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Article

Modelling current and future distribution of *Aedes aegypti* (Diptera: Culicidae) under climate change scenarios in Africa

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Abstract: Climate change is altering mosquito distribution by expanding the geographic range of species like *Aedes aegypti* (Diptera: Culicidae) into previously inhospitable areas due to rising temperatures and changing precipitation patterns. This shift increases the risk of mosquito-borne diseases in regions that were once unaffected, posing new public health challenges globally. *Ae. aegypti* is the vector that spreads the arboviral illnesses dengue fever, chikungunya, and zika. Studying *Ae. aegypti's* probable geographic distribution habitats in Africa under present and projected climatic circumstances is the goal of the current research. The scenarios used are the Beijing Climate Center Climate System Model (BCC-CSM2-MR) with two Shared Socio-economic Pathways (SSPs) for each of the general circulation model (GCMs): SSP126. Altitude, temperature, seasonality (standard deviation *100; bio4), and yearly precipitation (bio12) were found to be the most significant environmental factors influencing *Ae. aegypti's* spread.

Key words: Mosquitoes, prediction, geographic distribution, R Package, (BCC-CSM2-MR).

1. Introduction

Aedes aegypti hold significant medical importance as vectors of several debilitating human diseases **(Monath 1988, Diamond, 2009)**. These mosquitoes are primary carriers of the viruses responsible for dengue fever **(El-Bahnasawy *et al.*, 2011)**, Zika virus **(Morsy, 2018)**, chikungunya **(Mostafa, 2002)**, and yellow fever **(Carter, 1931)**. According to the report of **WHO, 2003** the infectious and vector-borne diseases epidemiology may be altered due to changes in host ranges from climate change.

Most climate change scenarios associate changes in the incidence of infectious diseases with variations in weather extremes, and variations in the transmission of communicable diseases with increases in average temperature **(Canyon *et al.*, 2016)**. Because they are poikilothermic body temperature varies depending on ambient temperature parasitic diseases carried by arthropod vectors, such as mosquitoes, are the main vectors of vector-borne diseases (VBDs), which are especially sensitive to changes in external climatic conditions **(Rocklöv, 2020)**. Insect population, dispersion, and abundance are influenced by habitat suitability. The rate at which pathogens develop and replicate in mosquitoes is also influenced by temperature, which raises the danger of infection **(Metcalf *et al.*, 2017, Caminade and McIntyre, 2019)**.

Depending on changes in mosquito vector ecology, precipitation also has a major impact on the dynamics of the vector-borne disease (VBD) network for diseases transmitted by vectors with aquatic developmental stages **(Paz, 2019)**. Changes in climate lead to a rise in diseases carried by mosquitoes. The 10% rise in mosquito-borne disease (MBD) in Canada over the previous 20 years has been mostly attributed to climate change **(Ludwig *et al.*, 2019)**. This is accurate given that temperature, precipitation, and land use all affect the life cycles, reproduction, and feeding of mosquitoes **(Wudel and Shadabi, 2016)**. Likewise, climate change affects the range, seasonality, and habitat of disease-carrying mosquitoes. Host range changes affect biodiversity and provide a risk to ecological processes, particularly for insects in many global ecosystems **(Nooten, 2014)**. Conversely, a significant contributing cause to the recurrence of insect pests is climate change. Changes in global temperature would force many pests that are detrimental to people, such as mosquitoes (Culicidae), to relocate to new habitats **(Reiter. 2001)**.

Future patterns of mosquito-transmitted diseases like malaria and dengue have been projected by studies examining the consequences of climate change. These trends include expanding the spatial dispersion of these diseases and intensifying their transmission **(Hales *et al.*, 2002 and Ogden *et al.*, 2008)**. Data are beginning to indicate that some mosquito species' host range ranges are already beginning to change as a result of shifting climatic conditions, and it is predicted that this pattern will likely continue as a result of climate change **(Ogden *et al.*, 2008)**. Abiotic factors like terrain and climate have a bigger impact on mosquito abundance at larger geographical scales than biotic factors like predation, competition, and vector control measures do at smaller regional dimensions **(Brownstein *et al.*, 2005)**. Ecological niche models (ENM) and bioclimatic envelope models have been used in an increasing number of research to model the possible impacts of climate change on species distributions **(Gonzalez *et al.*, 2010)**. Both adult and juvenile stage characteristics of insects, such as larval growth rates, development durations, body size, fertility, and longevity, are significantly influenced by the environment **(Loetti *et al.*, 2011)**. Temperature is an especially important abiotic factor for mosquitoes and other arthropods since it directly affects their mortality, life expectancy, and rates of development that could lead to morphological changes **(Debat *et al.*, 2003 and Beck, 2013)**.

Species distribution models (SDMs) are currently one of the most widely used scientific approaches for determining the effects of climate change on biodiversity due to the growing interest in biogeographic studies and conservation **(Beck. 2013)**. These models are successfully and widely used to assess the ecological and evolutionary dynamics that affect the global distribution of species and the suitability of their habitat **(Bosso *et al.*, 2013, Zhu *et al.*, 2013)**. Species distribution models (SDMs) are widely used in various ecological, biological, and biogeographical applications to anticipate past, present, and future species distributions **(Guisan *et al.*, 2017)**. The primary element influencing the spatial distribution of biodiversity worldwide has been extensively researched: climate **(Araújo *et al.*, 2005)**.

2. Materials and Methods

Global Distribution Data

The Global Biodiversity Information Facility (GBIF.org, https://doi.org/10.15468/dl.sgpgg0 , accessed in December 2022) provided the occurrence data for Ae. aegypti. Preserved specimens and human observations served as the sources of the 39424 geo-referenced, coordinate-based records found in the downloaded database. In order to remove duplicate geographic information and points outside the shapefile of the globe map, we verified the records using ArcGIS 10.3 **(ESRI, 2014)**. After deleting the corresponding missing values of the resampled environmental parameters of topography and climate, this produced 2369 distribution points, which were subsequently further reduced into 16,950 records (see Figure 1).

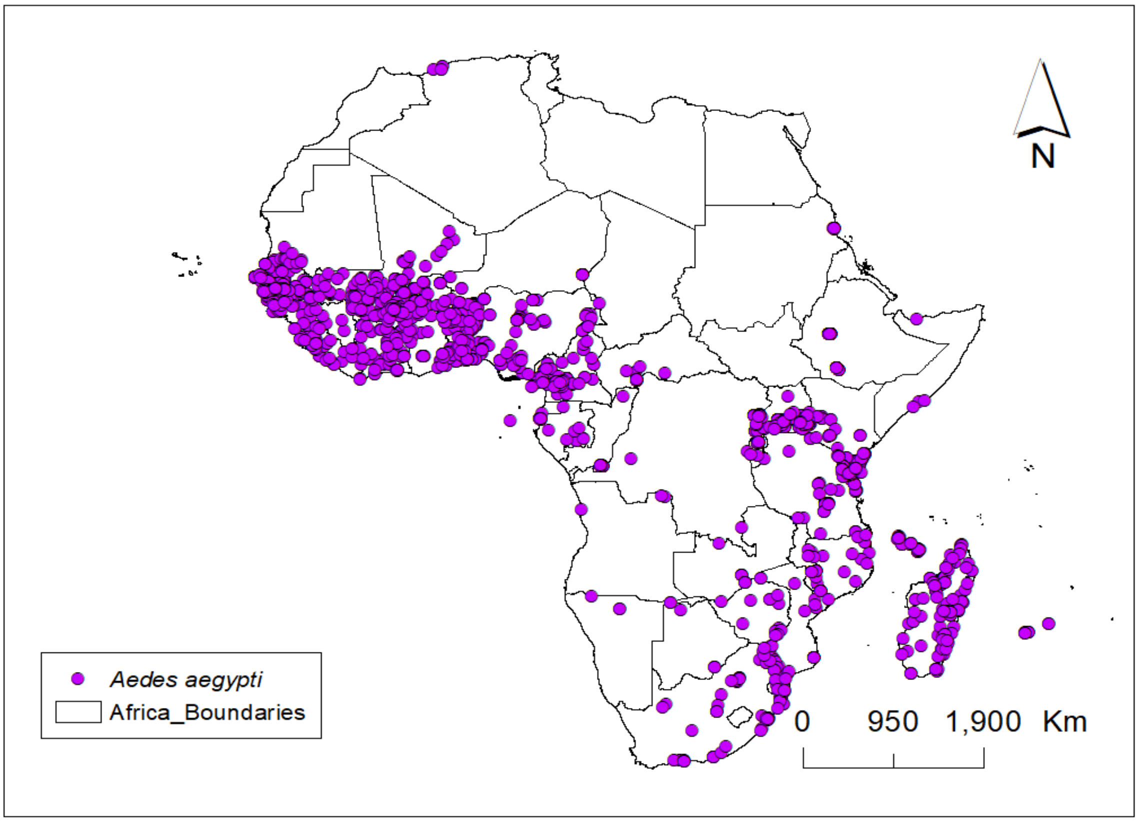

Fig. (1(. Observed distribution of *Ae. Aegypti* in Africa

Environmental Variables and Multicollinearity

Twenty characteristics were gathered as predictors to model the likely environmental niche of *Ae. aegypti* based on the dataset for its current presence. Specifically, the WorldClim database (http://www.worldclim.org) was used to gather data on 19 bioclimatic layers (bio01-bio19) and one topographical variable (elevation) at a spatial resolution of 2.5 arcminutes (5 km at the equator) **(Hijmans *et al.*, 2005)**. According to earlier studies, these environmental characteristics should be taken into account above all others when estimating the potential dispersal of a species **(Yi *et al.*, 2018)**.

Global general circulation models (GCMs): BCC-CSM1.1 (Beijing Climate Centre–Climate System Modelling 1.1) were used to assess the potential effects of climate change on the distribution of *Ae. aegypti* (http://forecast.bcccsm.ncc-cma.net/web/channel-34.htm). The WorldClim database provided the global climate model BCC-CSM1 for both the 2030 (average for 2021–2040) and 2090 (average for 2081–2100) eras.

We used global climate models (GCMs): BCC-CSM2-MR. For each of the GCMs, two Shared Socio-economic Pathways (SSPs) SSP126 and SSP585 were chosen. Next, it was determined that the two SSP emission scenarios represented a low and high forcing scenario of climate change coupled with economic development.

Model Performance

The goal of this study was to find uncorrelated environmental factors that affected the distribution of species. For the purpose of simulating present and projecting future possible suitable distribution locations, the SDM package in R, version 4.1.5, can be utilized (https://www.rproject. org, retrieved on March 1, 2021). Description and modeling of the occurrence data, thirty percent were used for testing and the remaining seventy percent for training. The hinge, product, linear, and quadratic functions were all set to automatic.

In order to avoid multicollinearity problems, predictor variables that were correlated and had variance inflation factor (VIF) values greater than five or a correlation threshold of 0.75 were eliminated. In the R process, three environmental variables (bio4, bio12, and Alt) were maintained. In this way, every one of these non-linear variables apart from elevation was used to model Ae. aegypti in the context of hypothetical future global warming scenarios. Twenty environmental variables' variance inflation factors (VIFs) were examined in order to eliminate multicollinearity and select the best-fitting predictors with the highest apparent contribution power to the model. Based on their variance inflation factor (VIF) we deleted the highly correlated variables, to reduce overfitting of SDM models, which measures how strongly each predictor can be explained by the rest of the predictors **(Naimi *et al.*, 2016)**.

The variables with VIF values larger than five and a correlation criterion of 0.75, as followed by28, were eliminated using the vifcor and vifstep functions of the package "usdm" **(Naimi, 2015)** in R Version 4.1.1 to perform a VIF analysis. Using the function "SDM" package in R Version 4.1.1, the relative relevance of predictor variables was evaluated.

3. Results

Climatic Variables Importance

The obtained results supported the use of three uncorrelated predictor variables in R models (Table 1). Temperature Seasonality (BIO4), Altitude (Alt), and Annual Precipitation (Bio 12) (mm) all demonstrated excellent sensitivity in *Ae. aegypti*. It was discovered that these significantly affected how suitable *Ae. aegypti* is for the current and upcoming climate. The distribution of *Ae. aegypti* was influenced by three environmental data points that were deemed most significant: bioclimatic factors. The most significant environmental variable that contributed most to the spread of *Ae. aegypti* was temperature, followed by seasonality (BIO4) (91.8%) and altitude (7.0%). The least significant variable was annual precipitation (mm) (bio12) (1.2%). The table below (Table 1 and Figure 2) summarizes the corresponding variable contributions.

Table 1. Permutation importance of variables for modeling

Code	Variables	Units	Percent Contribution
bio_04	Temperature Seasonality (standard deviation *100).	°C	91.8 %
Alt	Altitude	m	7.0 %
bio_12	Annual Precipitation (mm)	mm	1.2 %

Model Evaluations and Critical Environmental Variables

Potential habitats were estimated using the model, which had a mean AUC of 0.85. The models of Ae. aegypti had very high mean AUC values. Since the predicted results were extremely accurate, the findings of the possible distribution area could also be trusted (refer to Table 2).

The likelihood of the world existing might be evaluated based on the model's response curves for environmental factors. Sharp drops in the probability of *Ae. aegypti* occurrence were seen as annual precipitation (mm)) (bio12) and altitude (Alt) increased. Figure 3 illustrates the gradual increase in the probability of *Ae. aegypti's* presence in response to temperature seasonality (Bio4).

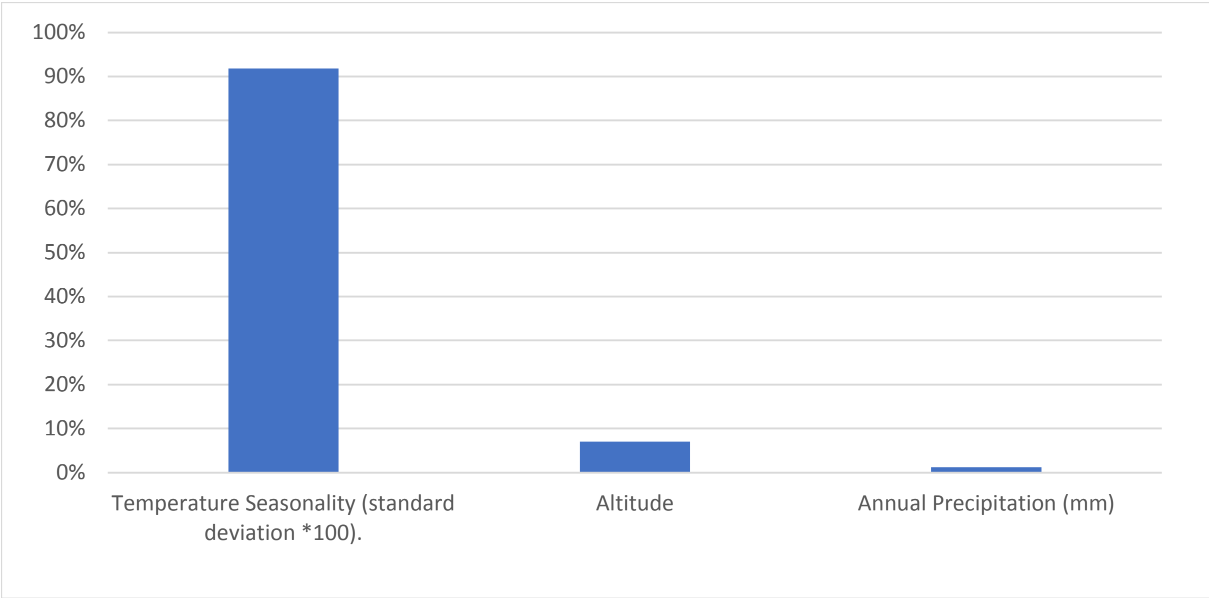

Fig. (2). Variable's importance to the prediction distribution model of *Ae. aegypti*

Table (2). The Area Under the Curve (AUC) values for the *Ae. aegypti* climatic suitability models run in R Version 4.1.1

Methods	Area Under the Curve (AUC)	True Skill Statistic (TSS)	Deviance
Generalized Linear Model (GLM)	0.85	0.62	0.89

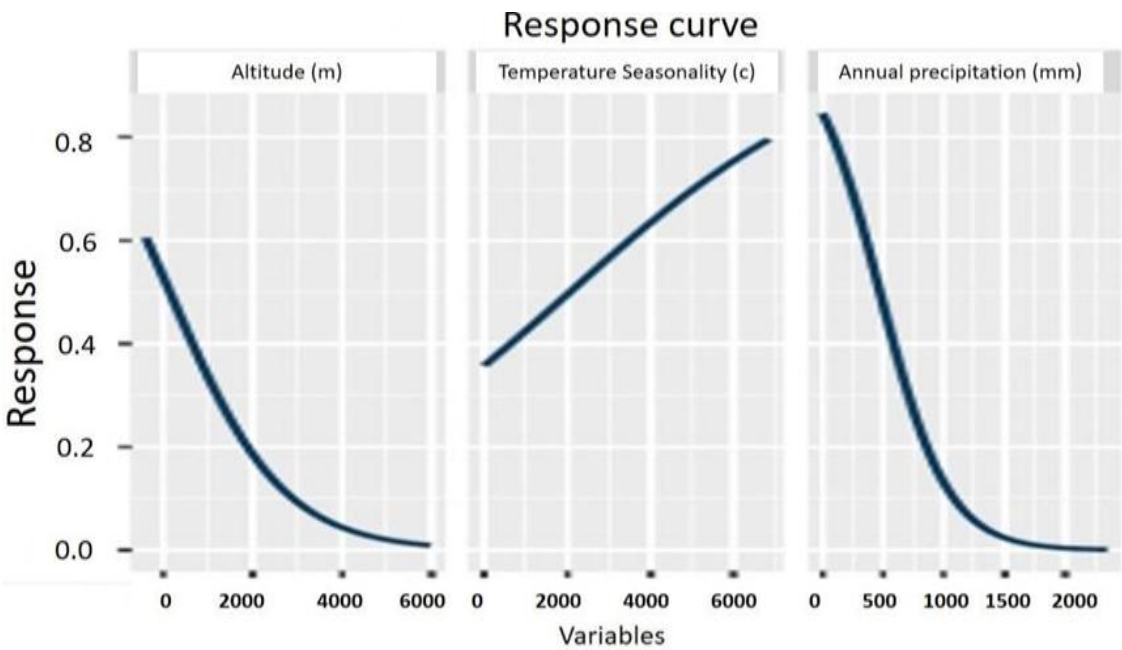

Fig. (3). Response curves of the most important predictor variables used in distribution modelling of *Ae. aegypti*

Climatic Suitability Under Current and Future Climate Change Current Potential Distribution of *Ae. aegypti*

When forecasting the climatically suitable locations for *Ae. aegypti* establishment under present and future climate scenarios, the models that used three bioclimatic factors showed varying findings. The findings showed that the possible global distribution pattern for *Ae. aegypti*, as depicted in Figure 4.

In Africa, the models showed very high and excellent habitat suitability of *Ae. aegypti* in the countries of middle Africa ranges from Ethiopia in the east to Mali, Chad, and Guinea in the west. While moderately suitable areas for *Ae. aegypti* in the north and South Africa. In North Africa, the resulting current models indicated low suitability in *Ae. aegypti* distribution over its land except for some parts of the north-western coast of Africa.

North and South Africa illustrated low suitability in the resulting models while Mozambique and west of Zimbabwe showed a suitable habitat. Finally, middle Africa illustrated high and very high suitability, but areas near the boundaries in the north and south appeared moderate suitability for the distribution of *Ae. aegypti* (see Figure 4).

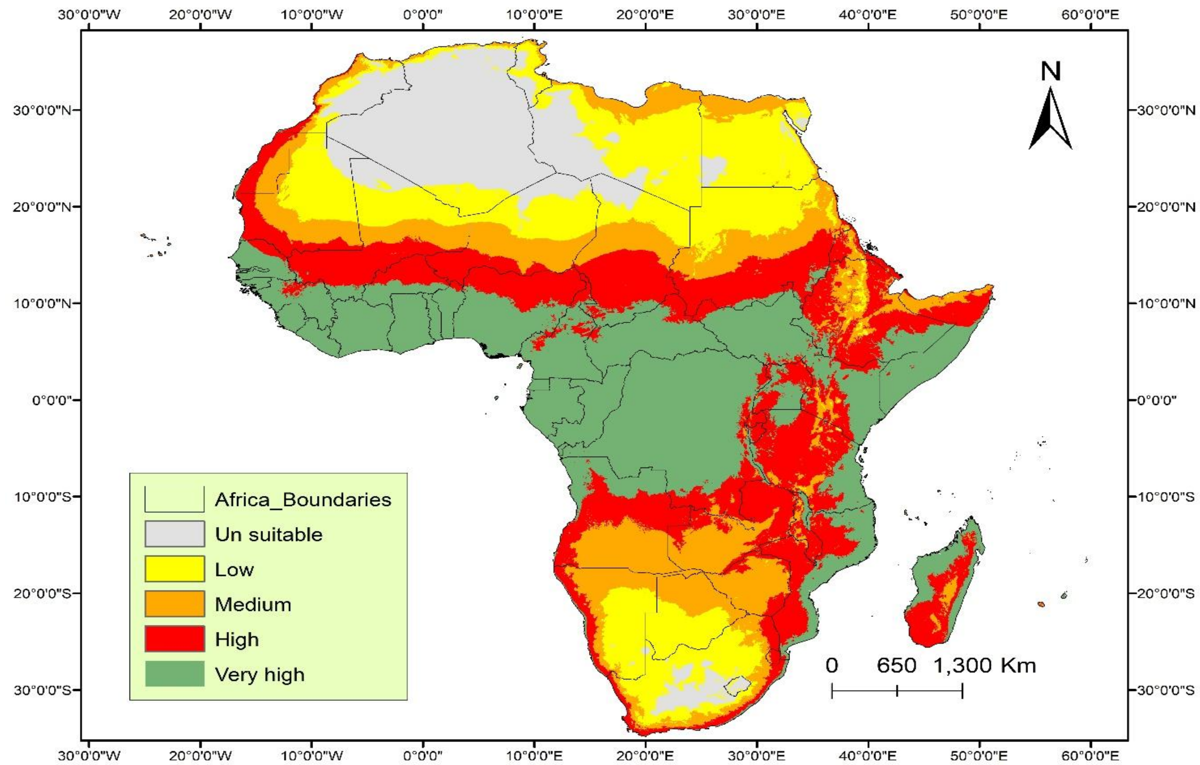

Fig. (4). The predicted current distribution range of *Ae. aegypti*

The Predicted Future Potential Distribution Areas of *Ae. aegypti*

Figure 5 shows the models for *Ae. aegypti's* possible distribution under future climate change scenarios BCC-CSM2-MR_ssp126 and ssp585 for the years 2020 and 2080. Distribution patterns throughout the scenarios between the present-day and future models showed reasonable similarities except in some regions. Furthermore, the future predictions showed some differences between BCC-CSM2-MR in 2020 and 2080. Under low hypothetical emissions of greenhouse gases (GHG) (BCC-

CSM2-MR_ssp126 in 2020 and 2080), the changes are simple and usually not notable on all countries. Although the species will lose some of their habitats as in Mauritania, Mali, Niger, Chad (Figure 5a, b). Additionally, for the highest hypothetical emissions of GHG (BCCCSM2-MR_ssp585 in 2020 and 2080), the insect will lose and gain almost the same area as in (BCC-CSM2-MR_ssp126 in 2020). The model appeared that under hypothetical emissions the insect invades large area in south, north Africa (Figure 5c, d).

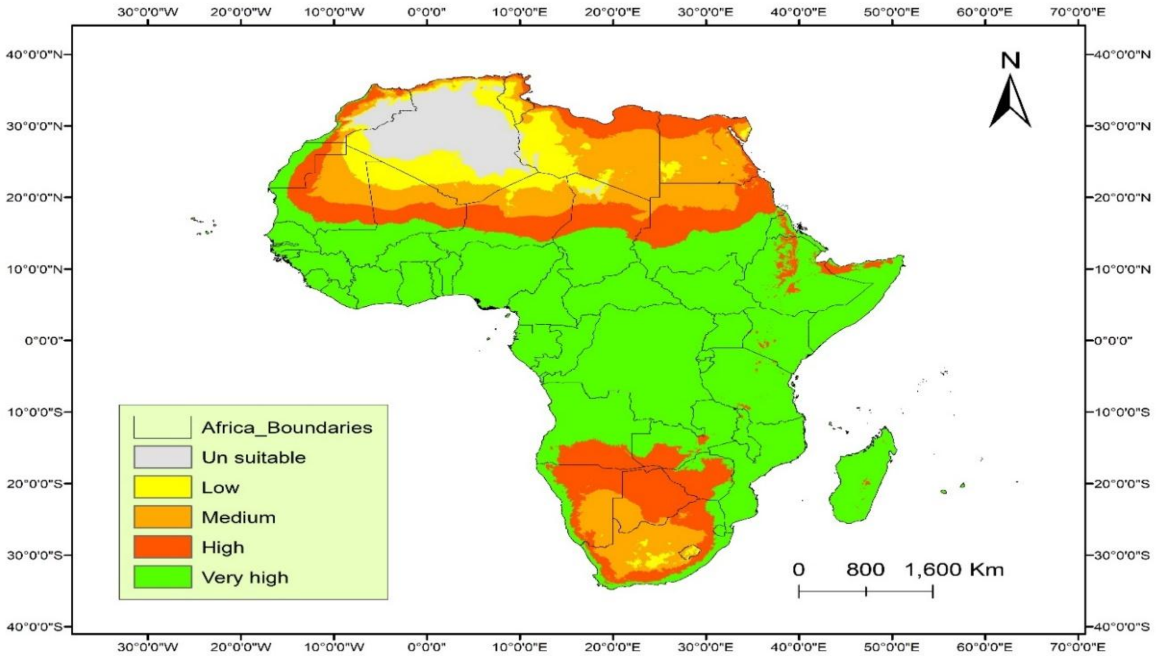

Fig. (5a). Potential future distribution under BCC-CSM2MR_ssp126_2021-2040 scenarios

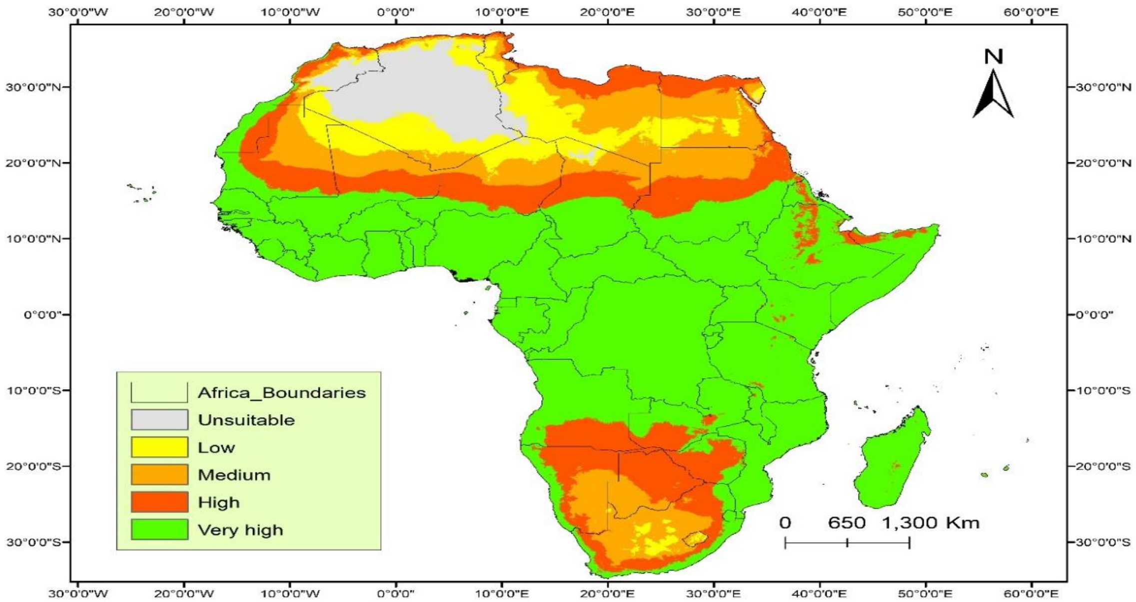

Fig. (5b). Potential future distribution under BCC-CSM2-MR_ssp126_ 2080-2100 scenarios

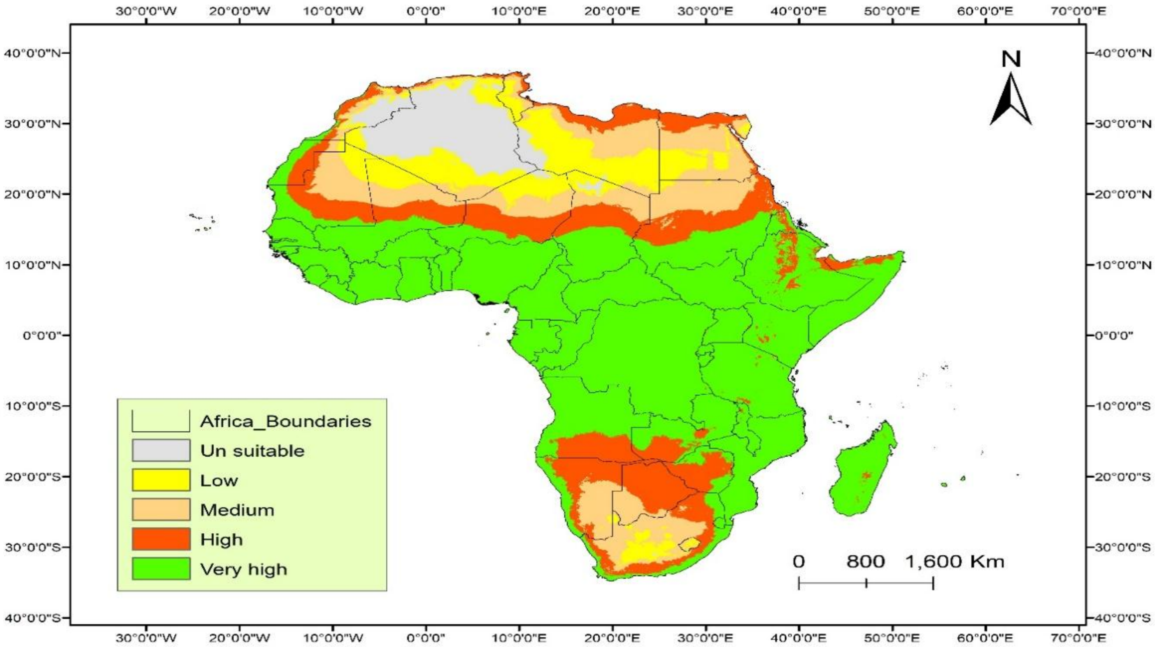

Fig. (5c). Potential future distribution under BCC-CSM2-MR_ssp585_2021-2040 scenarios.

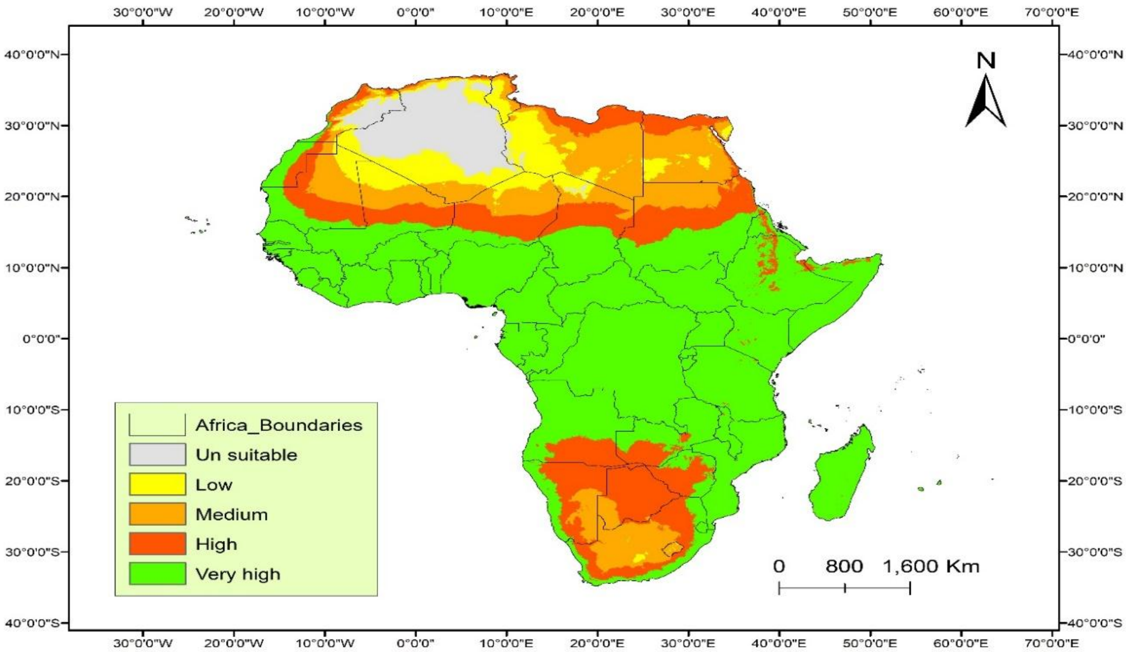

Fig. (5d). Potential future distribution under BCC-CSM2-MR_ssp585_2080-2100 scenarios

4. Discussion

The abundance of *Ae. aegypti* was primarily influenced by four bioclimatic variables: altitude (Alt), temperature, seasonality (BIO4), and annual precipitation (mm) (bio12). These outcomes concurred with those of other studies (**Wudel and Shadabi, 2016)**. These factors might be crucial in determining where *Ae. aegypti* is found. Changes in temperature and precipitation are the primary impacts of climate change on endemic mosquito populations. The potential habitat available to mosquitoes for laying eggs and raising larvae is often increased by an increase in precipitation.

The relationship is often non-linear: while excessive or violent precipitation may have a leaching effect by destroying mosquito eggs and flushing larvae out of specific habitats, above-average rainfall typically increases mosquito populations by increasing the availability of standing water **(Clements, 1992)**. Raising the temperature can hasten the mosquito life cycle's juvenile phases, boosting rates of reproduction and leading to exponential population expansion **(Alto and Juliano, 2001)**. Warm weather contributes to mosquito population and development, but it also amplifies virus replication in mosquitoes very quickly. This is consistent with recent studies **(Reisen *et al.*, 2014; Rios, 2009)** that found that one of the most significant abiotic variables affecting the physiology, behavior, ecology, and, consequently, the survival of insects, is ambient temperature.

Climate factors like rainfall, ambient temperature, and relative humidity have a direct impact on the length of larval development, survival of both larvae and adults, and gonotrophic cycle time of *Ae. aegypti*, the primary dengue vector **(Naish *et al.*, 2014)**. Furthermore, research on the threshold impacts of climate on dengue in Taiwan revealed a favorable association between temperature and rainfall and the larval and adult densities of *Ae. aegypti* **(Tran *et al.*, 2020)**. Temperature-related climatic variations have an impact on insect development and reproduction **(Costa *et al.*, 2010; Carrington *et al.*, 2013)**.

Climate change scenarios involving higher temperatures resulted in a shorter pathogen development period within the vector until it becomes transmissible **(Winokur *et al.*, 2020)**, as well as an increased distribution of *Ae. aegypti* worldwide and an accelerated adult emergence **(Kamal *et al.*, 2018 and Iwamura *et al.*, 2020).** Numerous research, including regional and worldwide forecasts, have projected future Aedes mosquito distributions and dengue hazards based on the GCMs of various climate change scenarios **(Ryan *et al.*, 2019 and Pörtner *et al.*, 2022).**

When different models are compared for the same scenario, different forecasts have different results. In the present scenario, for example, the BCC-CSM1 model predicted that the area of *Ae. aegypti* that is moderately suitable for human habitation will decrease in the future, while the future model predicted that it will slightly increase. Climate change is expected to affect the future spread of viral transmission by endemic mosquitoes due to the rise in populations and numbers of these species.

An overview of the likely future distribution of *Ae. aegypti* and dengue transmission is provided by the prospective alterations indicated by the results of climate change modeling. Certain regions that are currently home to mosquitoes and dengue fever may become unsuitable due to climate change. Every scenario taken into account for this analysis points to a general future reduction in the climatically favorable locations for Aedes. Some of the presently significant hotspots are covered by this decreased potential region for *Ae. aegypti* and dengue.

These findings identify regions where future climate suitability is predicted to decline, which may help decision makers when allocating resources for mosquito management. Because of future climatic changes, this study has identified additional regions of the world that might be vulnerable to *Ae. aegypti* and dengue transmission. These locations may need to implement strategic control measures to stop the disease's spread. Such locations may require a more comprehensive risk assessment for mosquito transmission.

In order to assess and control mosquito risk and identify danger levels, projections of habitat appropriateness are essential. The response of *Ae. aegypti* and dengue transmission to climate fluctuations must be included in such assessments. This study particularly identifies areas that are currently and will continue to be at risk from mosquitoes. Health managers can use our results to assist them prioritize locations for eradication and identify regions that need pest treatment. Given that different MBDs mosquitoes, reservoirs, and the environment have varying degrees of dependence on climate change, it is challenging to forecast how these entities will respond to it. Thus, even a slight alteration in the climate could lead to a notable rise in the spread of arboviruses. Additionally, the transmission cycles, reservoirs, and vectors of each MBD are unique. Since these may be rare in certain places of the world, variations in the occurrence of MBDs will occur depending on the environment or region.

5. Conclusion

When building models to assess the habitat suitability of specific insect pest species, GIS techniques and climatological data can be utilized. In our work, we have successfully simulated the global distribution of *Ae. aegypti*, both present and future. With a geographical resolution of 5 km2, the models pinpointed current at-risk areas as well as potential areas with sufficient habitat that might see future incursions of *Ae. aegypti* worldwide. Practical management solutions are required because controlling *Ae. aegypti* is a challenging and expensive task, and there are no vaccinations available for the majority of the viruses it transmits **(Facchinelli *et al.*, 2023)**. When determining whether to expedite adaptive management measures for pests that have a significant impact on human health, decision-makers and quarantine authorities may find these model patterns and their changes over time to be helpful.

Climate change is expected to have a major impact on endemic mosquito populations worldwide and, as a result, MBDs including dengue fever, chikungunya, and Zika. The model we have created also makes it possible to do more thorough local research, especially in areas where *Ae. aegypti* mosquitoes are predicted to thrive. By adding ecological elements like altitude and meteorological variables, the model's local resolution for these disease transmission vectors can be made more predictively accurate.

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