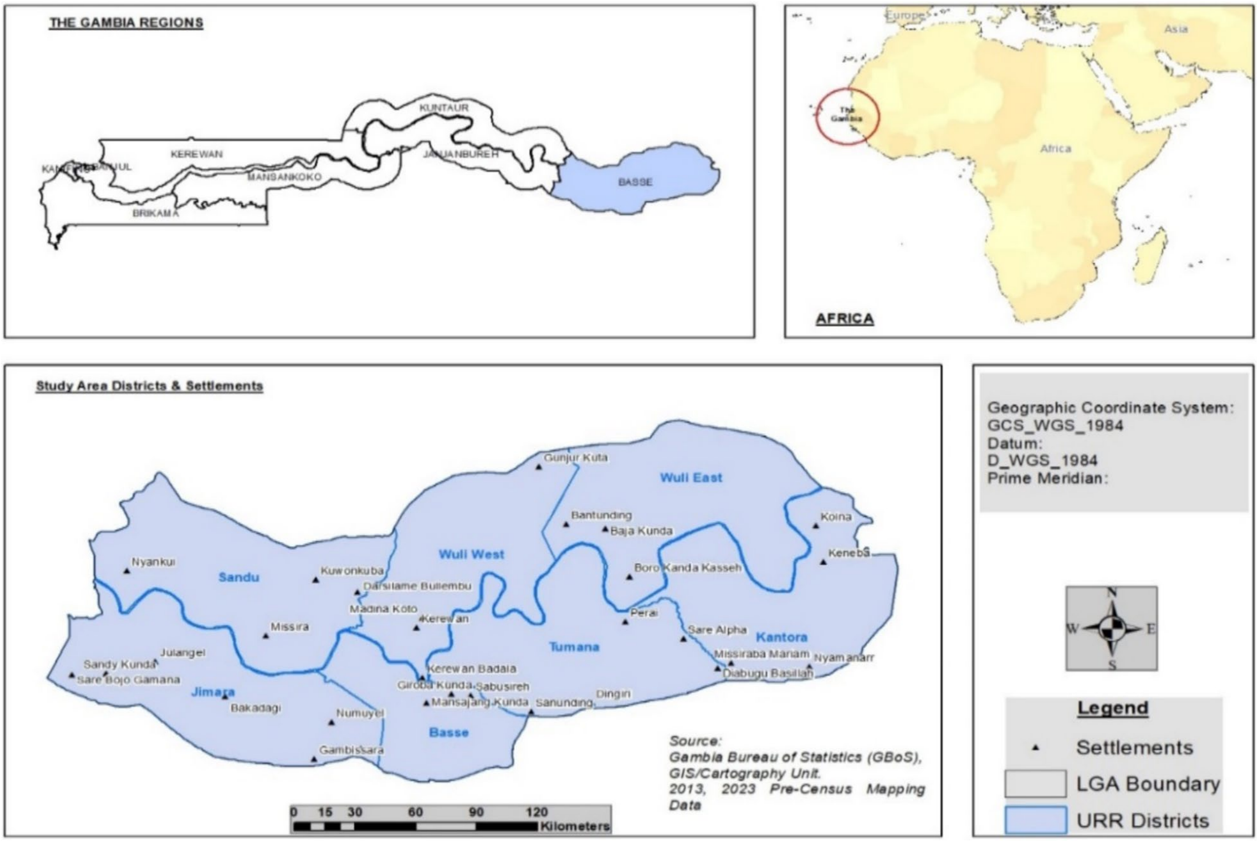

Fig. 1 Study area: Upper River Region of The Gambia

Data collection

This study was conducted with a combination of two data sets: climatic data and clinical malaria profiles. Monthly meteorological data (temperature, rainfall, and relative humidity) from the period of 12 years (2011–2022) was obtained from the archives of the Department of Water Resources Banjul, The Gambia, on June 2, 2023. The data was collected manually by the trained staff of the department. The corresponding monthly malaria data was obtained from the health database. A retrospective medical record review was conducted for all the health centers with proper malaria screening facilities in each health district in the region. The records were summed at the malaria control department, Kanifing, and National Health Service Kotu, The Gambia, where the full data set was obtained on June 30, 2023. Ethical approval was obtained from the medical school, the University of The Gambia, on May 24, 2023. All the malaria cases presented to all the hospitals in the region from 2011–2022 were included in the study. The malaria cases were further categorized by two age groups, under five years and above five years, to predict the risk of malaria associated with each group. The incidence of malaria was recorded per month and compared with corresponding climatic variables; maximum and minimum temperature, rainfall, and humidity.

Data processing

Both the meteorological and malaria data were cleaned to account for outlier or missing data to ensure the datasets' integrity and reliability. To enhance data quality, outliers were removed using a standard deviation technique, with lower limit and upper limit given as follows:

$$\text{Lower Bound } = \mu - k \times \sigma$$

$$\text{Upper Bound } = \mu + k \times \sigma$$

μ and σ are the mean and the standard deviation of the data, respectively, and k is a predefined threshold, commonly set to 3. Any data point that falls outside the range [Lower Bound, Upper Bound] is considered an outlier and removed [38].

Monthly climatic variables—maximum temperature, minimum temperature, relative humidity, rainfall, and corresponding malaria incidence were first used to choose the best machine learning algorithm suitable for the prediction. Monthly climatic variables and corresponding malaria incidence were first used to train and test four Machine Learning models used in solving regression problems, including the Linear Regression model (LiR), Support Vector Machine model (SVM), Random Forest model (RF), and Gradient Boosting (GB) to choose the best one suitable for the prediction. Secondly, data from climatic simulation prediction models: Model for Interdisciplinary Research on Climate (MIROC), Commonwealth Scientific and Industrial Research Organisation (CSIRO), and the National Centre for Meteorological Research (CNRM) were incorporated with the chosen ML algorithm for prediction under RCP4.5 and RCP8.5 from 2021 to 2050. R Studio environment and Python were the tools used for the data analysis and model implementation.

Furthermore, Earth System models (ESMs): MIROC, CSIRO, and CNRM, were used to predict the future incidence of malaria in the region. ESMs integrate the interaction of land, sea ice, ocean, atmosphere, and biosphere to estimate the state of global and regional climate under a wide range of conditions [39, 40]. The model resolution and grid system are chosen independently for each component, and time integration proceeds independently.

The dataset for the analysis comprises climate scenario predictions under various Representative Concentration Pathways (RCPs). The two RCPs represented include RCP 4.5, a moderate emission scenario where greenhouse gas emissions peak around 2040 and then decline, and RCP 8.5, a high emission scenario reflecting continued growth in emissions throughout the century. The projected satellite data were downloaded from the coordinated Regional downscaling experiment (CORDEX) simulation of the Rossby Centre Regional Atmospheric regional climate (RCA4). The model has a few limitations, just like most climate models, such as uncertainty in the future trajectory of greenhouse gas emissions and limitations in capturing short-term natural variability. A study using CORDEX-Africa indicated that projected precipitation over Africa is associated with uncertainties, which could be attributed to model uncertainty and internal variability [41]. However, the model simulation depicts high-level accuracy for forecasting as it has been used widely by scholars in modeling and projecting future malaria risk [13, 15].

The dataset spans the decades from 2021 to 2050, providing insight into future climatic and epidemiological trends. Each dataset combination includes MIROC/RCP4.5, CNRM/RCP4.5, CSIRO/RCP4.5, MIROC/RCP8.5, CNRM/8.5, and CSIRO/8.5. Attributes include year and month as columns for temporal identification and climatic variables: minimum temperature, maximum temperature, humidity, and rainfall. The data also provides the predicted number of malaria cases, derived using climatic input variables and machine learning models trained on historical data.

Download link: (https://esgf-data.dkrz.de/projects/esgf-dkrz/)

Project: CORDEX

Domain > AFR-44

Driving Model: MIROC, CSIRO, CNRM

Experiment: rcp45. Rcp85

Experiment family: RCP

RCM Name: RCA4

RCM Version: v1

Time–frequency: Monthly

Variables: relative humidity, maximum and minimum temperature, precipitation

Coordinates: geographical coordinates are 13° 19′ 0″ N and 14° 13′ 0″ W.

Development of machine learning model

Machine learning was used to forecast the prevalence of malaria in the region over the 2021–2050 period under two different climatic scenarios, RCP4.5 and RCP8.5. Machine learning is a subset of artificial learning that focuses on using various self-learning algorithms that derive knowledge from data to predict outcomes [34]. ML involves processes and algorithms that can mimic human intelligence, which includes learning, perception, and problem-solving. The output of ML is algorithmic models that are exceptionally capable of handling intricate issues with a substantial amount of data inputs and outputs [42]. Although it has been historically linked to large datasets [42], recent applications [15, 33] show that it can effectively extract insights from smaller datasets. This versatility makes machine learning a useful tool in healthcare influencing disease outlook, prediction, and important activities. The fundaments on which the models are built are often data collection, parameterization, and model learning/ validation [34]. The observable dataset was split into training and testing subsets, with the training set comprising 83.5% of the data and the testing set 16.5%. Stratified sampling ensures that the distribution of malaria cases is maintained across both subsets. Several machine learning algorithms were evaluated, including a Linear Regression model (LiR), a Support Vector Machine model (SVM), a Random Forest model (RF), and a Gradient Boosting (GB). Hyperparameter tuning was performed for all models to maximize predictive accuracy, using a Grid Search algorithm [43].

To evaluate the models, performance metrics including Mean Absolute Error (MAE), Mean Bias Error (MBE), Root Mean Squared Error (RMSE), and RSquared (R^2) were used. These metrics allowed for model comparison and thus selecting the best-fitting algorithm for future prediction. Also, a tenfold cross-validation approach was employed to ensure robustness, reducing the risk of overfitting and providing a reliable performance estimate. The model achieves a cross-validation mean R^2 score of 0.816, indicating strong predictive power.

Gradient Boosting (GB) was selected, as the error difference between the observed data and predicted values in both the two age groups is the lowest when compared with the other three models and with the highest R-squared closer to 1. Gradient Boosting (GB) is further known for its ability to join weaker regression algorithms in a sequence to learn from the error of other models, thus boosting its capacity and accuracy for prediction [32]. Their mathematical formulae are given in Eqs. 1–4.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|P_i - A_i\right|, \tag{1}$$

$$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n}(P_i - A_i), \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - A_i)^2}, \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - A_i)^2}{\sum_{i=1}^{n}\left(A_i - \overline{A}\right)^2}, \tag{4}$$

where P_i is the predicted value, A_i is the actual value, and n is the sample size.

The RMSE measures the average error in predictions as a percentage, with lower values indicating better accuracy. MAE measures the average magnitude of percentage errors, regardless of direction, and lower values again indicate better performance. MBE reflects the average bias in predictions, where positive values suggest overestimation and negative values suggest underestimation. R-squared indicates the proportion of variance explained by the model, with higher values suggesting a better fit. In other words, R-square (Coefficient Determination) shows how well the model fits with the data or the accuracy of the model from 0 to 1. If the data fits well, the R-square will be 1 or close to 1.

Results

Prediction of incidence of malaria in the region under RCP 4.5 and 8.5 climatic scenarios using machine learning model

This section predicted the incidence of malaria from the period of 12 years (2011–2022) first by determining the machine learning algorithms suitable for the analysis, after which three climatic simulation models that incorporated all the three observed climatic variables (MIROC, CNRM, CSIRO) under moderate (RCP4.5) and worst case (RCP8.5) climatic scenarios over 2021–2030, 2031–2040, 2041–2050 period.

Figures 2 and 3, which represent the testing period, compare actual values in confirmed malaria cases for under and above five years, respectively, with predicted values using different machine learning models. Then, Figs. 4 and 5 reveal the most suitable model for the analysis with the help of their statistical metrics. In general, all models present some discrepancies in predicting malaria

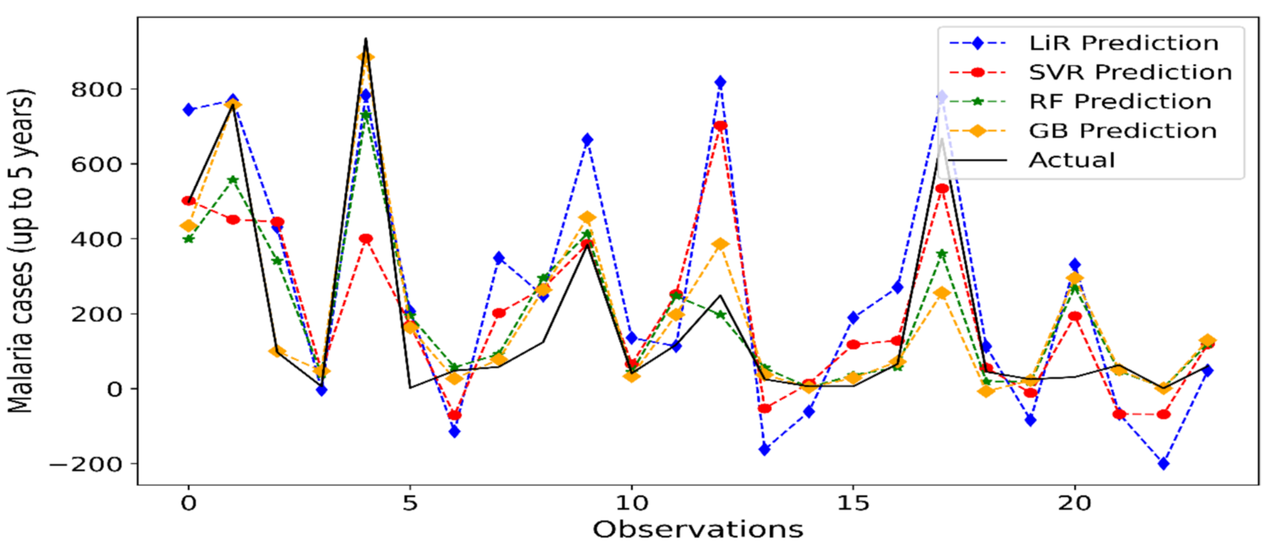

Fig. 2 Comparison between model predictions and actual data for children under five years old

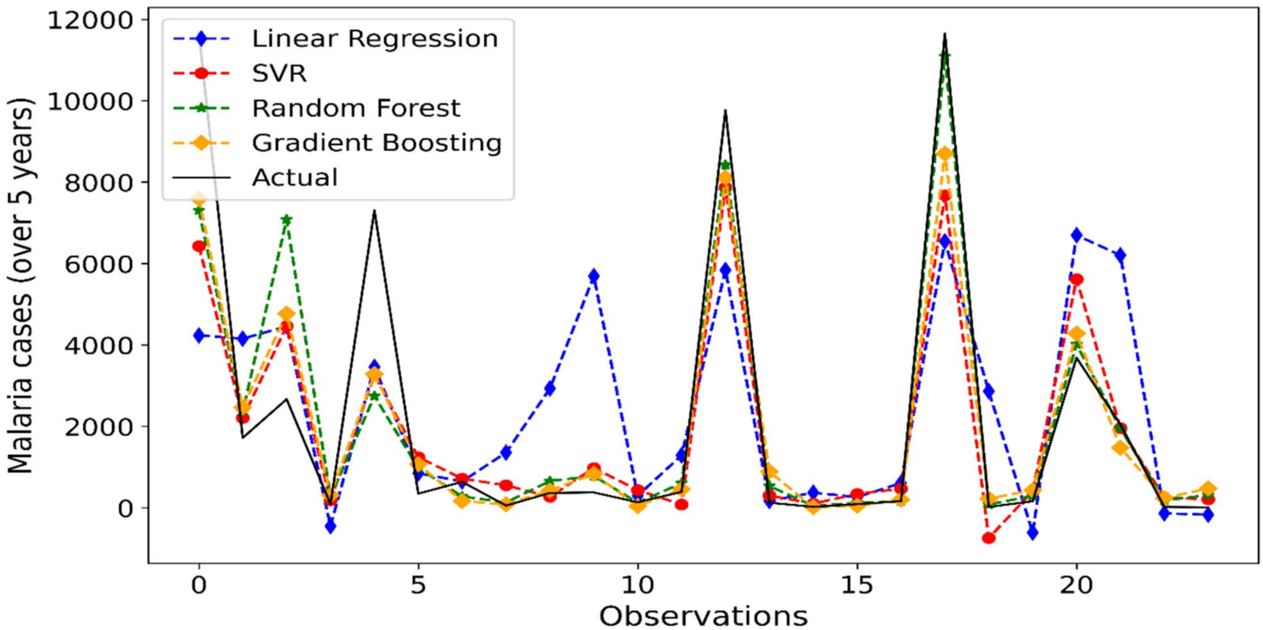

Fig. 3 Comparison between model predictions and actual data for the above five years

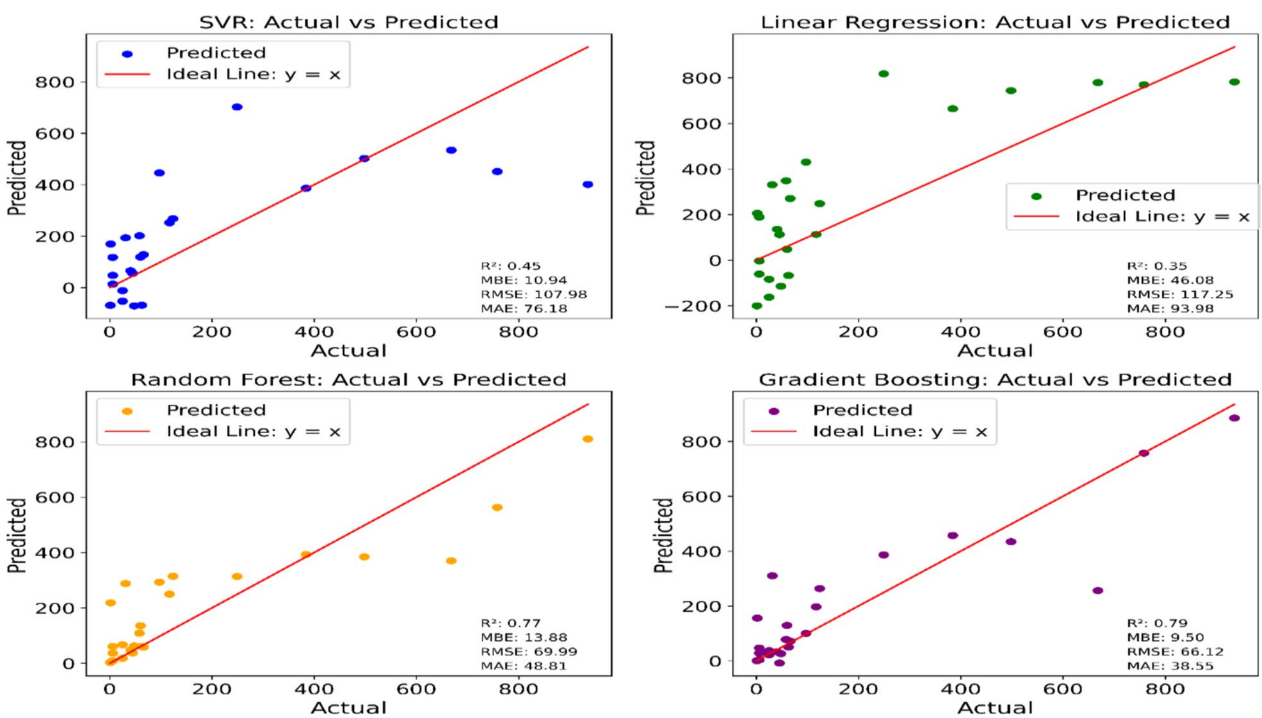

Fig. 4 Performance metrics for predicting malaria cases in children under 5 years

cases, with some differences in actual/observed data and predictions. However, random forest and gradient boosting seem more suitable for malaria case prediction in both age groups, as highlighted in the metrics shown in Figs. 4 and 5.

For the "Under 5 years" age group, Linear Regression (LiR) shows the highest RMSE (117.25%) and MAE (93.98%) with an R-squared of 0.35, making it the worst-performing model. The high positive MBE (46.08%) indicates a consistent overestimation of malaria

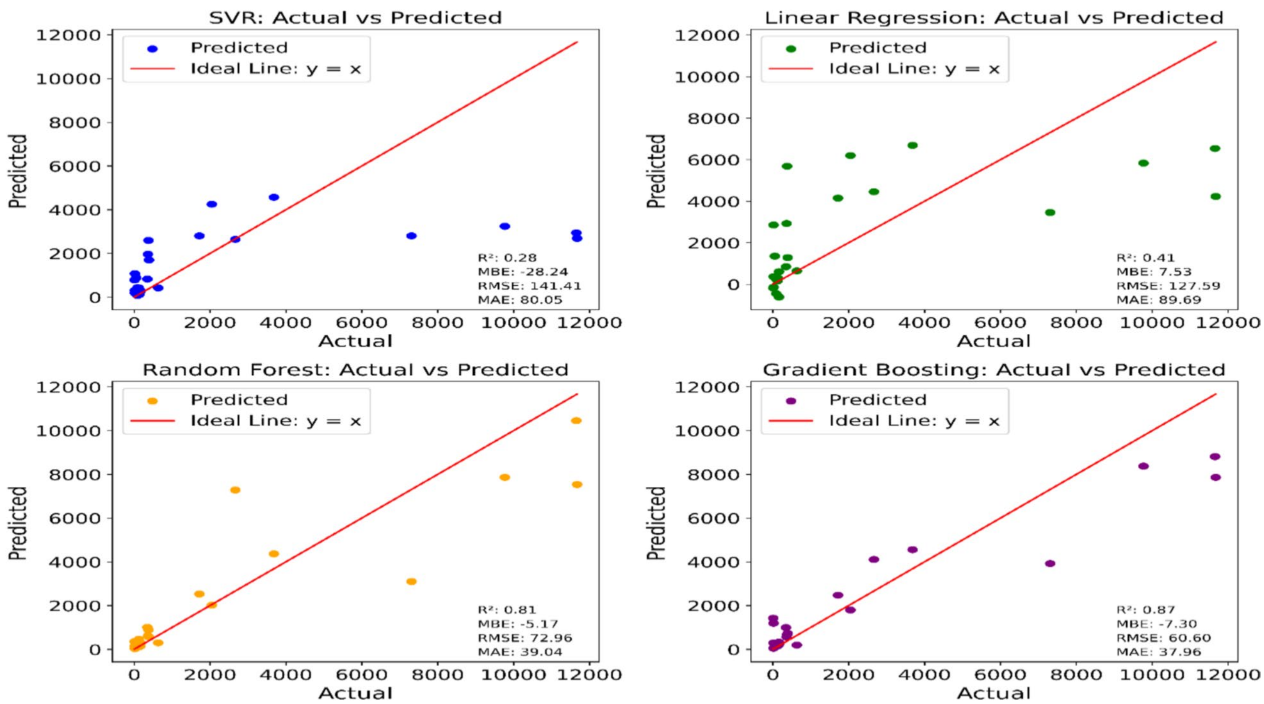

Fig. 5 Correlation and performance metrics for predicting malaria cases in the above five years

cases. Support Vector Regression (SVR) improves upon LiR, with an RMSE of 107.98%, MAE of 76.18%, and an R-squared of 0.45, explaining more variance. MBE (10.94%) suggests some overestimation. Random Forest (RF) performs significantly better with an RMSE of 69.99% and a MAE of 48.81%. Its R-squared of 0.77 indicates the model explains a large portion of the variance, and its MBE (13.88%) shows less bias. Gradient Boosting (GB) is the best-performing model in this group, with the lowest RMSE (66.12%) and MAE (38.55%), and the highest R-squared (0.79), indicating it explains the most variance. MBE (9.50%) shows a slight overestimation.

For the above-5-years age group, LiR has an RMSE of 127.59% and MAE of 89.69%, with an R-squared of 0.41, still showing poor performance. MBE (7.53%) reflects a slight overestimation. SVR shows a higher RMSE (141.41%) than in the younger group and a lower R-squared (0.28), explaining less variance. MBE (−28.29%) suggests underestimation. RF maintains good performance with an RMSE of 71.47%, MAE of 37.68%, and a high R-squared of 0.82. Its MBE (−6.62%) suggests a slight underestimation. GB once again performs the best, with the lowest RMSE (59.67%) and MAE (36.14%) and the highest R-squared (0.87), indicating the best fit. MBE (−9.11%) indicates a slight underestimation.

Overall, GB consistently outperforms the other models for both age groups, with the lowest error metrics (RMSE, MAE) and the highest R-squared values, making it the most effective model for predicting malaria cases. RF also performs well, especially in the "above 5 years" group, with good accuracy and high R-squared values. LiR shows the worst performance with the highest errors and lower R-squared, indicating that it is not well-suited for this task. SVR performs better than LiR but worse than RF and GB, especially in the "above 5 years" group. Thus, Gradient Boosting (GB) is the most effective model for predicting malaria cases in both age groups. This model is then chosen for malaria case prediction using RCP4.5 and RCP8.5 scenarios.

Prediction of malaria incidence for the above five years over 2021–2050 using RCP4.5 and RCP8.5 scenarios

The result of the projection of the incidence of malaria built with the Machine Learning Model (Gradient Boosting (GB)), under two representative concentration pathway (RCP) scenarios (RCP4.5 and RCP8.5); MIROC/RCP4.5, CNRM/RCP4.5, CSIRO/RCP4.5, MIROC/RCP8.5, CNRM/RCP8.5, CSIRO/RCP8.5, in the upper river region of the Gambia over the 2021–2030, 2031–2041 and 2041–2050 periods, revealed an overall increase in malaria incidence under the RCP4.5 and RCP8.5 scenarios. The Representative Concentration Pathway (RCP) 4.5 described by IPCC is an intermediate or moderate climatic scenario where emissions peak around 2040 and start declining. On the other hand, RCP8.5 is described as a worst-case climatic scenario where emission continues to rise throughout the twenty-first century.

According to the trendline slope, the result in Fig. 6 revealed that MIROC/RCP4.5, CNRM/RCP4.5, and CSIRO/RCP4.5 simulation model is associated with 0.17% (1.9965), 0.18% (2.6123), and 0.07% (0.9120) increase in malaria incidence respectively, with an average of 0.14% increase over 2021–2030 under a moderate climate scenario. Then, under the worst climate scenario over this same period, MIROC/RCP8.5 predicted an associated increase of 0.06% (0.5667) in malaria incidence, while CNRM/RCP8.5 and CSIRO/RCP8.5 model revealed 0.06% (1.0347) and 0.14% (1.6486) increase, respectively.

The projection of malaria incidence over the 2031–2040 period under a moderate climate scenario in Fig. 7 shows an increase of 0.22% (MIROC/RCP4.5; 2.3176), 0.35% (CNRM/RCP4.5; 3.9441) and 0.19% (CSIRO/RCP4.5; 3.3532), with an average increase of 0.25%. A corresponding increase of 0.20% (2.7827) was seen in MIROC/RCP8.5, 0.29% (CNRM/RCP8.5; 3.3761), and 0.13% (1.4414) in CSIRO/RCP8.5, with an average of 0.21% in the case for the worst climatic scenario.

Then over the 2041–2050 period under a moderate climate scenario (Fig. 8), the models predicted an increase of 0.23% (MIROC/RCP4.5; 2.4488), 0.18% (CNRM/RCP4.5; 2.1496), and 0.07% (CSIRO/RCP4.5; 0.7289), with an average percent increase of 0.16. Additionally, the result shows an increase of 0.33% (CSIRO/

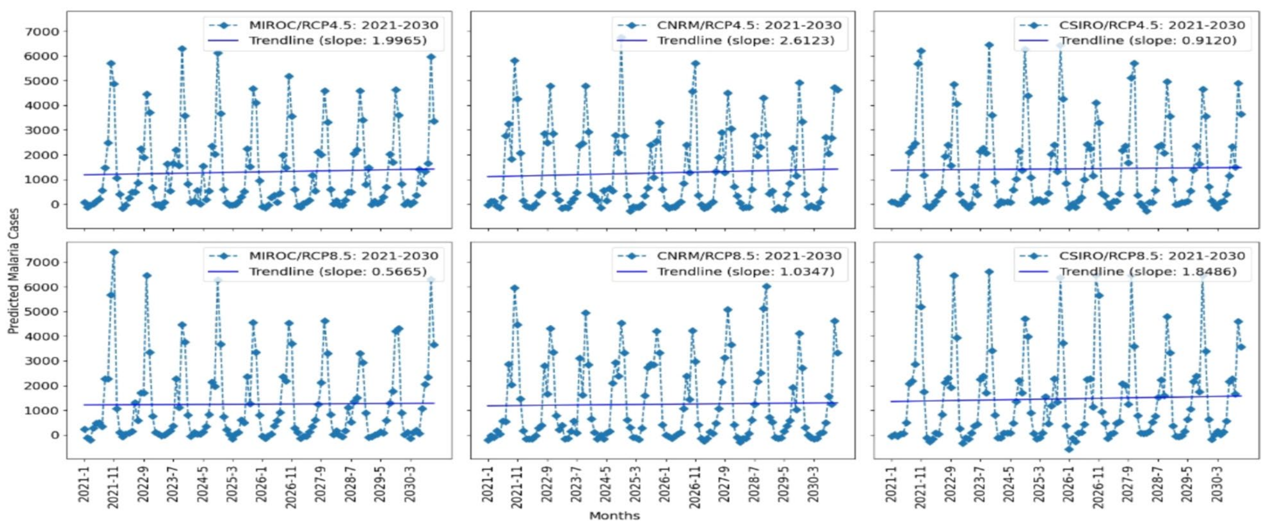

Fig. 6 Prediction of malaria incidence for the above five in the Upper River Region of the Gambia over 2021–2030

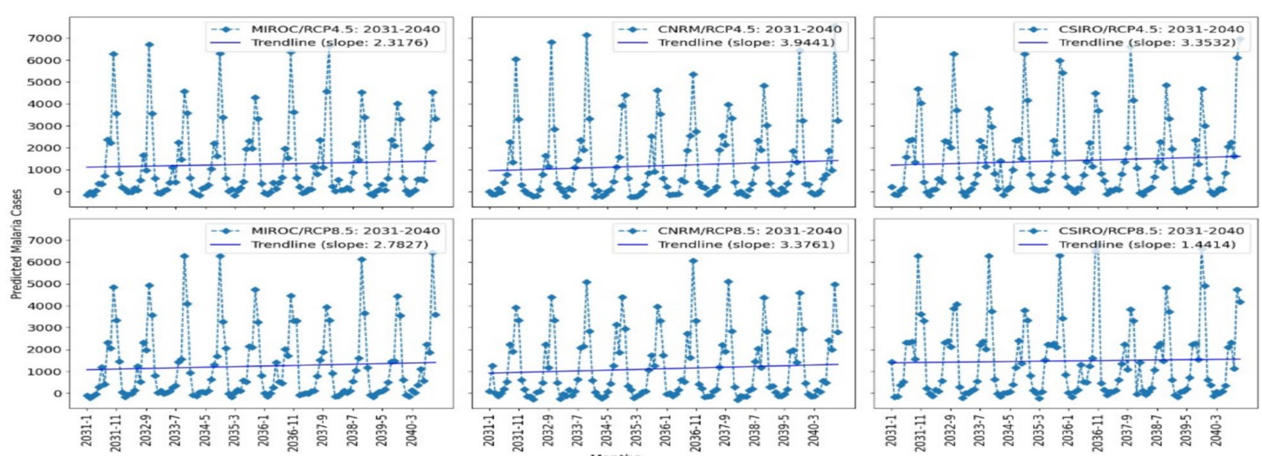

Fig. 7 Malaria incidence prediction for the above five years in the Upper River Region of the Gambia over 2031–2040

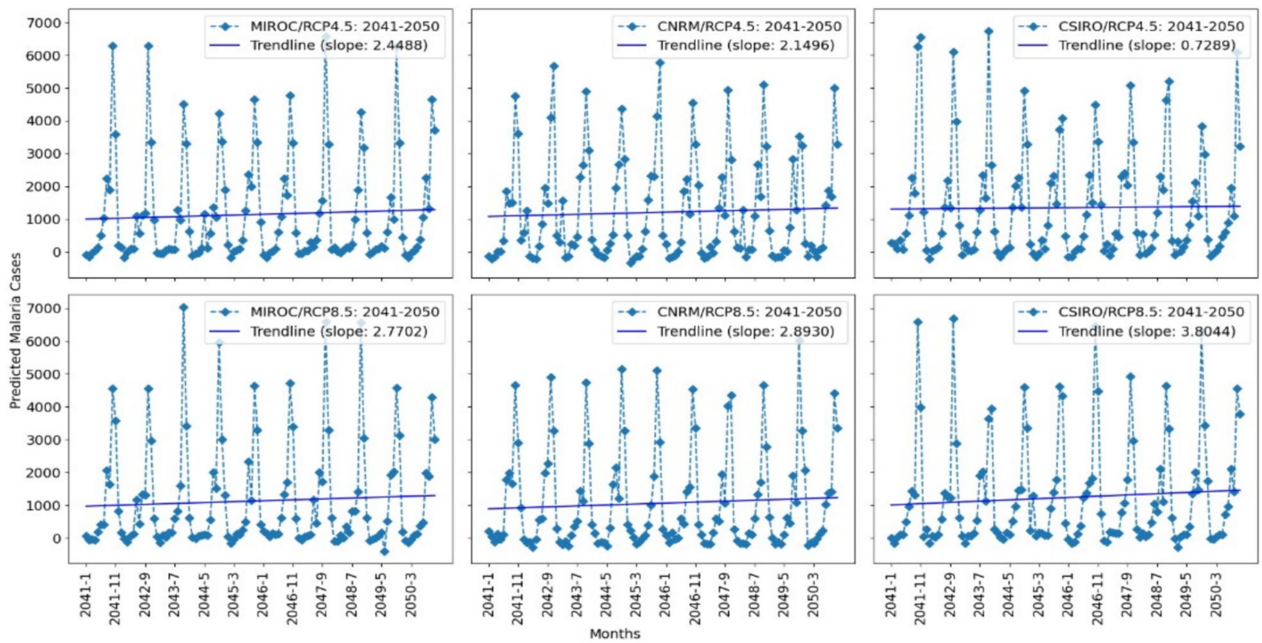

Fig. 8 Prediction of malaria incidence for the above five in the Upper River Region of the Gambia over 2041–2050

RCP8.5; 3.8044) and 0.26% (2.7702, 2.8930) in both MIROC/RCP8.5 and CNRM/RCP8.5, respectively, under the worst climatic scenario, having an average of 0.28% increase (Fig. 8).

The three climate models projected an increase in malaria incidence across the predicted years under the two examined climatic scenarios, with a slightly higher percentage increase under the moderate climatic scenario (average of 0.14% over 2021–2030; 0.25% over 2031–2040) than worst climatic scenario (0.09% over 2021–2030; 0.21% over 2031–2040). Also, the peak of the prevalence of malaria is predicted across all models, with the magnitude of the increase varying from model to model. However, the peak of malaria prevalence is predominantly predicted around November, with MIROC and CSIRO showing the highest prevalence, more in RCP8.5.

Prediction of malaria incidence for under-fives over 2021–2050 under RCP4.5 and RCP8.5 Scenarios

In the case of malaria incidence for under five years (up to five) Fig. 9, the incidence of malaria is predicted to decrease by 0.17% (−0.1703) as stimulated in MIROC/RCP4.5 and 0.15% (−0.2181) in CSIRO/RCP4.5 over the 2021–2030 period, while CNRM/RCP4.5 stimulation predicted an increase of 0.23% (0.2977) over the same period. The overall outcome of the projection of malaria incidence over the 2021 to 2030 period demonstrates an average percentage reduction of 0.16% in malaria cases for under five years under a moderate climate scenario. In the case of the worst-case climatic scenario over the same period, CNRM/RCP8.5 and CSIRO/RCP8.5 predicted an increase of 0.09% (0.0874) and 0.07% (0.1299) respectively in the incidence of malaria revealing an average increase of 0.08% contrasting MIROC/RCP8.5 prediction of 0.06% (0.0812) reduction of malaria incidence in the region for under five years (Fig. 9).

Over the 2031 to 2040 period under a moderate climate scenario, malaria incidence will increase by 0.10% (0.1072) and 0.31% (0.3407), as shown in the MIROC and CNRM simulation models, respectively (Fig. 10). However, the CSIRO/RCP4.5 model contrasts MIROC and CNRM, thus predicting a 0.11% (0.1442) reduction in malaria cases for children under five over the same period. Notwithstanding, the overall prediction suggests an approximated average percentage increase of 0.21% in malaria cases under five years from 2031 to 2040 under a moderate climatic scenario. Malaria incidence projection under the worst-case climatic scenario over the same period demonstrates an increase of 0.11% (0.1125) and 0.18% (0.1955) in MIROC/RCP8.5 and CNRM/RCP8.5 malaria cases, respectively, and approximately 0% (0.0009) in CSIRO/RCP8.5, thus, predicting an average increase of 0.10% approximately (Fig. 10).

There is a predicted increase in the incidence of malaria by 0.07% (0.0562) and 0.08% (0.0879) in the MIROC/RCP4.5 and CNRM/RCP4.5 models, respectively, the average approximated at 0.08% over 2041 to

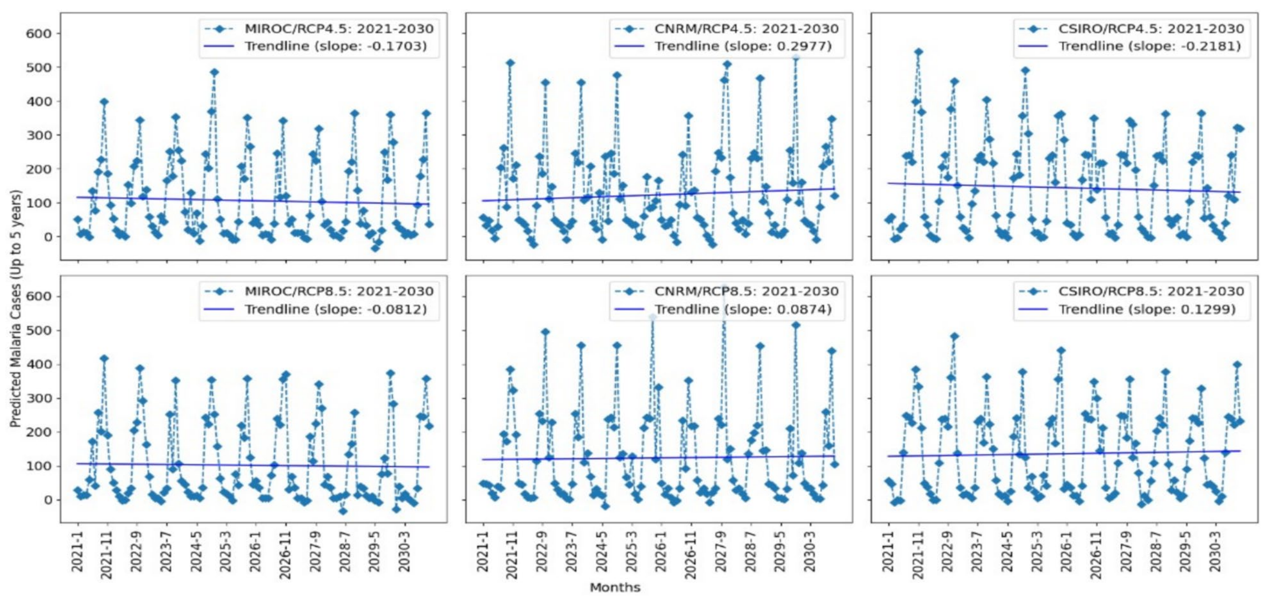

Fig. 9 Prediction of malaria incidence for under five in the Upper River Region of the Gambia over 2041–2050

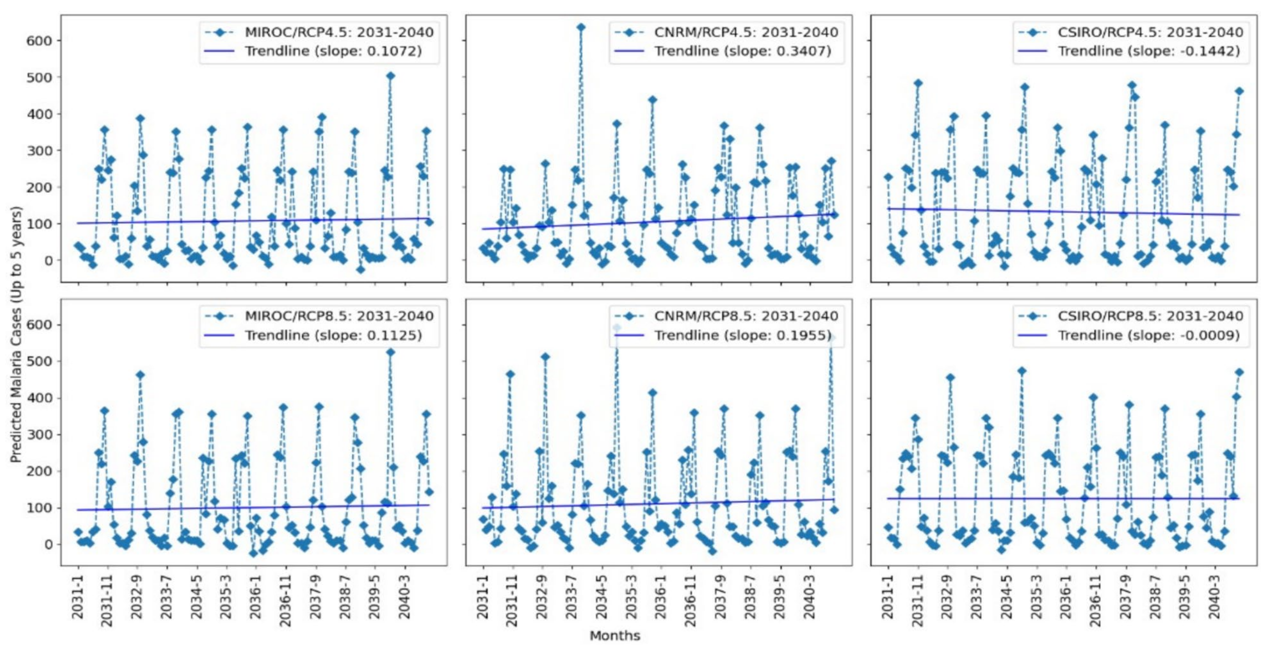

Fig. 10 Prediction of malaria incidence for the under-five in the Upper River Region of the Gambia over 2041–2050

2050, contrasting 0.26% (−0.3078) reduction predicted by CSIRO/RCP4.5 model (Fig. 11). Furthermore, under the worst-case climatic scenario, the incidence of malaria in under five years children in the upper river region of the Gambia is predicted to increase by 0.26% (MIROC/RCP8.5; 0.2190), 0.08% (CRNM/RCP8.5; 0.0774) and 0.31% (CSIRO/RCP8.5; 0.3480), with an average increase of 0.21% increase. The results further show variation in prevalence across models, with the highest burden seen in CNRM and CSIRO models, more under worst-case climatic conditions, especially over 2041–2050 (Fig. 11).

Discussion

The earth system models: MIROC, CNRM, and CSIRO Climate simulation models predicted an increase in malaria cases in both age categories with few exceptions

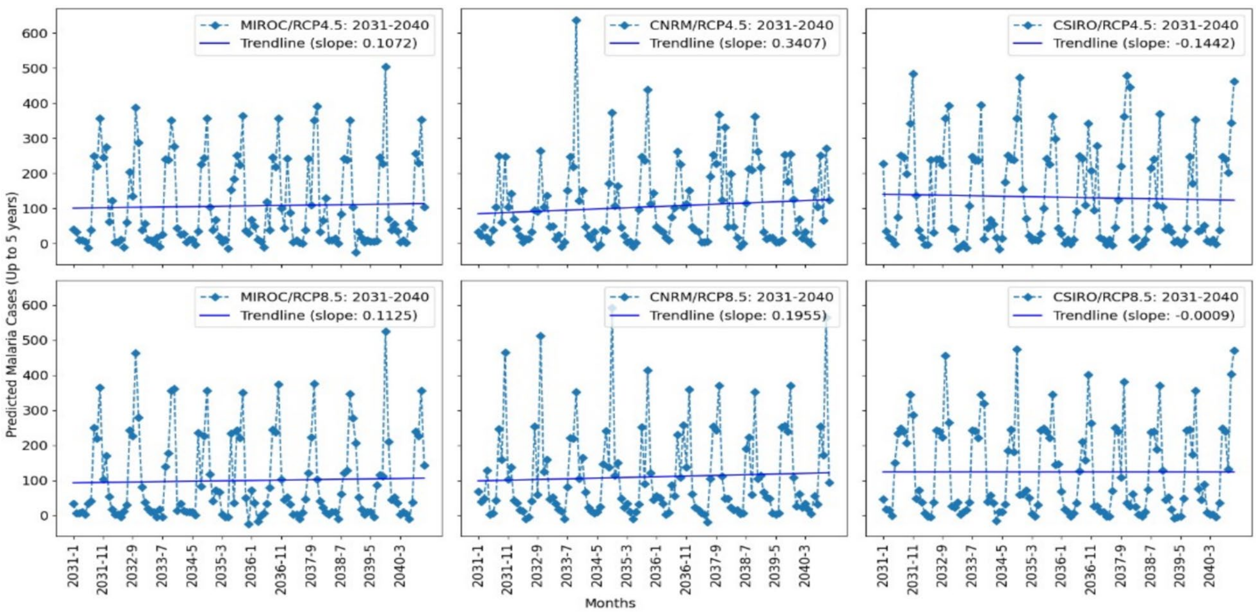

Fig. 11 Prediction of malaria incidence for the under-five in the Upper River Region of the Gambia over 2041–2050

over 2021–2030, 2031–2040, and 2041–2050 periods. Similarities also exist in RCP4.5 and RCP8.5 with a substantial malaria prevalence in RCP8.5 than in RCP4.5, especially with CSIRO/RCP4.5 in both age categories. The increase could result from climatic fluctuation, trends in temperature, and precipitation, presenting a suitable condition for *Anopheles* breeding and parasite transmission [44]. The climatic change condition determines the degree of variation and trend of malaria incidence in a region where the disease is already present and an area with fewer cases or no cases [44]. In the study region, with lower altitudes where malaria is already a problem, warmer temperatures will change the parasitic life cycle in a mosquito, enabling it to develop more quickly and increase transmission, thus having implications on the disease burden [4, 23–25].

The increased prevalence of malaria in both scenarios, with a slight percentage average increase in RCP4.5 than RCP8.5 in most cases (average of 0.14% (RCP4.5), 0.09% (RCP8.5) over 2021–2030, and 0.25% (RCP4.5) and 0.21% (RCP8.5) over 2031–2040, could mostly suggest a correlation with temperature, as both the vector carrier parasite and the parasite itself are temperature dependent with malaria transmission restricted as a certain range of temperature between 18 °C to 32 °C [45, 46]. It simply implies that when the temperature of the region is stretched beyond the malaria threshold in the case of the worst climate scenario, the risk of malaria will be considerably influenced by other climatic factors such as rainfall and relative humidity [14, 17]. Increased humidity is suitable for mosquito vectors to find hosts in a cooler or dry season, when surface water becomes sparse, limiting the laying of eggs and reducing adult mosquitoes [47]. Relative humidity affects the mating, longevity, dispersal, blood-feeding behavior, and oviposition of mosquitoes [48, 49]; thus, relative humidity equal to or greater than 60% encourages the breeding and proliferation of *Plasmodium* parasites, while humidity less than 60% may not lead to increase in the population of malaria parasites [14, 50]. Rainfall also exacerbates the flood activity, which in turn increases the moisture of the region and promotes the optimum condition for vector reproduction, thus increasing prevalence [13].

The risk of malaria in the region could also be exacerbated due to limited health infrastructure, unregulated land use in flood-prone areas, and inadequate emergency response capability [51, 52].

The development of resistance to a wide range of drugs and insecticides used for treatment and preventive options [29] could further result in the situation. The population's effort towards prevention and treatment might have been altered either through limited support from the government, climate change-induced poverty limiting their adaptation strategies, or reluctance to engage in good preventive and treatment options.

Climate change will indeed increase the risk of malaria infection in the study area. Directly, it can lead to unconsciousness, anaemia, and death; indirectly, it can reduce the income of the household, poverty, and absenteeism from school or work. A study carried out in Northern Benin by Gbaguidi et al. [15] shows that malaria incidence will increase over 2021–2050 under scenarios RCP4.5 and RCP8.5, except for the 2021–2030 period, when the incidence of malaria will decrease under RCP8.5 due to climate change, and thus increase the risk and vulnerability of the population to the disease condition. A projection of malaria incidence across West Africa under RCP4.5 and RCP8.5 scenarios by Fall et al. [14] shows that the prevalence of malaria is expected to increase in the southern part of the region. The results align with the study findings, in addition to the increase in malaria prevalence projected by IPCC on some previously unexposed regions of SSA in 2050 under the current climate change condition [4, 52, 53].

Malaria is predicted to increase more in the case of more than five than in those under, thus, being attributed to the mentioned factors with the inclusion of negligence exhibited by most adults toward their health. Younger children are more prioritized, and preventive efforts are being channeled toward them rather than the adults in most government intervention initiatives. This could also contribute to the predicted reduction seen over 2021–2030 in under five years in the region, thus the administration of chemopreventive therapy (SMC) and the use of Long-lasting insecticidal nets (LLINs) (13). As it stands now, the government of the Gambia is making an effort to address the issue of malaria in the region; more adverse effort is needed to avert the already predicted increase in malaria incidence and the associated risk across the region.

In conclusion, climate change or changing weather conditions tend to increase malaria prevalence in any given region due to the sensitivity of malaria-carry vectors and parasites to the changing weather conditions. Thus, changes in the pattern of climatic variables in the study region under RCP4.5 and RCP8.5 scenarios will favor malaria transmission and resultant malaria prevalence in the region. The development of an early malaria warning system using the Gradient Boost Machine Learning algorithm for the region serves as a powerful tool in the management of the disease condition through strategic malaria intervention planning, as malaria prevalence has been projected to increase in both the under-five and above-five population in almost all the models.

In this context, decision-makers planning public health measures in the region and other regions across West Africa should find the work highly valuable. Stakeholders might find these findings useful in creating adaptative and vector control strategies.

Future studies will combine RCPs, SSPs (Shared Socioeconomic Pathways), and CORDEX downscaling to investigate the probability environment of projected malaria prevalence across the regions in the Gambia and West Africa.

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Author contributions
Ugochinyere Agatha Okafor conceptualized the idea, reviewed the literature, collected data analyzed data, and wrote the paper. Pierre Claver Kakou downloaded the stimulated models used for the work, analyzed the data, and proofread the work. Sidat Yaffa, Umberto D'Alessandro, Vincent Nduka Ojeh, supervised and proofread the work.

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Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
The University of The Gambia Research Ethics Committee approved the study. All the respondents were informed about the confidentiality of the data.

Competing interests
The authors declare no competing interests.

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