
The Future of Agriculture

FSA

Article

Habitat Suitability of *Aedes aegypti* Under Current and Future Climate Scenarios in USA

Ahmed H. Abdelwahab

Piercing & Sucking insect Department, Plant Protection Research Institute, Agricultural Research Center, Dokki, Giza, Egypt.

*Corresponding author: ahmed.abdelwahab@arc.sci.eg

Future Science Association

Available online free at
www.futurejournals.org

Print ISSN: 2687-8151

Online ISSN: 2687-8216

DOI:
10.37229/fsa.fja.2024.06.22

Received: 20 April 2024
Accepted: 30 May 2024
Published: 22 June 2024

Abstract: The suitability of the environment for the occurrence of mosquitoes largely depends on ecological factors. Rising temperatures and precipitation patterns may increase transmission in temperate regions and higher elevations. *Aedes aegypti* (Culicidae) is the vector that spreads the arboviral illnesses dengue fever, chikungunya, and zika. Studying probable geographic distribution habitats of *Ae. aegypti* in the USA under both present and future climatic circumstances is the goal of the current research. The Institute Pierre-Simon Laplace scenario, 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 was used. 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* in USA.

Key words: Modelling, climate change, mosquitoes, prediction, R Package.

1. Introduction

The suitability of the environment for the occurrence of mosquitoes largely depends on ecological factors **(Asigau and Parker, 2018)**. However, climate change can lead to changes in the geographic distribution and activity of species, including geographical shifts in the distribution of vectors causing vector borne diseases **(Monath, 1988)**. The combined effects of an extended season and increased transmission potential due to rising temperatures and changing precipitation patterns may increase the transmission potential for these diseases in temperate regions and even allow higher elevations to become suitable for transmission. These factors have contributed to the reemergence of vector borne diseases, such as *Aedes aegypti* that being of particular interest, in the USA. Given that *Aedes aegypti* are vectors for a number of fatal human diseases, they are extremely important medically **(Monath, 1988 and Diamond, 2009)**. The viruses that cause dengue disease **(El-Bahnasawy *et al.*, 2011)**, Zika virus **(Morsy, 2018)**, chikungunya **(Mostafa, 2002)**, and yellow fever **(Carter, 1931)** are mostly transmitted by these insects. According to WHO report in 2003, host range alterations brought on by climate change may have an impact on the epidemiology of infectious and vector-borne diseases.

The majority of climate change scenarios link fluctuations in weather extremes to changes in the frequency of infectious diseases and increases in average temperature to variations in the transmission of communicable diseases **(Canyon *et al*., 2016)**. Since they are poikilothermic, their body temperature fluctuates in response to outside temperatures. The majority of vector-borne diseases (VBDs), which are particularly susceptible to variations in the external climate, are parasitic illnesses transmitted by arthropod vectors like mosquitoes **(Rocklöv, 2020)**. The suitability of the habitat affects the population, dispersion, and quantity of insects. Temperature also affects how quickly pathogens grow and reproduce in mosquitoes, increasing the risk of infection **(Metcalf *et al*., 2017; Caminade and McIntyre, 2019)**.

Precipitation also has a significant effect on the dynamics of the vector-borne disease (VBD) network for diseases carried by vectors with aquatic developmental stages, depending on shifts in mosquito vector ecology **(Paz, 2019)**. The diseases that mosquitoes transmit increase as a result of climate change. Climate change has been primarily blamed for the 10% increase in mosquito-borne disease (MBD) in Canada during the preceding 20 years **(Ludwig *et al*., 2019)**. This is true since mosquito life cycles, reproduction, and feeding are all impacted by temperature, precipitation, and land use **(Wudel and Shadabi, 2016)**. Similarly, the range, seasonality, and habitat of mosquitoes that spread disease are also impacted by climate change. In many worldwide ecosystems, host range changes have an impact on biodiversity and pose a risk to ecological processes, especially for insects.

Studies assessing the effects of climate change have forecast future patterns of mosquito-transmitted diseases such as malaria and dengue. These trends include the intensification of the diseases' transmission and the expansion of their regional dispersion **(Hales *et al*., 2002 and Ogden *et al*., 2008)**. Data are starting to show that the host range ranges of some mosquito species are changing already due to changing climatic circumstances, and it is expected that this pattern would likely persist due to climate change **(Ogden *et al*., 2008)**. At broader geographical scales, abiotic factors like as terrain and climate influence mosquito abundance more than biotic ones such as competition, predation, and vector control methods do at lower regional dimensions **(Brownstein *et al*., 2005)**.

Because of the increased interest in biogeographic research and conservation, species distribution models (SDMs) are currently one of the most popular scientific methods for assessing the effects of climate change on biodiversity **(Beck, 2013)**. These models are effectively and extensively employed to evaluate the ecological and evolutionary processes influencing the suitability of a species' habitat and its global distribution **(Bosso *et al*., 2013 and Zhu *et al*., 2013)**.

2. Materials and Methods

2.1. Global Distribution Data

The Global Biodiversity Information Facility provided the occurrence data for *Ae. Aegypti* (GBIF.org, https://doi.org/10.15468/dl.sgpgg0, accessed on December 2022). Preserved specimens and human observations served as the sources of the 88,888 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 10.3.30 After deleting the corresponding missing values of the resampled environmental parameters of topography and climate, this produced 17,465 distribution points, which were subsequently further reduced into 16,950 records (see Figure 1).

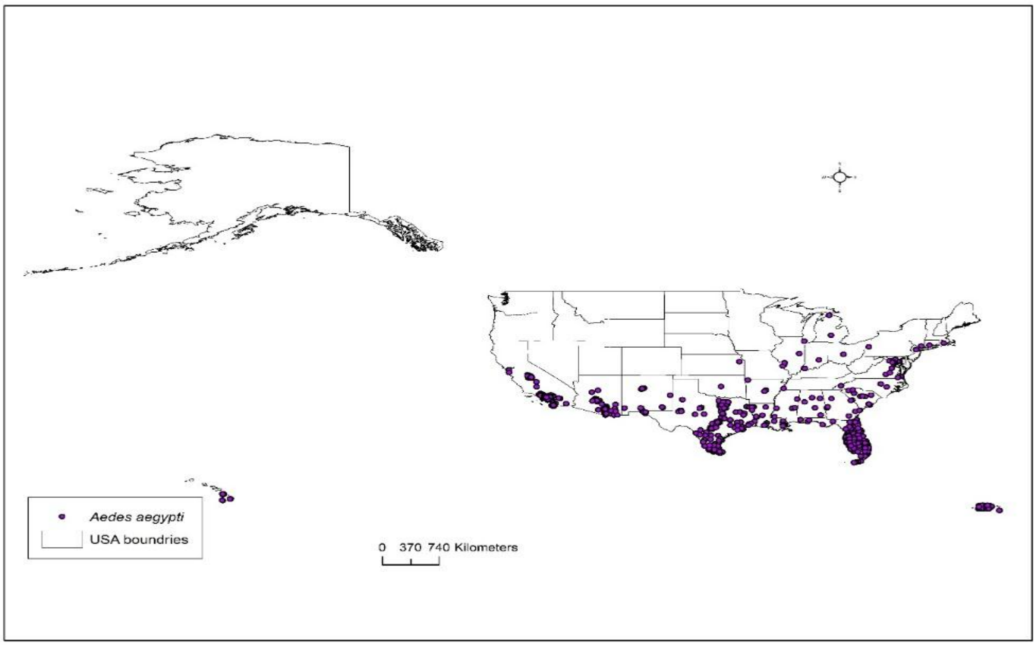

Figure (1). Observed distribution of *Ae. Aegypti* in USA

2.2. Environmental Variables and Multicollinearity

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 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 IPSL-CM6A-LR for both the 2030 (average for 2021–2040) and 2090 (average for 2081–2100) eras.

The global climate model: IPSL-CM6A-LR was made available by the WorldClim database for the 2030 (average for 2021–2040) and 2090 (average for 2081–2100) eras. The GCMs from the CMIP6 of the Intergovernmental Panel on Climate Change's sixth assessment report (AR6) were utilized by us (IPCC). 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.

2.3. Model Performance

An explanation and modeling 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). 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.

To lessen overfitting of SDM models, we eliminated the highly correlated variables based on their variance inflation factor (VIF), which quantifies the extent to which predictor may be explained by the remaining predictors. **(Naimi *et al*., 2016)**.

The variables with VIF values more than five and a correlation criterion of 0.75 were eliminated by applying the vifcor and vifstep functions of the package "usdm" **(Naimi *et al*., 2020)** in R Version 4.1.1, as directed by 28. The function "SDM" package in R Edition 4.1.1 was utilized to determine the relative relevance of predictor variables.

3. Results

3.1. Climatic Variables Importance

Three uncorrelated predictor variables were found to be useful in R models (Table 1). In *Ae. aegypti*, the following parameters showed excellent sensitivity: annual precipitation (Bio 12) (mm), temperature seasonality (BIO4), and altitude (Alt). 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 distribution of *Ae. aegypti* was most significantly influenced by temperature, seasonality (BIO4) (83%) and altitude (6.3%), with the least significant environmental variable being annual precipitation (mm) (bio12) (1.1%). 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	82%
alt	Altitude	m	7.1%
bio_12	Annual Precipitation (mm)	mm	1.3%

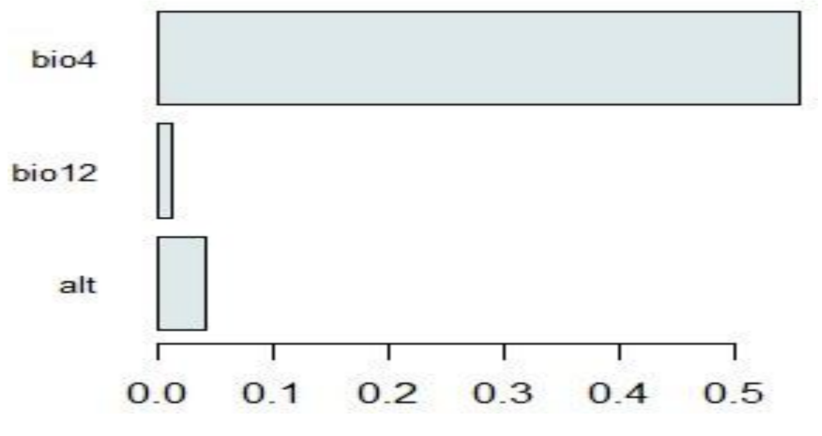

Figure (2). Variable's importance to the prediction distribution model of *Ae. aegypti.*

3.2. 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 prediction results were extremely accurate, the findings of the possible distribution area could also be trusted **(refer to Table 2)**.

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

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).

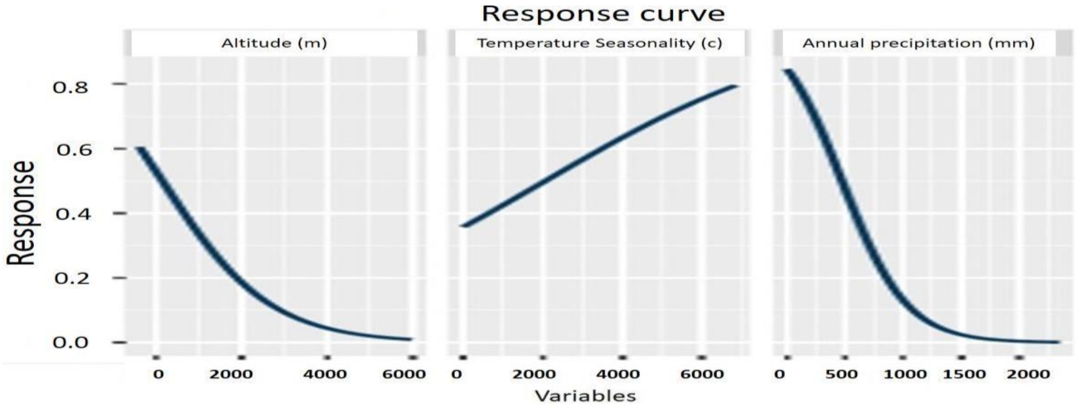

Figure (3). Response curves of the most important predictor variables used in distribution modelling of *Ae. aegypti*.

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

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 USA distribution map of *Ae. aegypti* as it exists today is depicted in Figure 4. The models indicated that *Ae. aegypti* has very high and good habitat appropriateness in the East and South states, which stretch from North Carolina in the east to California in the west. Florida and Texas are somewhat appropriate regions for *Ae. aegypti*. While, Montana, North and South Dakota showed no signs of being suitable for Ae. aegypti's current distribution.

The eastern and southern coasts of Mexico had reasonably appropriate habitat, whereas Central states looked to have extremely high and exceptional suitability. In conclusion the current models in North America suggested low suitability in *Ae. aegypti* distribution over its land, with the exception of certain parts of the United States as we described before. (see Figure 4).

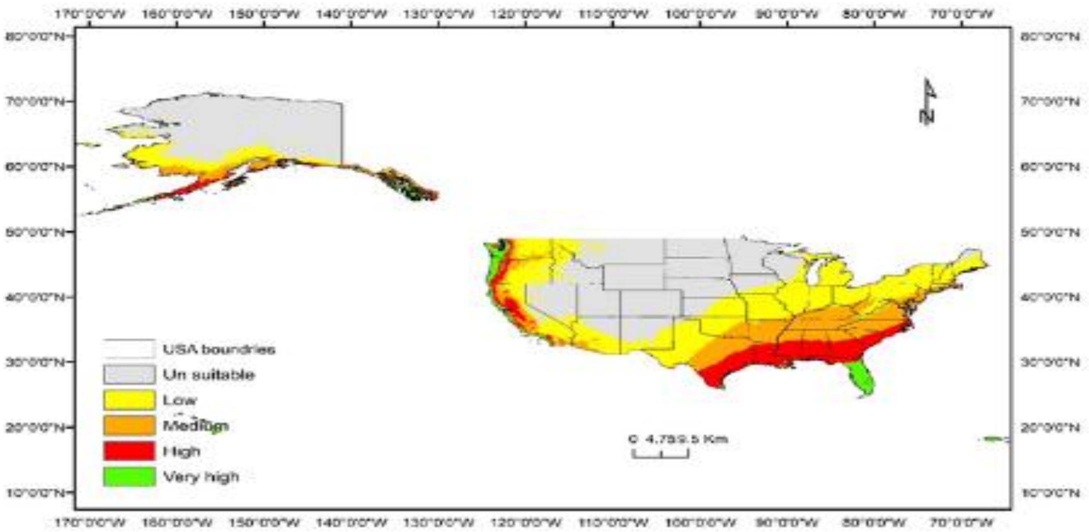

Figure (4). The predicted current distribution range of *Ae. Aegypti* in USA

3.4. The Predicted Future Potential Distribution Areas of *Ae. aegypti* in USA

Figure 5 shows the models for Ae. aegypti's possible distribution under future climate change scenarios IPSL-CM6A-LR _ssp126 and ssp585 for the years 2030 and 2090.

The changes are straightforward and typically not significant across all continents with low hypothetical greenhouse gas (GHG) emissions (BCC-CSM2-MR_ssp126 in 2030 and 2090). Despite this, the species will lose portions of its habitats in the western States, like Idaho, Nevada and Wyoming. Certain locations, including parts Kansas, Missouri, Illinois, Indiana, Ohai, and Kentucky, will benefit (Figure 5a, b).

According to the model, the insect spreads far throughout Louisiana, Mississippi, and Alabama when subjected to fictitious emissions (Figure 5c, d).

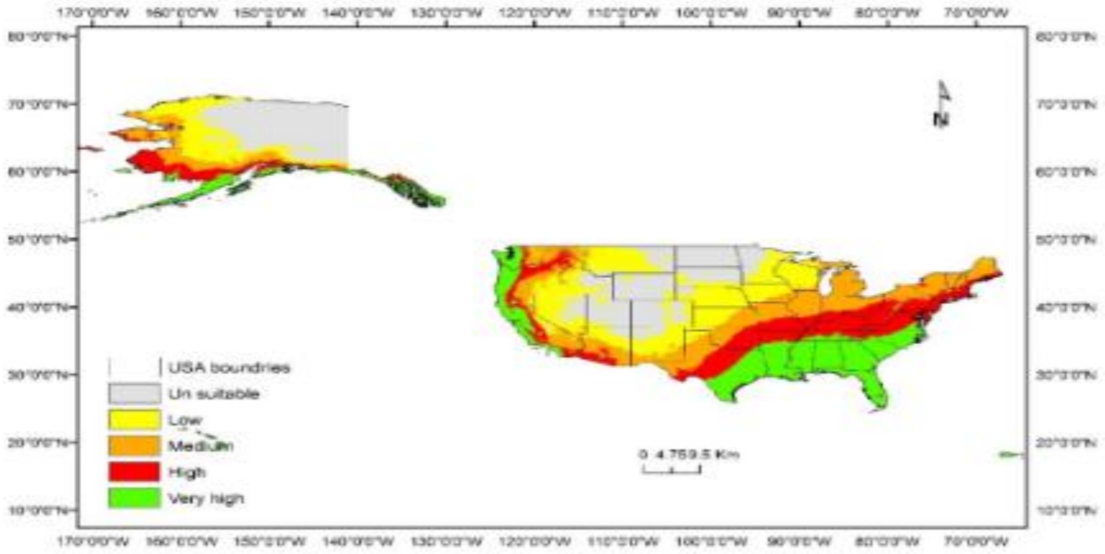

Figure (5a). IPSL-CM6A-LR _ssp126_ 2021-2040

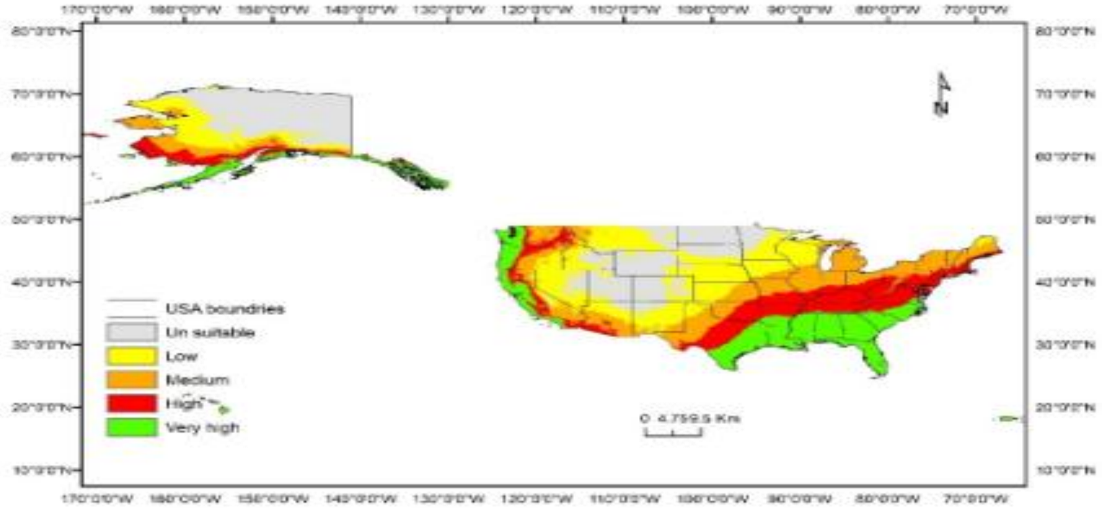

Figure (5b). IPSL-CM6A-LR _ssp585_ 2021-2040

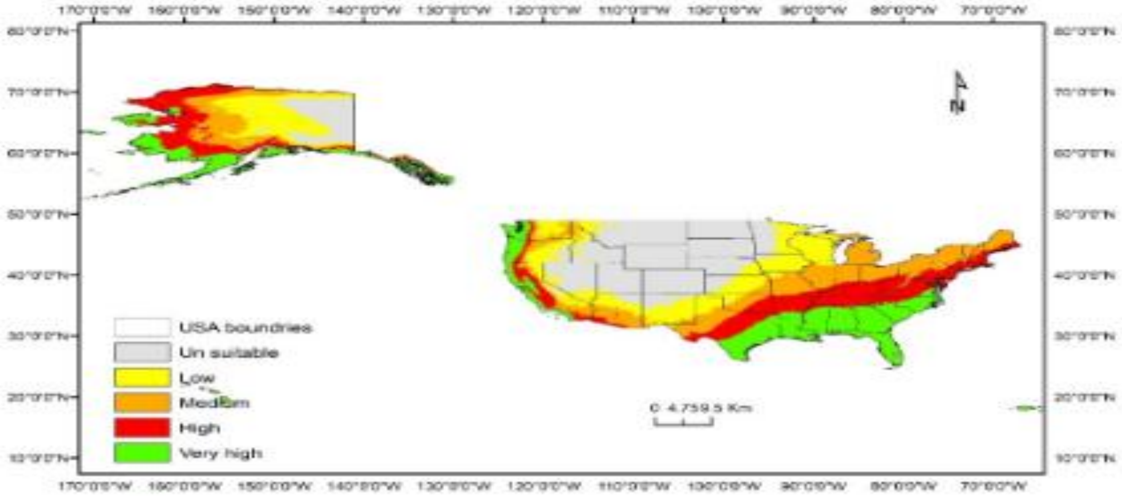

Figure (5c). IPSL-CM6A-LR _ssp585_ 2080-2100

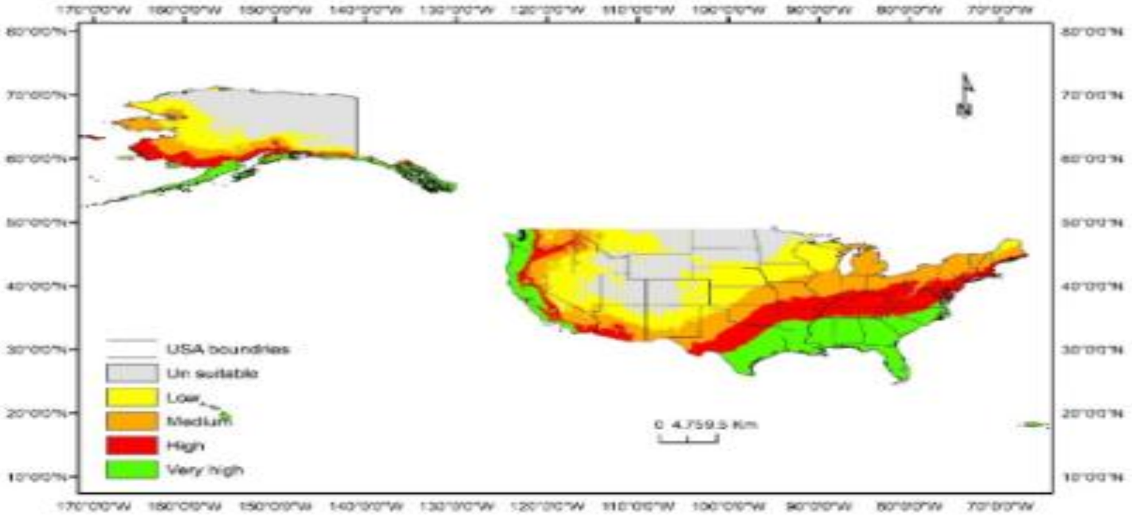

Figure (5d). IPSL-CM6A-LR _ssp585_ 2080-2100

An illustration of the degree to which *Ae. aegypti* distribution varies due to global warming may be found in maps of the two IPSL-CM6A-LR ssp126 and ssp585 projections for the years 2040 and 2080 (refer to Figure 6c,d). Despite this, the species will still exist in some areas, including Georgia North and South Carolina. Very few places in the USA, including Arkansas and Tennessee have seen a rise in *Ae. aegypti* under low-severity hypothetical greenhouse gas (GHG) emissions (IPSL-CM6A-LR ssp126 in 2040 and 2100). (c and d of Figure 5).

Moreover, the insect loses a sizable chunk of its range with the greatest feasible GHG emissions (IPSLCM6A-LR ssp585 between 2040 and 2100), whereas other regions grow into acceptable habitats. The worst case scenario, known as IPSLCM6A-LR_ssp585 (2080–2100), sees the insect spread throughout much of the South East of the USA including Florida Georgia and South Carolina (Figure 5 d).

4. Discussion

Four key bioclimatic factors impacted the abundance of Ae. aegypti: temperature, altitude (Alt), seasonality (BIO4), and yearly precipitation (mm) (bio12). These results were consistent with previous research **(Wudel and Shadabi, 2016)**. These variables may be important in identifying the distribution of *Ae. aegypti*. The main effects of climate change on populations of endemic mosquitoes are variations in temperature and precipitation. More precipitation frequently increases the possible habitat that mosquitoes have for laying eggs and rearing larvae.

The relationship is frequently non-linear: above-average rainfall usually increases mosquito populations by increasing the availability of standing water35, but excessive or violent precipitation may have a negative impact by killing mosquito eggs and washing larvae out of particular areas. An increase in temperature may accelerate the juvenile stages of the mosquito life cycle, increasing rates of reproduction and resulting in exponential population growth36. In addition to increasing mosquito population and growth, warm weather has the uncanny ability to accelerate viral replication in mosquitoes. This is in line with recent study **(Rios, 2009 and Reisen *et al*., 2014)** which discovered that environmental temperature is one of the most important abiotic factors influencing the physiology, behavior, ecology, and, ultimately, the survival of insects. The length of larval growth, larval and adult survival, and gonotrophic cycle time of Ae. aegypti, the major dengue vector, are all directly impacted by climate parameters such as rainfall, ambient temperature, and relative humidity **(Naish *et al*., 2014)**. Additionally, studies conducted in Taiwan on the threshold impacts of climate on dengue found a positive correlation between temperature and rainfall and the densities of *Ae. aegypti* larvae and adults **(Tran *et al*., 2020)**. Variations in temperature have an effect on the growth and reproduction of insects **(Costa *et al*., 2010; Carrington *et al*., 2013)**. The duration of pathogen growth within the vector before it becomes transmissible was shortened in climate change scenarios by increasing temperature, which also led to an increase in Ae. aegypti's distribution and rapid adult emergence **(Kamal *et al*, 2014; Iwamura *et al*, 2020)**. Future Aedes mosquito distributions and dengue dangers have been anticipated by numerous studies, including regional and global predictions **(Ryan *et al*., 2019; Pörtner *et al*., 2022).** These estimates are based on the GCMs of various climate change scenarios. 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. Due to climate change, some areas that are currently home to dengue disease and mosquitoes may no longer be suitable. All of the scenarios considered in this analysis indicate that the number of futures climatically appropriate places for Aedes will generally decrease. This reduced potential zone covers some of the already prominent hotspots for Ae. aegypti and dengue.

These results pinpoint areas where future climate appropriateness is expected to deteriorate, thereby assisting policymakers in their resource allocation for mosquito control. This study has discovered more places of the world that may be susceptible to Ae. aegypti and dengue transmission due to future climatic changes. To stop the disease's spread, these locations might need to put strategic control measures in place. Such areas might need a more thorough risk analysis for mosquito transmission. Projections of habitat appropriateness are necessary to determine danger levels, control mosquito risk, and evaluate the suitability of the habitat. Such assessments must take into account the response of *Ae. aegypti* and dengue transmission to climate fluctuations. The model we have developed also enables more comprehensive local research, particularly in areas where *Ae. aegypti* mosquitoes are expected to thrive; the model's local resolution for these disease transmission vectors can be made more predictively accurate by incorporating ecological elements such as altitude and meteorological variables.

References

Alto, B. W. and Juliano, S. A. (2001). Precipitation and temperature effects on populations of Aedes albopictus (Diptera: Culicidae): Implications for range expansion. J. Med. Entomol., 38: 646–656.

Araújo, M. B.; Pearson, R. G.; Thuiller, W. and Erhard, M. (2005). Validation of species–climate impact models under climate change. Glob. Change Biol., 11:1504 – 1513.

Asigau, S., and Parker, P. G. (2018). The influence of ecological factors on mosquito abundance and occurrence in Galápagos. Journal of Vector Ecology, 43(1), 125-137.

Beck, J. (2013). Predicting climate change effects on agriculture from ecological niche modeling: who profits, who loses? Climate Change, 116:177-189.

Bosso, L.; Rebelo, H.; Garonna, A. P. and Russo, D. (2013). Modelling geographic distribution and detecting conservation gaps in Italy for the threatened beetle Rosalia alpina. J. Nat. Conserv., 21:72-80.

Brownstein, J. S.; Holford, T. R. and Fish, D. (2005). Effect of climate change on Lyme disease risk in North America. EcoHealth, 2(1):38e46.

Caminade, C.; McIntyre, K. M. and Jones, A. E. (2019). Impact of recent and future climate change on vector-borne diseases. Ann. N Y Acad. Sci.,1436(1):157–73.

Canyon, D. V.; Speare, R. and Burkle, F. M. (2050). Forecasted impact of climate change on infectious disease and health security in Hawaii by. Disaster Med. Public Health Prep., 10(6):797- 804 (2016).

Carrington, L. B.; Armijos, M. V.; Lambrechts, L.; Barker, C. M. and Scott T. W. (2013). Effects of fluctuating daily temperatures at critical thermal extremes on Aedes aegypti life-history traits. PLoS One, 8:e58824.

Carter, H. R. (1931). Yellow Fever An Epidemiologica and Historical Study of its Place of Origin.: xii+-308.

Clements, A. N. (1992). The Biology of Mosquitoes, Vol. 1, Development, Nutrition and Reproduction. CABI Publishing. 532 p. www.cabi.org/bookshop/book/9780851993744.

Costa, E.; Santos, E.; Correia, J. and Albuquerque, C. (2010). Impact of small variations in temperature and humidity on the reproductive activity and survival of *Aedes aegypti* (Diptera, Culicidae). R.B.E., 54:488–93.

Debat, V.; Begin, M.; Legout, H. and David, J. R. (2003). Allometric and nonallometric components of Drosophila wing shape respond differently to developmental temperature. Evolution, 57(12):2773-84.

Diamond, M. S. (2009). West Nile Encephalitis Virus Infection Viral Pathogenesis and the Host Immune Response. New York: Springer. doi: 10.1007/978-0-387-79840-0.

El-Bahnasawy, M. M.; Khalil, H. H.; Morsy, A. T. and Morsy T. A. (2011). Threat of dengue fever and dengue hemorrhagic fever to Egypt from travelers. J. Egypt Soc. Parasitol., 41(2): 289-306

ESRI (Environmental Systems Research Institute) (2014). ArcGIS®Desktop Help 10.3 Geostatistical Analyst. https://desktop.arcgis.com/en/arcmap/10.3

Facchinelli, L; Badolo, A. and McCall, P. J. (2023). Biology and Behaviour of *Aedes aegypti* in the Human Environment: Opportunities for Vector Control of Arbovirus Transmission. Viruses, 15(3):636.

Gonzalez, C.; Wang, O.; Strutz, S. E.; Gonzalez-Salazar, C.; Sanchez-Cordero, V. and Sarkar, S. (2010). Climate change and risk of Leishmaniasis in North America: predictions from ecological niche models of vector and reservoir species. PLoS Negl. Trop. Dis., 4(1): e585

Guisan, A.; Thuiller, W. and Zimmermann, N.E. (2017). Habitat Suitability and Distribution Models*:* With Applications in R, Cambridge University Press: Cambridge, UK, ISBN 0521765137.

Gunay, F.; Alten, B. and Ozsoy E. D. (2011). Narrow sense heritability of body size and its response to different developmental temperatures in *Culex quinquefasciatus*(Say 1923). J. Vector Ecol., 36(2):348-54.

Hales, S.; de Wet, N.; Maindonald, J. and Woodward, A. (2002). Potential effect of population and climate changes on global distribution of dengue fever: An empirical model. Lancet, 360(9336):830–834.

Hijmans, R. J.; Cameron, S. E.; Parra, J. L.; Jones, P. G. and Jarvis, A. J. (2005). Very high-resolution interpolated climate surfaces for global land areas. Int. J. Climatol., 25:1965-1978.

Iwamura, T.; Guzman-holst, A. and Murray, K. A. (2020). Accelerating invasion potential of disease vector *Aedes aegypti* under climate change. Nat. Commun., 11:1–10.

Kamal, M.; Kenawy, M. A.; Rady, M. H.; Khaled, S. and Samy, A. M. (2018). Mapping the global potential distributions of two arboviral vectors *Aedes aegypti* and *Ae. albopictus* under changing climate. PLoS One., 13: e0210122.

Loetti, V.; Schweigmann, N. J. and Burroni, N. E. (2011). Temperature effects on the immature development time of Culex eduardoi Casal & Garcia (Diptera: Culicidae). Neotrop. Entomol., 40(1):138-42.

Ludwig, A.; Zheng, H.; Vrbova, L.; Drebot, M.A.; Iranpour, M and Lindsay, L.R. (2019). Increased Risk of Endemic Mosquito-Borne Diseases in Canada Due to Climate Change. Canada Communicable Disease Report, 45:91–97. https://doi.org/10.14745/ccdr.v45i04a03.

Metcalf, C. J. E.; Walter, K. S.; Wesolowski, A.; Buckee, C. O.; Shevliakova, E.; Tatem, A. J., Boos, W. R.; Weinberger, D. M. and Pitzer, V. E. **(2017).** Identifying climate drivers of infectious disease dynamics: recent advances and challenges ahead. Proc Biol Sci., 284(1860):20170901

Monath, T. P. (1988). The Arboviruses: Epidemiology and Ecology. Boca Raton: CRC Press.

Morsy, T. A. (2018). *Aedes aegypti* and dengue virus infections. J. Egypt Soc. Parasitol., 48(1): 183-96

Mostafa, A. A.; Allam, K. and Osman, M. (2002). Mosquito species and their densities in some Egyptian Governorates. J. Egypt Soc. Parasitol., 32(1): 9-20.

Naimi, B. and Araújo, M. B. (2016). A reproducible and extensible R platform for species distribution modelling. Ecography, 39: 368-375

Naimi, B. usdm (2020). Uncertainty Analysis for Species Distribution Models. R Package Version 1.1–15. R Doc. accessed on 12 December http//www.rdocumentation.org/packages/usdm.

Naish, S.; Dale, P.; Mackenzie, J. S.; McBride, J.; Mengersen, K. and Tong, S. (2014). Climate change and dengue: A critical and systematic review of quantitative modelling approaches. BMC Infect. Dis., 14:167.

Nooten, S. S.; Andrew, N. R. and Hughes, L. (2014). Potential impacts of climate change on insect communities: a transplant experiment. PloS One., 9, e85987.

Ogden, N. H.; St-Onge, L.; Barker, I. K.; Brazeau, S.; Bigras-Poulin, M.; Charron, D. F.; Francis, C. M.; Heagy, A.; Lindsay, L. R.; Maarouf, A.; Michel, P.; Milord, F.; O'Callaghan, C. J.; Trudel, L. and Thompson R.A. (2008). Risk maps for range expansion of the Lyme disease vector, Ixodesscapularis, in Canada now and with climate change. Int. J. Health Geogr., 22;7:24.

Paz, S. (2019). Effects of climate change on vector-borne diseases: An updated focus on West Nile virus in humans. Emerg. Top. Life Sci., 3(2):143–52.

Pörtner, H. O.; Roberts, D. C.; Adams, H.; Adler, C.; Aldunce, P.; Ali, E. and Begum, R. A. (2022). Climate change 2022: impacts, adaptation, and vulnerability. Contribution of working group ii to the sixth assessment report of the intergovernmental panel on climate change. https://report.ipcc.ch/ar6/wg2/IPCC_AR6_WGII_FullReport.pdf.

Reisen, W. K.; Fang, Y. and Martinez, V.M. (2014). Effects of temperature on the transmission of West Nile virus by *Culex tarsalis* (Diptera: Culicidae*)*. J Med Entomol., 43(2):309-17. https://doi.org/10.1093/jmedent/43.2.309.

Reiter, P. (2001). Climate change and mosquito-borne disease. Environ. Health Perspect.,109:141–161.

Rios, M. (2009). Climate change and vector-borne viral diseases potentially transmitted by transfusion. ISBT Sci Ser., 4 (1):87-94. https://doi.org/10.1098%2Frstb.2013.0552.

Rocklöv, J. and Dubrow R. (2020). Climate change: an enduring challenge for vector-borne disease prevention and control. Nat. Immunol., 21(5):479–83.

Ryan, S.J.; Carlson, C.J.; Mordecai, E.A. and Johnson, L.R. (2019). Global expansion and redistribution of Aedes-borne virus transmission risk with climate change. PLoS Negl Trop Dis., 13(3): e0007213.

Tran, B. L.; Tseng, W. C.; Chen, C. C. and Liao, S. Y. (2020). Estimating the threshold effects of climate on dengue: a case study of Taiwan. Int. J. Environ. Res. Public Health., 17(4):1392.

WHO (2003). Guidelines for Dengue Surveillance and Control. 2nd Edition, WHO Library Cataloguing in Publication Data, Geneva, Switzerland. https://cdn.centreinfection.ca/wp/sites/2/20170307163055/RapidReviewClimateMosquito-EN.pdf.

Winokur, O. C.; Main, B. J; Nicholson, J. and Barker, C. M. (2020). Impact of temperature on the extrinsic incubation period of Zika virus in *Aedes aegypti*. PLoS Negl Trop Dis., 14:1–15.

Wudel, B. and Shadabi, E. (2016). Mosquito-Borne Disease in the Americas. Rapid Review NCCID. https://nccid.ca/wp-content/uploads/sites/2/2016/07/RapidReviewClimateMosquito-EN.pdf

Yi, Y. J.; Zhou, Y.; Cai, Y. P.; Yang, W.; Li, Z. W. and Zhao, X. (2018). The influence of climate change on an endangered riparian plant species: The root of riparian Homonoia. Ecol. Ind., 92:40–50.

Zhu, G.; Liu, G.; Bu, W. and Lis, J. A. (2013). Geographic distribution and niche divergence of two stinkbugs, *Parastrachia japonensis* and *Parastrachia nagaensis*. J. Insect Sci., 13(1):102.

Availability of data and materials

The Global Biodiversity Information Facility (GBIF.org, https://doi.org/10.15468/dl.sgpgg0; accessed on December 2022)) provided the Ae. aegypti occurrence data. The WorldClim database (http://www.worldclim.org) provided 19 bioclimatic layers (bio01–bio19) and one topography variable (elevation) with a spatial resolution of 2.5 arcminutes (5 km at the equator)