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Original Research Article

Predicting the potential worldwide distribution of *Aedes aegypti* under climate change scenarios

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ABSTRACT

Background: Climate change is one of the most important factors associated with medically important insect pests such as mosquitoes (Diptera: Culicidae). Diseases spread by mosquitoes are increasing due to changes in global temperature and weather patterns that are altering vector host ranges allowing spread into new regions. Zika, dengue fever, chikungunya and yellow fever are arboviral infections that are spread by *Aedes aegypti* (Culicidae). The objective of the current research is to study the potential geographic distribution habitats of *Ae. aegypti* in the world under current and future climate conditions.
Methods: Data of *Ae. aegypti was* obtained from the global biodiversity information facility and used 19 bioclimatic layers (bio01-bio19) and elevation from the WorldClim database (http://www.worldclim.org). The scenarios used are the Beijing climate center climate system model (BCC-CSM2-MR) and the institute Pierre-Simon Laplace, coupled model intercomparison project (IPSL-CM6A-LR) with two shared socio-economic pathways (SSPs) for each of the general circulation model (GCMs): SSP126 and SSP585.
Results: The results revealed that altitude, temperature, seasonality (standard deviation *100) (bio4), and annual precipitation (bio12) were the most important environmental variables that affect the distribution of *Ae. aegypti*.
Conclusions: The models showed that Africa and South America maintained very high and excellent habitat suitability for *Ae. Aegypti* under the current potential distribution map.

Keywords: Mosquitoes, *Aedes aegypti*, Prediction, R Package, Climate change

INTRODUCTION

Mosquitoes are the main vectors of many pathogens that cause diseases in humans such as rift valley fever, West Nile encephalitis, and lymphatic filariasis.[1-3] *Ae. aegypti* is generally considered the main vector of zoonotic arboviruses including yellow fever, dengue fever, chikungunya viruses and Zika fever.[4-7] Infectious and vector-borne diseases epidemiology may be altered due to changes in host ranges from climate change.[8]

Most climate change scenarios connect the changes in infectious disease frequency to changes in weather extremes, and changes in the spread of communicable diseases to average temperature increases.[9] Parasitic diseases carried by arthropod vectors, like mosquitoes, are the primary vectors of vector-borne diseases which are particularly sensitive to changes in external climatic conditions given they are poikilothermic (body temperature is variable based on ambient temperature).[10] The suitability of habitat influences the population, distribution, and abundance of insects. Furthermore, temperature affects the rate of pathogen development and replication in mosquitoes, increasing risk of infection.[11,12]

Precipitation also significantly affects the dynamics of the vector-borne disease network for diseases carried by vectors with aquatic developmental stages, depending on the alterations in the ecology of mosquito vectors.[13] An increase in diseases spread by mosquitoes is a result of climate change. Climate change has been a major factor in the 10% increase in mosquito-borne disease (MBD) in Canada during the past 20 years.[14] This is due to alterations of life cycles, reproduction, and feeding of mosquitoes are impacted by temperature, precipitation, and land use.[15]

The habitat, seasonality, and range of mosquitoes that spread disease are affected by climate change. Changes in host range pose a hazard to ecological processes and has an influence on biodiversity, especially for insects in many habitats across the world.[16] Climate change, on the other hand, is a major factor in the resurgence of insect pests. Numerous pests that are harmful to humans, including mosquitoes (Culicidae), will move into new habitat locations due to changes in global temperature.[17]

Studies investigating climate change effects have predicted future trends, which include increasing transmission intensity and expanded spatial dispersion of mosquito-transmitted diseases such as malaria and dengue.[18,19] Increasingly, data suggests that the host range distributions of some mosquito species have already begun to vary because of changing climatic conditions, and it forecasts that this pattern is likely to continue further with climate change.[19] At smaller regional dimensions, biotic factors like predation, competition, and vector control efforts have a significant impact on mosquito abundance, but at greater geographical sizes, abiotic factors like terrain and climate have a more significant impact.[20]

A growing number of studies have employed ecological niche models (ENM) and bioclimatic envelope models to simulate potential effects of climate change on species distributions.[21] Environmental influences have significant variation in both adult and immature stage features of insects, including larval growth rates, development durations, body size, fertility, and longevity.[22] For mosquitoes and other arthropods, temperature is a particularly significant abiotic element since it has direct impact on mortality, life expectancy, and development rates that might result in morphological alterations.[23,24]

As a result of the increased interest in conservation and biogeographic studies, species distribution models (SDMs) are currently one of the most popular scientific methods for identifying potential impacts of climate change on biodiversity.[25] To evaluate the ecological and evolutionary dynamics that influence the geographic distribution of species and the suitability of their habitat, these models are successfully and widely used.[26,27] SDMs are commonly applied in many ecological, biological, and biogeographical applications are commonly use species distribution models to forecast past, present, and future species distributions.[28] Climate has frequently been studied as the main factor in the spatial distribution of global biodiversity.[29]

METHODS

Global distribution data

The occurrence data of *Ae. aegypti* was obtained from the global biodiversity information facility (GBIF.org https://doi.org/10.15468/dl.sgpgg0) for the time period January 1900 to December 2022. The database that was downloaded contained 88,888 geo-referenced records with coordinates and the source of these occurrence data was preserved specimens and human observations. We used ArcGIS 10.3 to verify the records in order to delete duplicate geographic records and points outside the shapefile of the world map.[30] This resulted in 17,465 distribution points, and then reduced further into 16,950 records after removing the reciprocated missing values of the resampled environmental factors of climate and topography (Figure 1).

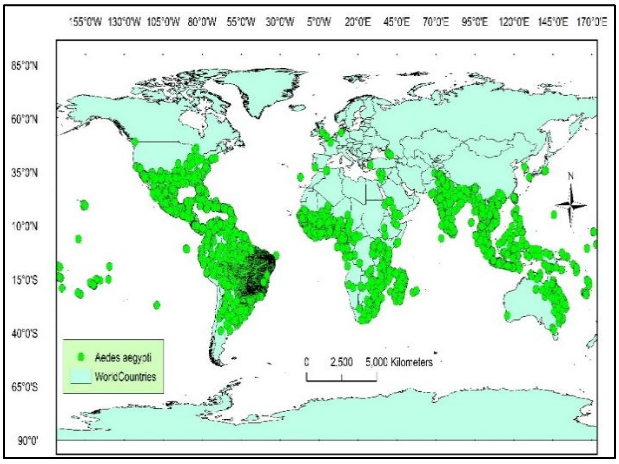

Figure 1: Observed distribution of *Ae. aegypti.*

Environmental variables and multicollinearity

Based on the dataset for its current presence, twenty factors were collected as predictors to simulate the potential environmental niche of *Ae. aegypti*. In particular, 19 bioclimatic layers (bio01-bio19) and one topography variable, namely Altitude (Alt), with a spatial resolution of 2.5 arcminutes (5 km at the equator) were collected from the WorldClim database (http://www.worldclim.org).[31] Previous research indicated that these environmental parameters were the most important factors to consider when calculating prospective species dispersal.[32]

In order to evaluate the possible effects of climate change on the dispersal of *Ae. aegypti*, global general circulation models (GCMs): BCC-CSM1.1 (Beijing climate centre-climate system modelling 1.1 were applied, http://forecast.bcccsm.ncc-cma.net/web/channel-34.htm).

Global climate model BCC-CSM1 was obtained from WorldClim database under both scenarios over periods 2030 (avg for 2021-2040) and 2090 (avg of 2081-2100).

We applied two global climate models (GCMs): BCC-CSM2-MR and IPSL-CM6A-LR. We used the GCMs from the CMIP6 of the sixth assessment report (AR6) of the intergovernmental panel on climate change (IPCC). Two shared socio-economic pathways (SSPs) were selected for each of the GCMs: SSP126 and SSP585. The two SSPs emission scenarios were then considered to represent a low-forcing and high-forcing scenario of climate change with economic development.

Model performance

Description and modeling for this study was applied to obtain uncorrelated environmental variables that influenced species distribution. The SDM package in R, version 4.1.5, can be used to simulate current and project future potential suitable distribution regions (https://www.rproject.org). Thirty percent of the occurrence data were used for testing, while the other seventy percent were used for training. The linear, quadratic, product and hinge were set as automatic.

The significance of predictor variables in the possible distribution of *Ae. aegypti* to prevent multicollinearity issues, correlated variables with variance inflation factor (VIF) values > 5 and a correlation threshold of 0.75 were deleted. Three environmental variables (bio4, bio12 and Alt) were kept in the process in R. All these non-linear variables-aside from elevation were similarly employed in the modelling of *Ae. aegypti* under potential future global warming scenarios. VIFs of 20 environmental variables were investigated to remove multicollinearity and choose the most fitting predictors that appear more contribution power to the model.

Based on their 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.[33]

To make VIF analysis, we applied the vifcor and vifstep functions of the package "usdm" in R version 4.1.1 to eliminate the variables with VIF values greater than 5 and a correlation threshold of 0.75, as followed by.[28,34] The relative importance of predictor variables ware estimated using function "SDM" package in R version 4.1.1.

RESULTS

Climatic variables importance

Our findings supported the use of three uncorrelated predictor variables in R models (Table 1). Altitude (Alt), temperature seasonality (bio4), and annual precipitation (bio12) (mm) all demonstrated excellent sensitivity in *Ae. aegypti*. These were found to have a major impact on the climatic suitability of *Ae. aegypti* under current and future climatic conditions. These bioclimatic variables were the most important three environmental data that affected the distribution of *Ae. aegypti*. Temperature Seasonality (bio4) (83%) was the most important environmental variable that had the highest contribution to the distribution of *Ae. aegypti* then altitude (6.3%) while, (Annual precipitation (mm)) (bio12) (1.1%) had the least contribution. Respective variable contributions are summarized in Table below (Table 1 and Figure 2).

Table 1: Permutation importance of variables for modeling.

Code	Variables	Units	Percent contribution
bio_04	Temp. seasonality (SD*100).	°C	83
alt	Altitude	m	6.3
bio_12	Annual precipitation (mm)	mm	1.1

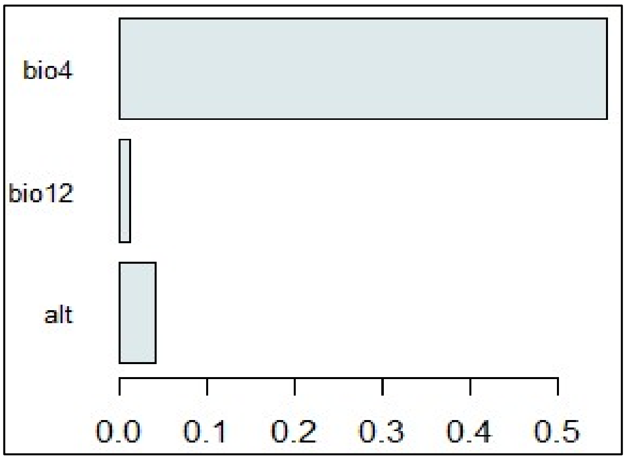

Figure 2: Variable's importance to the prediction distribution model of *Ae. aegypti.*

Model evaluations and critical environmental variables

The model was performed to estimate potential habitats with a mean AUC of 0.85. The mean AUC values for the models of *Ae. aegypti* were noticeably high. Prediction results were very accurate, which also meant that results of the potential distribution area were reliable (Table 2).

Table 2: AUC values for the *Ae. aegypti* climatic suitability models run in R version 4.1.1.

Methods	AUC	True skill statistic (TSS)	Deviance
Generalized linear model	0.85	0.62	0.89

According to the response curves for environmental variables in the model, the probabilities for the presence of the world could be assessed. The likelihood of *Ae.*

aegypti presence exhibited sharp decreases with the increase of annual precipitation (mm) (bio12) and the altitude (Alt). The probability of the presence of *Ae. aegypti* increased in response to temperature seasonality (bio4), gradually as shown in Figure 3.

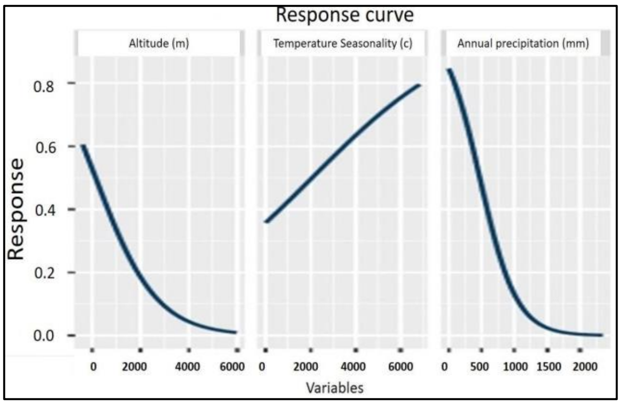

Figure 3: Response curves of the most important predictor variables used in distribution modelling of *Ae. aegypti*.

Climatic suitability under current and future climate change current potential distribution of Ae. aegypti

The models using three bioclimatic variables exhibited varied results for predicting the areas climatically suitable to *Ae. aegypti* establishment under current and future climate scenarios. The results revealed that the current potential distribution map for *Ae. aegypti* in the world shown in Figure 4. In Africa, the models showed very high and excellent habitat suitability of *Ae. aegypti* in the counties 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 Asia, China, North and South Korea, and southern parts of Japan illustrated no suitability for the distribution of *Ae. aegypti* in the present time.

In Europe, the resulting models revealed low suitability throughout major European lands, including Italy, France, Spain, Portugal, Netherlands, England, Greece, and Turkey except for the United Kingdom, which are moderately suitable habitats for *Ae. aegypti*. In North America, the resulting current models indicated low suitability in *Ae. aegypti* distribution over its land except for some parts of US, eastern–southern coast of Mexico showed moderately suitable habitat and Central America appeared very high and excellent suitability. South America, Brazil, Uruguay, and Colombia illustrated very high suitability in the resulting models while Chile showed moderately suitable habitat. Finally, middle Australia illustrated moderate suitability, but areas near boundaries in north and south appeared high suitability for the distribution of *Ae. aegypti* (Figure 4).

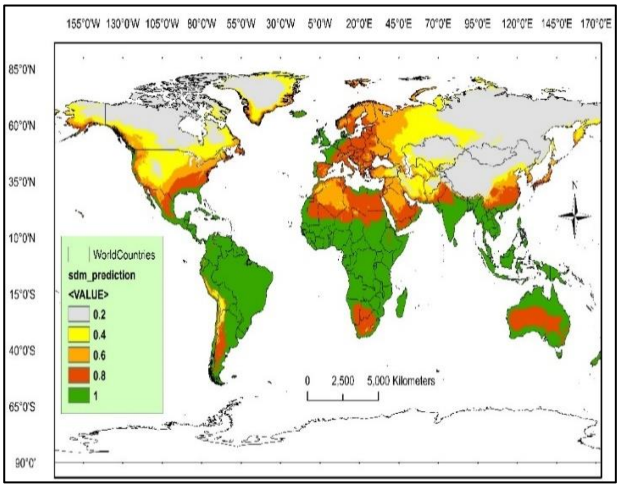

Figure 4: Predicted current distribution range of *Ae. aegypti*.

Predicted future potential distribution areas of Ae. aegypti

The models for the potential distribution of *Ae. aegypti* under future climate change scenarios BCC-CSM2-MR_ssp126 and ssp585 for the years 2030 and 2090 are illustrated in Figure 5.

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 2030 and 2090.

The calibration maps of current and future predictions for two different BCC-CSM2-MR_ssp126 and ssp585 in 2030 and 2090 are used to summarize the level of changes in *Ae. aegypti* distribution owing to global warming (Figure 5).

Under low hypothetical emissions of greenhouse gases (GHG) (BCC-CSM2-MR_ssp126 in 2030 and 2090), changes are simple and usually not notable on all continents. Although the species will lose some of their habitats as in Mauritania, Mali, Niger, Chad, West France, West Germany, central parts of India, the western area of US of America and North Spain. Some regions will gain such as Sudan, South Yemen, East Oman, some parts of Ethiopia, Finland and some parts of Australia (Figure 5 A and B).

Additionally, for the highest hypothetical emissions of GHG (BCCCSM2-MR_ssp585 in 2030 and 2090), the insect will lose and gain almost the same area as in (BCC-CSM2-MR_ssp126 in 2030). The model suggests that under hypothetical emissions the insect invades large areas of India, South China and some parts of Bangladesh and Myanmar (Figure 5 C and D).

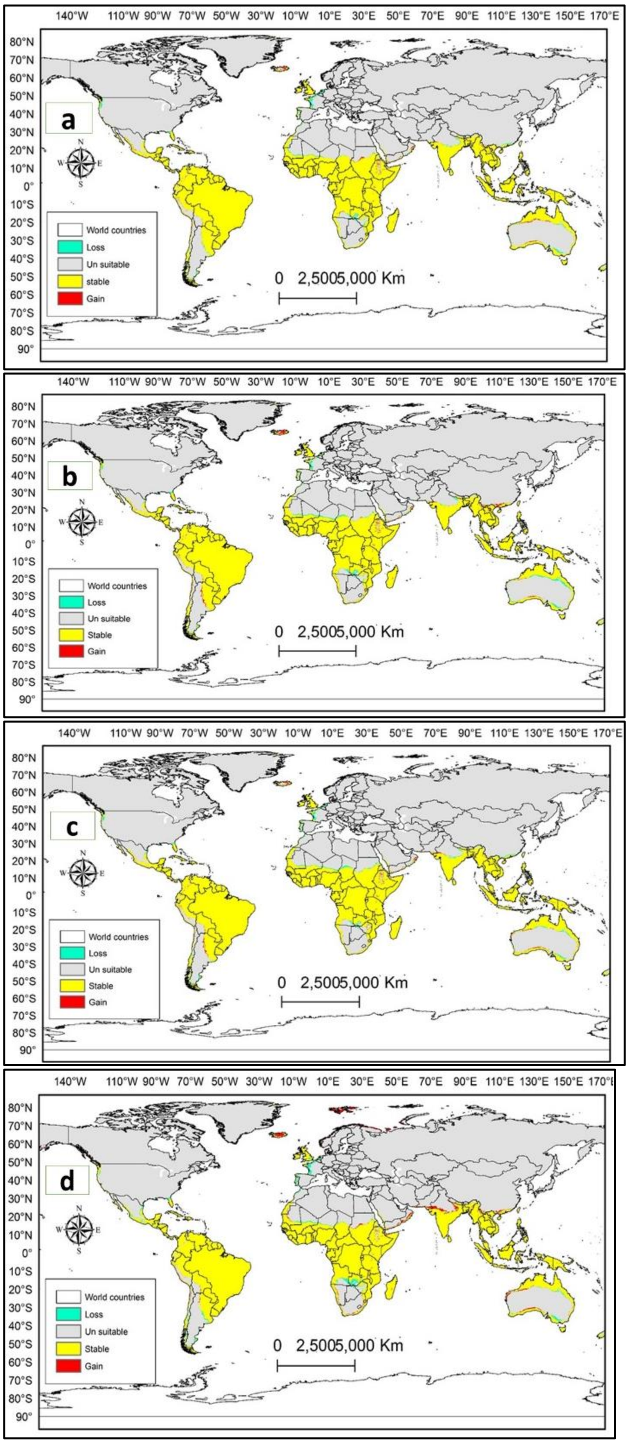

Figure 5 (A-D): Calibration maps showing gain and loss in habitat suitability of *Ae. aegypti* through the four future scenarios against the current status: BCC-CSM2MR_ssp126_2021-2040, BCC-CSM2-MR_ssp126_ 2080-2100, BCC-CSM2MR_ssp585_ 2021-2040 and BCC-CSM2-MR_ssp585_ 2080-2010.

The calibration maps of the two IPSL-CM6A-LR ssp126 and ssp585 forecasts for the years 2030 and 2090 are used to illustrate the level of changes in the distribution of *Ae. aegypti* is caused by global warming (see Figure 6). Although *Ae. Aegypti* will lose some of its habitat such as Mauritania, Mali, Niger, Chad, West France, West Germany, and some parts of Australia, it will gain other areas of the world including North Australia, Oman, and Angola under low hypothetical emissions of greenhouse gases (GHG) (IPSL-CM6A-LR ssp126 in 2030 and 2090). (Figure 6 A and B).

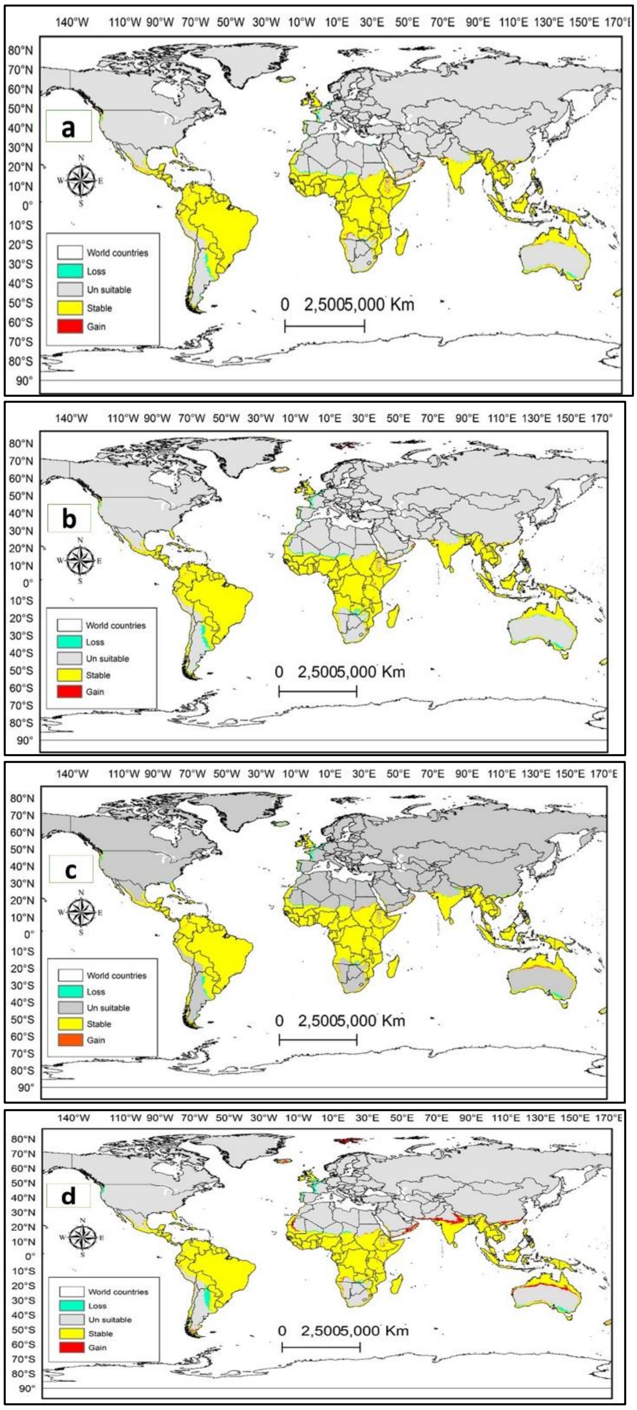

Figure 6 (A-D): Calibration maps showing gain and loss in habitat suitability of *Ae. aegypti* through the four future scenarios against the current status with, IPSL-CM6ALR_ssp126_2021-2040, IPSL-CM6A-LR_ssp126_2080-2100, IPSL-CM6ALR_ssp585_ 2021-2040, and IPSL-CM6A-LR_ssp585_ 2080-2100.

Furthermore, under the highest possible GHG emissions (IPSLCM6A-LR ssp585 between 2030 and 2090), the insect loses significant portion of its range, while other regions develop into suitable habitats. IPSLCM6A-LR_ssp585 (2081-2100) is the worst scenario in which the insect invades a wide range of the world including some parts of northern Australia, India, South China and some parts of Bangladesh, South Pakistan, South Iran and loses host range in some regions including West Germany, West France, North America and South Australia (Figure 6 C and D).

DISCUSSION

The most important bioclimatic variables affecting the presence of *Ae. aegypti* were altitude (Alt), temperature seasonality (bio4), and annual precipitation (mm) (bio12). These results were similar to those of previous research.[15] These variables could play a pivotal role in the distribution of *Ae. aegypti*. The main effects of climate change on endemic mosquitoes are variations in rainfall and temperature. An increase in precipitation generally increases the potential egg-laying and larval habitat for mosquitoes in the environment.

Relationship is frequently non-linear, with above-average rainfall typically increasing mosquito populations by increasing the availability of standing water, while excessive or violent precipitation may have a leaching effect by destroying mosquito eggs and flushing larvae out of particular habitats.[35] Elevated temperature can speed up the development of immature stages rates of mosquito life cycle, increasing reproduction rates and causing exponential population growth.[36] High temperatures help increase mosquito abundance and accelerate mosquito development, but they also help to rapidly amplify viral replication in mosquitoes. This is in agreement with other research that reported environmental temperature is one of the most important abiotic factors influencing physiology, behavior, ecology and by extension, survival of insects.[37,38]

Larval development duration, larval and adult survival, and gonotrophic cycle time of the main dengue vector, *Ae. aegypti*, are directly affected by climactic conditions like rainfall, ambient temperatures, and relative humidity.[39] In addition, the threshold effects of climate on dengue in Taiwan were studied and found that the larval and adult density of *Ae. aegypti* has a positive correlation with rainfall and temperature.[40] Climatic changes affected by temperature change influences insect reproduction, and development behavior.[41,42]

An increase in temperature of climate change scenarios decreased the pathogen development period inside the vector until it is capable of being transmitted and increased the global distribution of *Ae. aegypti* by accelerated adult emergence.[43-45] Based on the GCMs of various climate change scenarios, numerous studies have predicted future *Aedes* mosquito distributions and dengue risks, including regional and global predictions.[46-49]

Analysis of the predictions made by multiple models for the same scenario reveals that the outcomes of the forecasts vary. For instance, in the current scenario, the predicted results of the BCC-CSM1 model indicated that the area of *Ae. aegypti* that is moderately suitable for human habitation will decrease in the future, whereas the predicted results of the future model indicated that it would slightly increase in the future.

With an increase in numbers and populations of endemic species, climate change will likely have an impact on how widely endemic mosquitoes transmit viruses in future.

The possible changes by the results of the climate change modeling give an overview of the potential future distribution of *Ae. aegypti* and dengue transmission. Some areas where mosquito and dengue currently occur may become climatically unsuitable as the climate changes. All the scenarios considered in this study indicate an overall contraction in the climatically suitable areas for *Aedes* in the future. Some of this reduced potential area for *Ae. aegypti* and dengue covers currently important hotspots. These results may be useful in making informed choices about the allocation of resources for mosquito control by highlighting areas where climate suitability is expected to decrease in the future. This study has identified new areas of the world that may be at risk for *Ae. aegypti* and dengue transmission due to changes in climate in the future, which may warrant strategic control measures to prevent its spread. Such places might need a more thorough risk analysis of mosquito transmission. Projections of habitat appropriateness are crucial for the assessment and management of mosquito risk so that danger levels can be determined. Such analyses must include the response of *Ae. aegypti* and dengue transmission to climatic variations. This study specifically identifies locations that are at risk now and will remain at risk from the mosquito in the future. Our results are helpful in making informed decisions in prioritizing areas for eradication, and for determining areas for pest control by health managers.

It is difficult to predict how other MBDs (e.g., Zika, yellow fever and chikungunya) will react to climate change since different MBDs-mosquitoes, reservoirs, and the environment-have different reliance on it. Therefore, even a small degree of climate change may result in significant increases in arbovirus transmission. Each MBD also has its own distinct transmission cycles, reservoirs, and vectors. These might only be found in localized areas worldwide, so changes in the prevalence of MBDs will vary from one region/environment to another.

CONCLUSION

GIS techniques and climatological data can be used when creating models to evaluate the habitat suitability of particular insect pest species. We have successfully modelled the current and future *Ae. aegypti* global distribution in our work. The models identified existing at-risk areas and other regions with adequate habitat that could experience future *Ae. aegypti* incursions with a spatial resolution of 5 km^2 across the globe. Control of *Ae. aegypti* is difficult and costly, and vaccines are unavailable for some viruses it transmits e.g. chikungunya virus, thus practical management solutions are needed. Decision-makers and quarantine authorities may find these model patterns and their changes over time useful when deciding whether to accelerate adaptive management initiatives for pests that seriously affect human health.

It is projected that endemic mosquito populations around the world and consequently MBDs like Zika, dengue fever, yellow fever and chikungunya will be significantly impacted by climate change. The model we have developed also opens the door to more in-depth local research, particularly in regions that are expected to be highly suitable to mosquitoes such as *Ae. aegypti.*

The predictive accuracy of the model's local resolution for these disease transmission vectors can be further improved by incorporating ecological parameters such as altitude and meteorological variables.

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