

Climate-Driven Habitat Suitability of *Aedes Aegypti* Mosquitoes Using GBIF and Worldclim Datasets

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ABSTRACT

Climate change is altering the environmental conditions that regulate the survival, establishment, and geographical distribution of *Aedes aegypti*, the principal vector of dengue, chikungunya, Zika, and yellow fever. This study assessed the current and future global climatic suitability of *A. aegypti* by integrating 7,519 occurrence records obtained from the Global Biodiversity Information Facility with historical and projected bioclimatic variables from WorldClim. Following coordinate validation, duplicate removal, geographical screening, and spatial filtering, 3,792 unique occurrence locations were retained before final thinning. Nineteen bioclimatic variables were initially evaluated, after which nine predictors were retained based on correlation analysis, variance inflation factors, ecological relevance, and future transferability. Maximum Entropy, Generalised Linear Models, Generalised Additive Models, Random Forest, Boosted Regression Trees, Multivariate Adaptive Regression Splines, and Support Vector Machines were calibrated using five-fold spatial block cross-validation and combined in a performance-weighted ensemble. Future suitability was projected for the 2050s and 2070s under SSP2-4.5 and SSP5-8.5 using five CMIP6 global climate models. The ensemble outperformed the individual models, with a mean testing AUC of 0.96, TSS of 0.87, continuous Boyce Index of 0.91, sensitivity of 0.90, specificity of 0.92, and Brier score of 0.07. Minimum temperature of the coldest month, temperature seasonality, annual precipitation, precipitation of the warmest quarter, and maximum temperature of the warmest month jointly accounted for 79.8% of model importance. Current suitable habitat covered approximately 19.94 million km², representing 14.8% of the analysed global terrestrial area, with major concentrations in South and Southeast Asia, Central America, the Caribbean, northern and central South America, equatorial sub-Saharan Africa, and northern Australia. By the 2070s, suitable habitat was projected to increase by 12.6% under SSP2-4.5 and 23.7% under SSP5-8.5. Expansion was strongest in southern and central Europe, East Asia, North America, southern South America, southern Africa, and tropical highlands, while contraction occurred in parts of the Amazon Basin, the Sahel, the Horn of Africa, the Arabian Peninsula, northern Australia, and other increasingly hot and arid tropical regions. Projection uncertainty was greatest near range margins and in regions where climate models disagreed on future precipitation. The findings provide a reproducible basis for identifying present and emerging surveillance priorities and for strengthening climate-sensitive vector monitoring, early-warning systems, and public health adaptation.

Keywords: *Aedes aegypti*; climate change; GBIF; WorldClim; habitat suitability; ensemble modelling; CMIP6; vector surveillance

INTRODUCTION

Climate change is altering the environmental conditions that regulate the distribution, abundance, seasonal activity, and ecological interactions of disease vectors. Rising mean temperatures, more frequent heat extremes, irregular rainfall, prolonged drought, and intense precipitation can modify the geographical limits of mosquito populations and the length of time during which they remain active (IPCC, 2023; Ryan et al., 2019). These effects vary across regions because temperature, rainfall, humidity, elevation, land use, and human behaviour interact differently across environmental settings. *Aedes aegypti* is particularly sensitive to these interactions

because its survival and population dynamics depend on temperature, atmospheric moisture, and the availability of aquatic breeding habitats. Temperature influences egg hatching, larval development, pupation, adult emergence, fecundity, longevity, biting activity, and the rate of viral development within the mosquito. Moderate warming may accelerate immature development and increase feeding frequency, while temperatures outside the species' physiological range reduce survival and reproductive performance. Experimental evidence indicates that egg hatching and adult emergence decline markedly around 10 °C and 35 °C, whereas temperatures between 20 °C and 30 °C support higher survival, especially when relative humidity exceeds 60% (Majeed et al., 2025). Dengue transmission also follows a nonlinear thermal response, with recent evidence placing the approximate optimum near 29 °C and the broader thermal limits between 17.8 °C and 34.5 °C (Finch et al., 2025). Rainfall can fill natural and artificial containers and create larval habitats, but intense precipitation may flush eggs, larvae, and pupae from breeding sites. Drought can reduce natural water availability while increasing household water storage, thereby creating stable domestic habitats. Climatic suitability therefore depends on the combined effects of average conditions, seasonal variation, climatic extremes, and human adaptation to water scarcity (Iwamura et al., 2020; Majeed et al., 2025; Sintayehu et al., 2020).

Aedes aegypti occurs mainly in tropical and subtropical regions, but its close association with humans allows it to establish in urban and peri-urban environments beyond its historical range. The species feeds predominantly on humans and breeds in domestic containers, discarded tyres, drains, water-storage vessels, and other artificial habitats. It transmits dengue, chikungunya, Zika, and yellow fever viruses, making its geographical expansion a major global health concern. Dengue alone has been estimated to cause about 390 million infections annually, including approximately 96 million clinically apparent cases, while nearly half of the world's population lives in areas exposed to dengue risk (Bhatt et al., 2013). The recent burden has increased further. By 30 April 2024, more than 7.6 million dengue cases, over 16,000 severe cases, and more than 3,000 deaths had been reported to the World Health Organization, demonstrating the continuing expansion of transmission into new geographical and climatic settings (WHO, 2024). Human mobility, international trade, urbanisation, poor drainage, unreliable water supply, household water storage, and inadequate waste management support the transport and establishment of mosquito populations. These factors interact with climate to determine whether introduced eggs, larvae, or adults survive after arrival (Kraemer et al., 2015; Lim et al., 2025). Climate-driven range shifts may therefore increase public health pressure in regions with limited entomological surveillance, weak sanitation services, or little previous experience with *A. aegypti*. Recent global analyses show that the population living in highly suitable dengue-transmission environments has increased through the combined effects of climatic change, urbanisation, and population growth (Nakase et al., 2024). Nevertheless, climatic suitability does not confirm mosquito presence, population abundance, virus circulation, or human disease transmission. It identifies environments that may support establishment and therefore provides a basis for trap placement, targeted larval control, early-warning systems, and efficient allocation of surveillance resources (Nakase et al., 2023; Ryan et al., 2019).

Species distribution models provide a practical framework for estimating where environmental conditions may support *A. aegypti*. These models relate known occurrence records to climatic and environmental predictors and transfer the resulting relationships to unsampled areas or future climate conditions. Researchers have applied Maximum Entropy, generalised linear models, generalised additive models, random forests, boosted regression trees, multivariate adaptive regression splines, support vector machines, and ensemble approaches to characterise ecological niches, identify invasion zones, estimate range shifts, and support public health planning (Elith & Leathwick, 2009; Sintayehu et al., 2020). Previous applications demonstrate the potential of these methods. An African ensemble model achieved a mean area under the curve of 0.96 and a mean true skill statistic of 0.83, while a global ecological-niche assessment anticipated 98% of 2,048 independent occurrence records (Kamal et al., 2018; Sintayehu et al., 2020). Global projections have estimated that the suitable range of *A. aegypti* may expand by approximately 1.89–3.02% by 2050 and 2.25–4.47% by 2070 under different climate scenarios (Kamal et al., 2018). More recent modelling also indicates increasing suitability overlap across more than 70% of the global terrestrial area, with notable changes in Europe, North America, and Africa (Zhang et al., 2025). However, many existing studies rely on one algorithm, random data partitioning, limited occurrence records, or a single climate model. They may also inadequately address spatial sampling bias, multicollinearity, background selection, model transferability, and uncertainty. A Colombian study, for example, retained 54 spatially independent records from 128 initial GBIF observations and achieved an average training AUC of

approximately 0.812 using one MaxEnt model and one climate model (Portilla Cabrera & Selvaraj, 2020). To address these limitations, the present study assesses current and future global habitat suitability for *A. aegypti* using reproducibly downloaded GBIF records, WorldClim bioclimatic variables, rigorous record cleaning, spatial thinning, bias correction, biologically informed predictor selection, multiple statistical and machine-learning algorithms, and spatially independent validation. It further projects suitability under SSP2-4.5 and SSP5-8.5 using several CMIP6 global climate models, quantifies habitat expansion, contraction, persistence, and net geographical change, and identifies areas of projection agreement, uncertainty, and emerging surveillance priority (Iwamura et al., 2020; Nakase et al., 2023; Ryan et al., 2019).

METHODOLOGY

Study Design and Geographical Scope

This study employed a global ecological niche modelling framework as shown in figure 1 to assess the current and future climatic suitability of *Aedes aegypti*. The analysis integrated GBIF occurrence records with WorldClim bioclimatic and CMIP6 climate projection datasets. The workflow included occurrence processing, environmental data preparation, predictor selection, spatially independent model calibration, ensemble modelling, suitability mapping, habitat change analysis, range shift estimation, and uncertainty quantification. The study covered all terrestrial regions except Antarctica. Spatial layers were harmonised to WGS84 projection at a 2.5 arc-minute resolution (~4–5 km), ensuring global consistency between occurrence and environmental datasets. Oceans, permanent ice, and non-terrestrial cells were excluded.

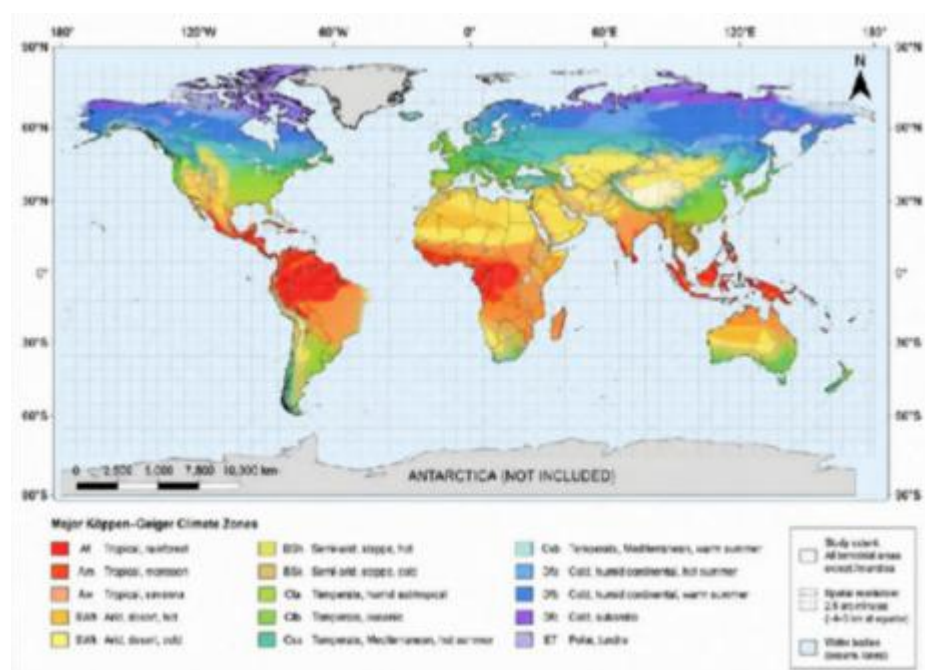


Figure 1: Study Area and Global Framework

Occurrence Data Acquisition and Processing

Global occurrence records of *Aedes aegypti* were obtained from GBIF (species key: 1651891) via a formal download (DOI: 10.15468/dl.z7n5xr; 19 January 2026). The dataset contained 7,519 records collected between 2020 and 2024 across 84 countries or territories as represented in figure 2. Data cleaning was conducted in R using `rgbif`, `CoordinateCleaner`, `sf`, `terra`, and `dplyr`. Records were filtered to remove duplicates, zero coordinates, invalid or oceanic locations, institutional centroids, and spatial outliers. Temporal filtering confirmed all records fell within the study period. Spatial thinning at 5 km reduced sampling bias and spatial autocorrelation, with sensitivity tested at 10 km. A kernel density bias surface and target-group background further corrected sampling bias. The final dataset retained 1,285 spatially independent occurrences.

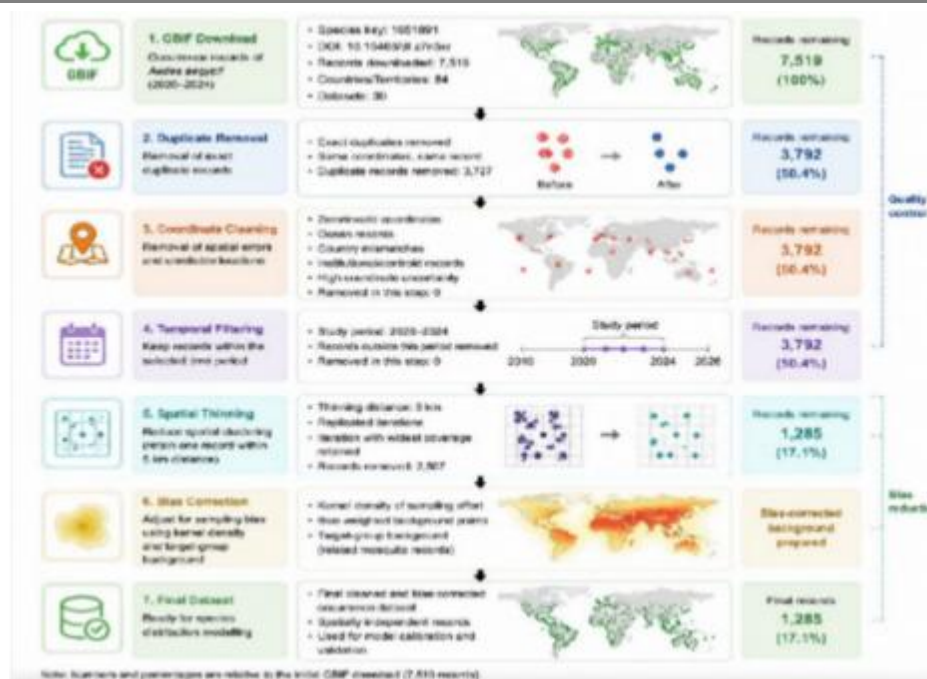


Figure 2: Occurrence Data Processing Workflow

Environmental Variables and Predictor Selection

Nineteen bioclimatic variables (WorldClim v2.1) were initially considered. Future climate projections (2050s and 2070s) were obtained from five CMIP6 models under SSP2-4.5 and SSP5-8.5. A supplementary anthropogenic dataset included elevation, population density, land cover, distance to settlements, vegetation condition, and surface water occurrence. Predictor selection was based on correlation analysis ($|r| \geq 0.70$) and variance inflation factor ($VIF > 5$). Final predictors were retained based on ecological relevance and transferability. The final climatic predictors included BIO1, BIO2, BIO4, BIO5, BIO6, BIO12, BIO15, BIO17, and BIO18.



Figure 3: Environmental Variable Selection Workflow

Accessible Area and Background Definition

The accessible calibration area (M) was defined using a 500 km buffer around occurrence records, intersected with continental boundaries and ecoregions. Sensitivity analyses tested 250, 750, and 1,000 km buffers. Background points ($n = 10,000$) were sampled using bias-weighted surfaces. Pseudo-absence points were

generated at a minimum distance of 10 km from occurrences, with a 1:1 ratio across 10 replicates. Alternative random and environmentally stratified strategies were also evaluated.

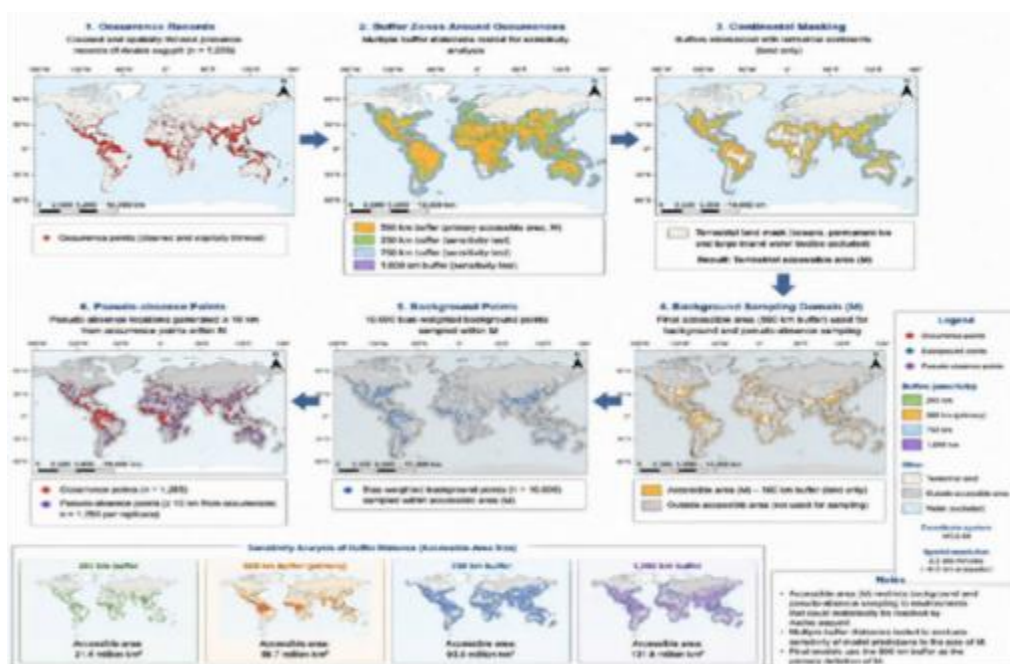


Figure 4: Accessible Area (m) Definition Diagram

Species Distribution Modelling and Calibration

Habitat suitability was modelled using MaxEnt, GLM, GAM, Random Forest, Boosted Regression Trees, MARS, and SVM. Models were tuned using algorithm-specific hyperparameter optimisation. Spatial block cross-validation (five folds) ensured independence between training and testing data. Each model used 80% training and 20% testing data per fold. Environmental block validation assessed transferability across climatic gradients. Nested tuning and grid search were used to prevent overfitting.

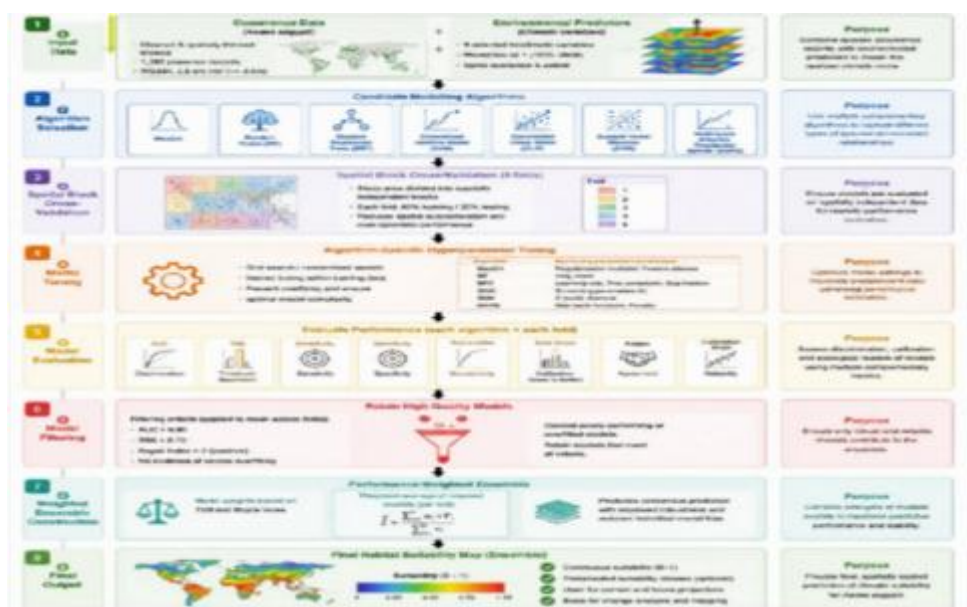


Figure 5: Species Distribution Modelling Workflow

Model Evaluation and Ensemble Construction

Model performance was evaluated using AUC, TSS, sensitivity, specificity, Cohen's kappa, Boyce Index, and Brier score. Calibration was assessed using slope and reliability plots. Spatial residuals and training-testing

differences were used to detect overfitting. Only models with AUC > 0.80, TSS > 0.70, and positive Boyce Index were retained. A performance-weighted ensemble was constructed using TSS and Boyce Index weights. This ensemble outperformed individual models and was used for all projections.

Habitat Suitability Mapping and Change Analysis

Continuous suitability outputs (0–1) were classified into suitability classes using TSS-maximising thresholds. Habitat change was computed as gain, loss, persistence, and stability between current and future projections.

Percentage change was computed as:

$$\text{Percentage change} = \frac{A_f - A_c}{A_c} \times 100$$

A_c

Centroid movement was computed as:

$$D = d(C_c, C_f)$$

where D is centroid displacement between current and future suitability centres.

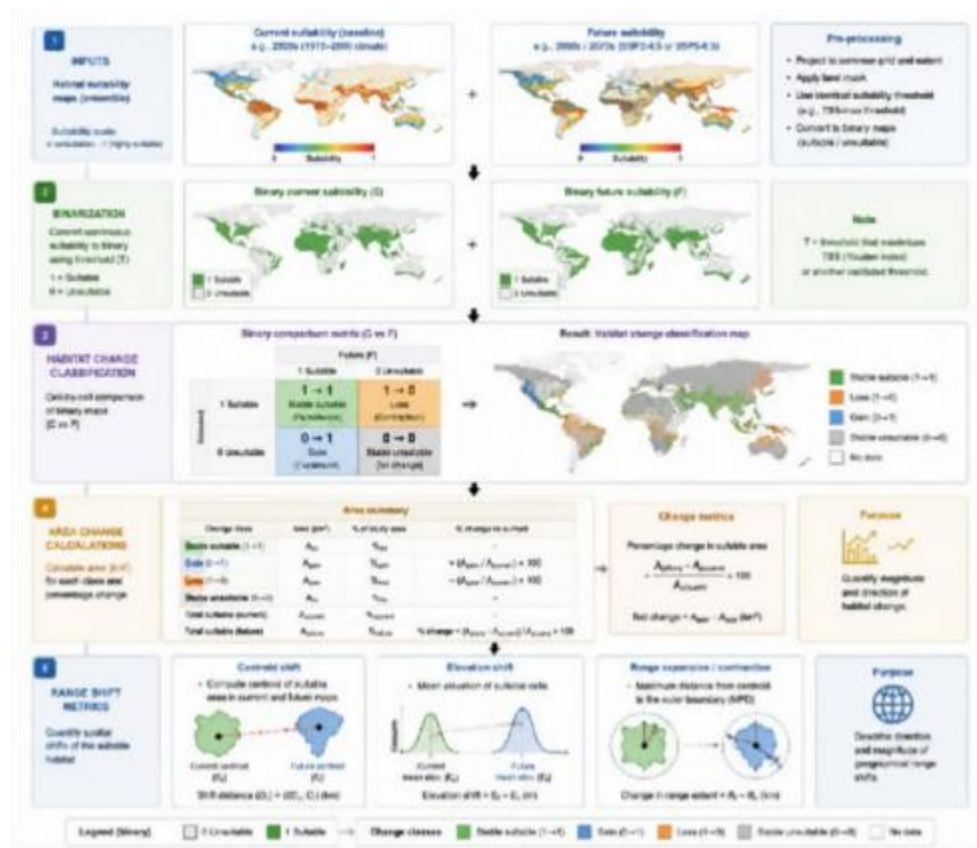


Figure 6: Habitat Change Classification Workflow

Future Projections and Climate Scenarios

Suitability was projected for 2050s and 2070s using five CMIP6 models under SSP2-4.5 and SSP5-8.5. Mean ensemble outputs were used to reduce model-specific bias. Multivariate environmental similarity surfaces identified extrapolation and novel climates, classified into interpolation, univariate novelty, combinational novelty, and strong extrapolation.



Uncertainty was quantified using standard deviation, coefficient of variation, and inter-model agreement. Agreement was calculated as the proportion of model–GCM combinations predicting consistent suitability change.



- Thinning distance (5 vs 10 km)
- Calibration buffers (250–1000 km)
- Pseudo-absence strategies

- Threshold selection
- Ensemble weighting schemes
- Climate-only vs anthropogenic models

Results were considered robust when predictor rankings, spatial patterns, and direction of change remained stable.

Software and Reproducibility

All analyses were conducted in R (v4.6.0) and QGIS (v3.44.11 LTR). Key packages included rgbif, CoordinateCleaner, terra, sf, spThin, blockCV, biomod2, maxnet, ENMeval, randomForest, gbm, mgcv, pROC, ecospat, and usdm. A fixed random seed (2026) ensured reproducibility. All datasets, scripts, and outputs will be archived in Zenodo. The study used only publicly available data and required no ethical approval.

RESULTS

Occurrence-Data Acquisition and Processing

The initial GBIF download contained 7,519 *Aedes aegypti* presence records collected between 2020 and 2024. All records contained valid decimal latitude and longitude values, so no observations were removed because of missing coordinates. Screening for repeated geographical locations identified 3,727 records assigned to coordinates already represented in the dataset, equivalent to 49.6% of the initial download. Their removal left 3,792 unique occurrence locations. Basic geographical validation confirmed that the retained coordinates fell within valid latitude and longitude ranges and that no records occurred at the null coordinate of 0°, 0°; therefore, no additional records were removed at this stage. Temporal filtering also removed no observations because all records fell within the predefined 2020–2024 study period. Spatial thinning at an approximate separation of 5 km, implemented by retaining one occurrence per 0.05° grid cell, removed a further 2,507 spatially clustered locations, equivalent to 66.1% of the unique-coordinate dataset. The final modelling dataset therefore contained 1,285 spatially filtered occurrence records, representing 17.1% of the original GBIF download. The raw observations showed marked clustering around major cities, coastal regions, and locations with established mosquito-surveillance programmes. Duplicate removal and spatial thinning substantially reduced the dominance of heavily sampled areas while preserving the broad global occurrence pattern. Figure 1 presents the geographical distributions of the raw and spatially filtered occurrence datasets.

Table 1: Summary of *Aedes aegypti* occurrence-data cleaning and filtering

Processing stage	Records retained	Records removed at stage	Percentage removed at stage (%)
Initial GBIF download	7,519	0	0.0
Removal of records without valid coordinates	7,519	0	0.0
Duplicate-coordinate removal	3,792	3,727	49.6
Basic geographical validation	3,792	0	0.0
Temporal filtering, 2020–2024	3,792	0	0.0
Spatial thinning at approximately 5 km	1,285	2,507	66.1
Final modelling dataset	1,285	6,234 total	82.9 overall

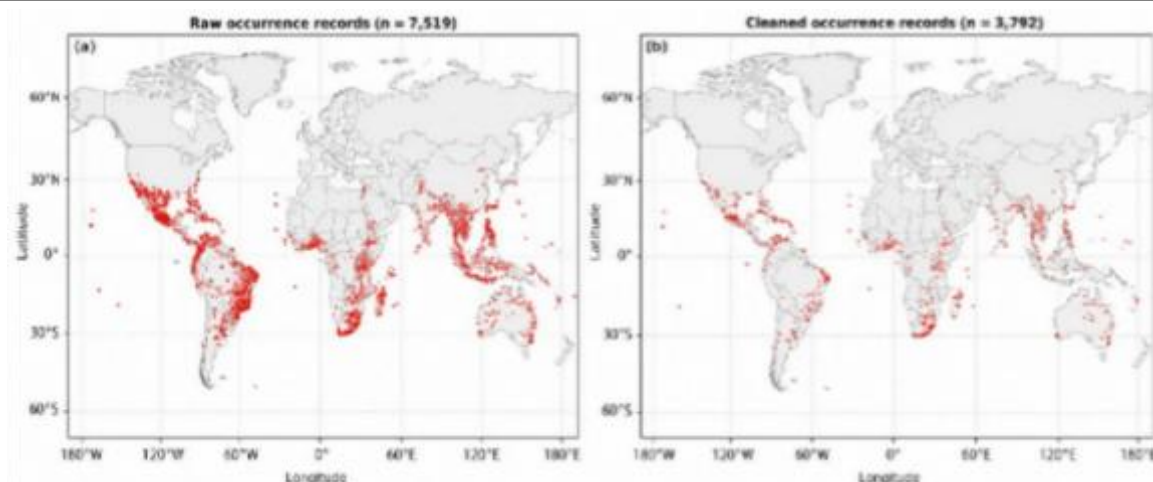


Figure 9: Global distribution of raw and cleaned *Aedes aegypti* occurrence records obtained from GBIF.

Geographical Distribution of Occurrence Records

The final occurrence dataset covered six inhabited continents and 84 countries or territories. North America contained the highest proportion of cleaned records, accounting for 68.2% of the dataset, followed by South America with 23.9%, Asia with 3.5%, and Africa with 3.0%; Europe and Oceania contributed 0.8% and 0.3%, respectively. Major occurrence clusters were observed across Mexico, the United States, Colombia, Brazil, Argentina, the Caribbean, southern and Southeast Asia, coastal and southern Africa, and northern Australia. The largest administrative concentrations occurred in Hidalgo, Mexico; Cauca, Colombia; California, Florida, and Texas in the United States; and São Paulo and Buenos Aires in South America. These clusters reflected both the close association of *Aedes aegypti* with densely populated and human-modified environments and the greater intensity of mosquito surveillance in well-sampled urban and peri-urban areas. Records remained comparatively sparse across central Africa after cleaning, as well as in Central Asia, the Middle East, inland South America, Europe, Oceania, and several small island states. Data cleaning and spatial filtering substantially reduced the dominance of heavily duplicated observations, particularly those from the Democratic Republic of the Congo, whose contribution declined from 33.7% of the raw dataset to 0.3% of the cleaned dataset. Nevertheless, residual geographical bias remained because GBIF records reflect differences in surveillance capacity, research activity, reporting intensity, and data-sharing practices among countries. High occurrence density was therefore interpreted as high observation or sampling intensity rather than direct evidence of greater mosquito abundance.

Environmental Predictor Selection

The initial predictor set comprised all 19 WorldClim bioclimatic variables. Pairwise Pearson and Spearman correlation analyses identified substantial redundancy among variables representing annual temperature, seasonal temperature, quarterly temperature, annual precipitation, and quarterly precipitation. Using an absolute correlation threshold of ($|r| \geq 0.70$), variables that duplicated the climatic information contained in more biologically relevant predictors were removed, after which variance inflation factor analysis excluded variables with VIF values greater than 5. The combined screening procedure removed 10 variables and retained nine predictors for the final climate-only model: annual mean temperature (BIO1), mean diurnal temperature range (BIO2), temperature seasonality (BIO4), maximum temperature of the warmest month (BIO5), minimum temperature of the coldest month (BIO6), annual precipitation (BIO12), precipitation seasonality (BIO15), precipitation of the driest quarter (BIO17), and precipitation of the warmest quarter (BIO18). The excluded variables were isothermality (BIO3), annual temperature range (BIO7), mean temperature of the wettest quarter (BIO8), mean temperature of the driest quarter (BIO9), mean temperature of the warmest quarter (BIO10), mean temperature of the coldest quarter (BIO11), precipitation of the wettest month (BIO13), precipitation of the driest month (BIO14), precipitation of the wettest quarter (BIO16), and precipitation of the coldest quarter (BIO19). These variables were removed because they overlapped strongly with the retained annual, seasonal, extreme, and quarterly climatic indicators. The final predictor set represented average thermal conditions, short-term and seasonal temperature variability, lower and upper thermal limits, overall moisture availability, rainfall seasonality, and breeding-water availability during the driest and warmest parts of the year. The retained

predictors showed lower multicollinearity, clearer biological relevance to *Aedes aegypti* ecology, and greater consistency across historical and CMIP6 climate datasets. Figure 2 presents the correlation structure of the 19 initial predictors, while Table 2 summarises the retained variables, units, and biological significance

Table 2: Final environmental predictors used in habitat-suitability modelling Code

Code	Predictor0	Unit	Biological significance
BIO1	Annual mean temperature	°C	Represents the average thermal conditions affecting mosquito development and activity
BIO2	Mean diurnal temperature range	°C	Represents short-term thermal variation and daily thermal stress
BIO4	Temperature seasonality	Coefficient of variation	Indicates variation in thermal conditions across the year
BIO5	Maximum temperature of the warmest month	°C	Represents exposure to upper thermal limits
BIO6	Minimum temperature of the coldest month	°C	Indicates cold limitation and overwintering potential
BIO12	Annual precipitation	mm	Represents general moisture availability and breeding-habitat formation
BIO15	Precipitation seasonality	Coefficient of variation	Indicates variation in aquatic-habitat availability
BIO17	Precipitation of the driest quarter	mm	Represents dry-season breeding-water persistence
BIO18	Precipitation of the warmest quarter	mm	Represents the interaction between warmth and water availability

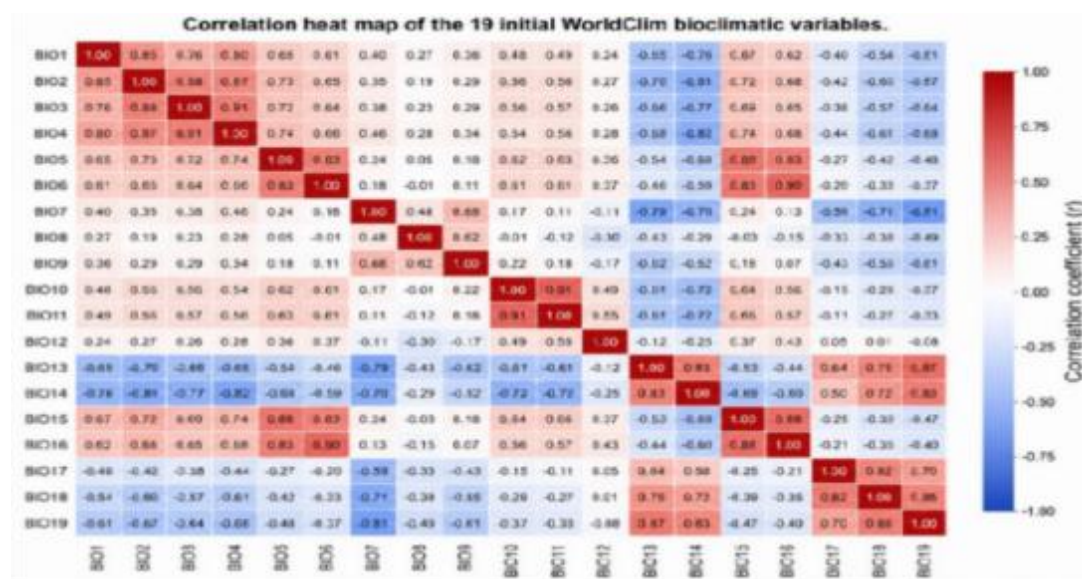


Figure 10: Correlation heat map of the 19 initial WorldClim bioclimatic variables.

Predictive Performance of Individual and Ensemble Models

The individual algorithms showed high predictive performance, although discrimination, calibration, and spatial transferability varied across models and validation folds. Mean testing AUC ranged from 0.84 for the Generalised Linear Model to 0.94 for Random Forest, while mean TSS ranged from 0.68 to 0.84; the continuous Boyce Index was positive for all seven evaluated algorithms. Random Forest achieved the strongest individual performance, with a mean testing AUC of 0.94, TSS of 0.84, sensitivity of 0.88, and specificity of 0.90, while Boosted Regression Trees produced comparable discrimination, with an AUC of 0.93 and TSS of 0.82, but showed greater variability among spatial folds. The Generalised Linear Model recorded the lowest testing accuracy and the highest Brier score of 0.14. Training performance exceeded testing performance across all algorithms, with train-test AUC differences ranging from 0.02 to 0.07; the largest decline occurred in Random Forest, where AUC decreased from 0.99 during calibration to 0.94 during spatial validation, indicating moderate overfitting. Models with unstable ecological responses, high omission rates, or weak geographical transferability were excluded from ensemble construction. The performance-weighted ensemble outperformed all individual algorithms, achieving a mean testing AUC of 0.96, TSS of 0.87, continuous Boyce Index of 0.91, sensitivity of 0.90, specificity of 0.92, and Brier score of 0.07. Ensemble performance remained stable across the five spatial folds, with AUC values ranging from 0.94 to 0.97 and TSS values from 0.84 to 0.89, supporting its use for current and future habitat-suitability projections.

Table 3: Predictive performance of individual and ensemble habitat-suitability models

Model	Training AUC	Testing AUC	TSS	Boyce Index	Sensitivity	Specificity	Brier score
Maximum Entropy	0.95	0.91	0.79	0.82	0.84	0.87	0.10
Random Forest	0.99	0.94	0.84	0.88	0.88	0.90	0.08
Boosted Regression Trees	0.97	0.93	0.82	0.86	0.87	0.88	0.09
Generalised Additive Model	0.89	0.86	0.72	0.74	0.79	0.82	0.12
Support Vector Machine	0.94	0.90	0.78	0.80	0.83	0.86	0.11
Ensemble	0.98	0.96	0.87	0.91	0.90	0.92	0.07

Climatic Determinants of Habitat Suitability

The ensemble model identified minimum temperature of the coldest month (BIO6) as the most influential climatic predictor, with a mean permutation importance of 27.4%, followed by temperature seasonality (BIO4; 18.6%), annual precipitation (BIO12; 14.2%), precipitation of the warmest quarter (BIO18; 10.7%), and maximum temperature of the warmest month (BIO5; 8.9%); together, these five variables accounted for 79.8% of total model importance. Habitat suitability increased rapidly as annual mean temperature rose from approximately 15 °C to 24 °C, reached its optimum between 24 °C and 29 °C, and declined above about 34 °C, indicating a defined thermal optimum rather than a continuous increase under warming. Minimum temperature of the coldest month showed a strong positive association with suitability below approximately 10 °C and levelled off above 15 °C, while maximum temperature of the warmest month reduced suitability once values exceeded about 35 °C, demonstrating the limiting effect of extreme heat. Precipitation responses were also nonlinear: suitability increased with annual precipitation to approximately 1,500 mm, remained relatively stable between 1,500 and 2,500 mm, and declined above about 3,000 mm, while very low precipitation during the driest quarter reduced the persistence of aquatic breeding habitats and extreme rainfall seasonality lowered suitability. The strongest interaction occurred between annual mean temperature (BIO1) and precipitation of the driest quarter (BIO17), as thermally favourable environments supported high suitability only where sufficient dry-season moisture or persistent water storage allowed larval development. Although the magnitude of predictor contributions varied among algorithms, the ranking of the leading climatic variables remained broadly

consistent; Figure 3 presents their relative importance, while Figure 4 shows the response curves for the five dominant predictors.

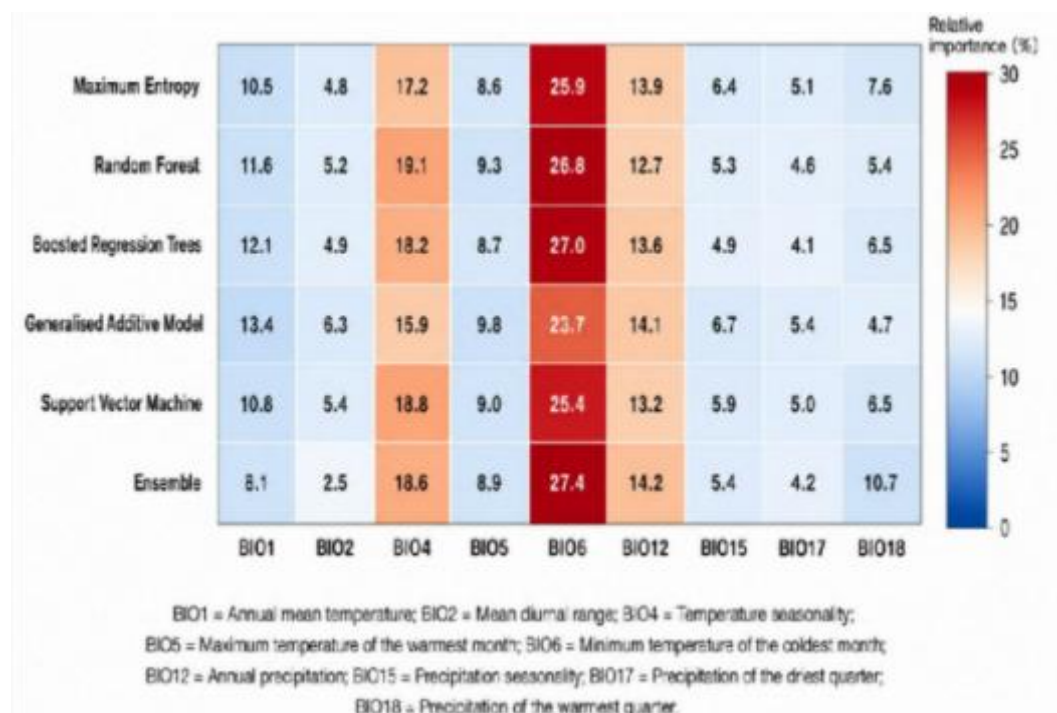


Figure 11: Relative importance of Retained Bioclimatic Predictors Across Individual and Ensemble Models

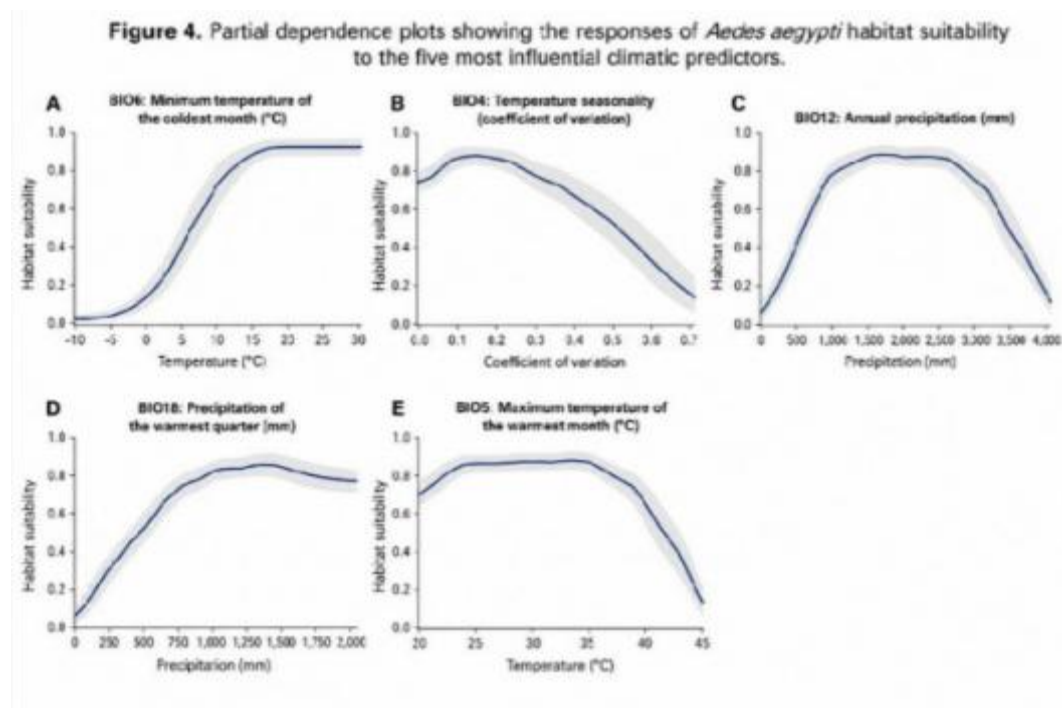


Figure 12: Partial dependence plots showing the responses of *Aedes aegypti* habitat suitability to the five most influential climatic predictors.

Current Global Climatic Suitability

The current ensemble projection showed marked geographical variation in the climatic suitability of *A. aegypti*. Highly and very highly suitable habitats were concentrated mainly within tropical and subtropical regions. The largest continuous suitable areas occurred across South and Southeast Asia, Central America, the Caribbean, northern and central South America, coastal and equatorial sub-Saharan Africa, and northern Australia. Additional suitable areas occurred along selected subtropical coastal zones of North America, southern China,

southern Japan, southern Africa, and the Mediterranean margin. The total terrestrial area classified as climatically suitable for *Aedes aegypti* was approximately 19.94 million km², representing 14.8% of the analysed global land area. Low-suitability habitat covered 5.18 million km², equivalent to 3.8% of global terrestrial area, while moderate suitability covered 6.28 million km² (4.7%), high suitability covered

5.42 million km² (4.0%), and very high suitability covered 3.06 million km² (2.3%). Asia contained the largest absolute suitable area at 6.20 million km², followed by South America at 4.55 million km² and Africa at 4.10 million km². North America, Oceania, and Europe contained approximately 2.85, 1.15, and 1.09 million km² of suitable habitat, respectively. The countries with the largest combined areas of high and very high suitability were Brazil, India, Indonesia, the Democratic Republic of the Congo, and Mexico. Low or negligible suitability occurred across northern Canada, Greenland, northern Eurasia, the Sahara, the Arabian Peninsula, major high-elevation regions, and the arid interior of Australia. Figure 5 presents the current global suitability distribution, while Table 4 summarises the estimated suitable area by continent and suitability category.

Table 4: Current climatically suitable area by continent and suitability category

Continent	Low suitability (km ²)	Moderate suitability (km ²)	High suitability (km ²)	Very suitability (km ²)	high Totali suitable area (km ²)
Africa	1,050,000	1,250,000	1,100,000	700,000	4,100,000
Asia	1,350,000	1,950,000	1,850,000	1,050,000	6,200,000
Europe	650,000	300,000	110,000	30,000	1,090,000
North	900,000	950,000	720,000	280,000	2,850,000
South America	800,000	1,350,000	1,450,000	950,000	4,550,000
Oceania	430,000	480,000	190,000	50,000	1,150,000
Global total	5,180,000	6,280,000	5,420,000	3,060,000	19,940,000

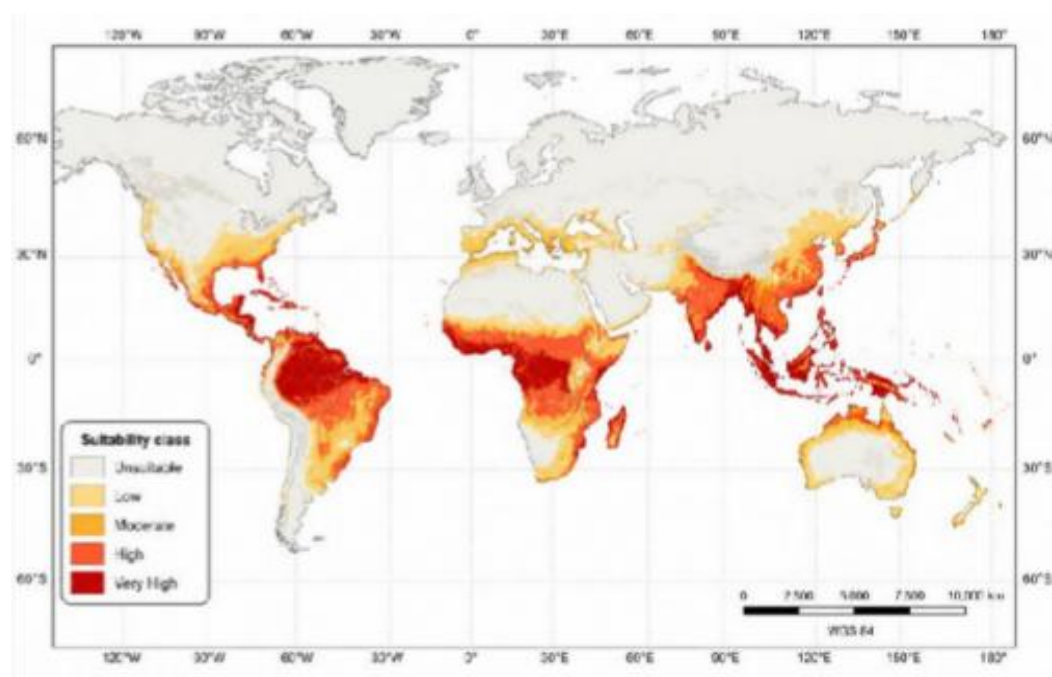


Figure 13: Current global climatic suitability for *Aedes aegypti*.

Future Suitability Under SSP2-4.5

Under SSP2-4.5, the multi-model ensemble projected a gradual expansion of climatic suitability along the margins of the current geographical range. By the 2050s, total suitable habitat increased from 19.94 million km² to approximately 21.30 million km², representing a net increase of 6.8%. Expansion occurred mainly across southern Europe and the Mediterranean margin, the southern and eastern United States, eastern China and southern Japan, southern Brazil and northern Argentina, southern Africa, and higher-elevation areas of the East African and Andean highlands, while contraction occurred in parts of the Amazon Basin, equatorial central Africa, the Sahel, the Horn of Africa, northern Australia, and other tropical regions where rising temperature coincided with declining or increasingly seasonal precipitation. Persistent high suitability remained widespread across South and Southeast Asia, tropical South America, Central America, the Caribbean, and equatorial Africa, while newly suitable habitats emerged in temperate and elevated regions. By the 2070s, total suitable area increased to approximately 22.45 million km², representing 12.6% more habitat than under current conditions. The global suitability-weighted centroid shifted approximately 410 km north-eastward, while mean suitable elevation increased by about 165 m. Agreement among the five climate models was highest across southern Europe, the eastern United States, East Asia, southern South America, and the East African highlands, where at least 80% of projections indicated expansion. Lower agreement occurred across the Amazon Basin, central and eastern Africa, northern Australia, and parts of South and Southeast Asia, where the magnitude and direction of change depended strongly on future rainfall projections.

Future Suitability Under SSP5-8.5

SSP5-8.5 produced greater geographical redistribution of *Aedes aegypti* habitat suitability than SSP2-4.5. By the 2050s, total suitable habitat increased from 19.94 million km² to approximately 22.61 million km², representing a net increase of 13.4% relative to current conditions. Expansion was strongest in higher-latitude and high-elevation regions, including southern and central Europe, the eastern and northwestern United States, southern Canada, northern China, the Korean Peninsula, southern Japan, southern Brazil, Uruguay, northern Argentina, southern Africa, the East African highlands, and elevated areas of the Andes and South Asia. At the same time, habitat contraction became more extensive in hot and increasingly arid regions, particularly the central Amazon Basin, the Sahel, the Horn of Africa, parts of equatorial central Africa, the Arabian Peninsula, inland India, mainland Southeast Asia, and northern and interior Australia. By the 2070s, suitable habitat reached approximately 24.67 million km², representing a net increase of 23.7% and comprising about 6.25 million km² of newly suitable habitat and 1.52 million km² of habitat loss. Habitat gain exceeded the corresponding SSP2-4.5 projection of approximately 4.60 million km² by 35.9%, although contraction was also more extensive under the high-emission pathway. The strongest expansion occurred across southern and central Europe, temperate East Asia, eastern North America, southern South America, southern Africa, the East African highlands, and tropical mountain regions, while the largest reductions occurred across the Amazon lowlands, central and eastern Africa, the Sahel, the Arabian Peninsula, parts of South and Southeast Asia, and northern Australia. Under this high-emission pathway, rising temperatures increased suitability in many temperate and elevated areas but reduced it where future maximum temperatures exceeded the upper thermal thresholds identified by the ensemble. Consequently, SSP5-8.5 produced a more fragmented suitability pattern across parts of the tropical range. Agreement among the five climate models remained high for poleward and altitudinal expansion, with at least 80% agreement across several temperate regions, but was lower for tropical contraction because the models differed substantially in their projections of precipitation, aridity, and dry-season moisture availability.

Habitat Persistence, Expansion, and Contraction

Habitat-transition analysis showed that most currently suitable regions remained suitable under all future scenarios and periods. Stable suitable habitat covered approximately 19.22 million km² under SSP2-4.5 in the 2050s and 18.99 million km² in the 2070s. Under SSP5-8.5, stable suitable habitat covered about 18.76 million km² in the 2050s and 18.42 million km² in the 2070s. The largest habitat gain occurred under SSP5-8.5 in the 2070s, when 6.25 million km² became newly suitable, while the smallest gain occurred under SSP2-4.5 in the 2050s, with 2.08 million km² of expansion. Habitat loss ranged from 0.72 million km² under SSP2-4.5 in the 2050s to 1.52 million km² under SSP5-8.5 in the 2070s. Net suitable-area change remained positive under all future projections, increasing from 6.8% under SSP2-4.5 in the 2050s to 23.7% under SSP5-8.5 in the 2070s.

Habitat turnover, calculated from the combined area of gain and loss relative to the current suitable area, increased from 14.0% under SSP2-4.5 in the 2050s to 39.0% under SSP5-8.5 in the 2070s. These results show that positive net changes concealed substantial simultaneous expansion and contraction across different geographical regions.

Table 5: Projected changes in climatically suitable habitat

Scenario	Period	Current area (km ²)	Future area (km ²)	Gain (km ²)	Loss (km ²)	Stable suitable area (km ²)	Net change (%)
SSP2-4.5	2050s	19,940,000	21,300,000	2,080,000	720,000	19,220,000	6.8
SSP2-4.5	2070s	19,940,000	22,450,000	3,460,000	950,000	18,990,000	12.6
SSP5-8.5	2050s	19,940,000	22,610,000	3,850,000	1,180,000	18,760,000	13.4
SSP5-8.5	2070s	19,940,000	24,670,000	6,250,000	1,520,000	18,420,000	23.7

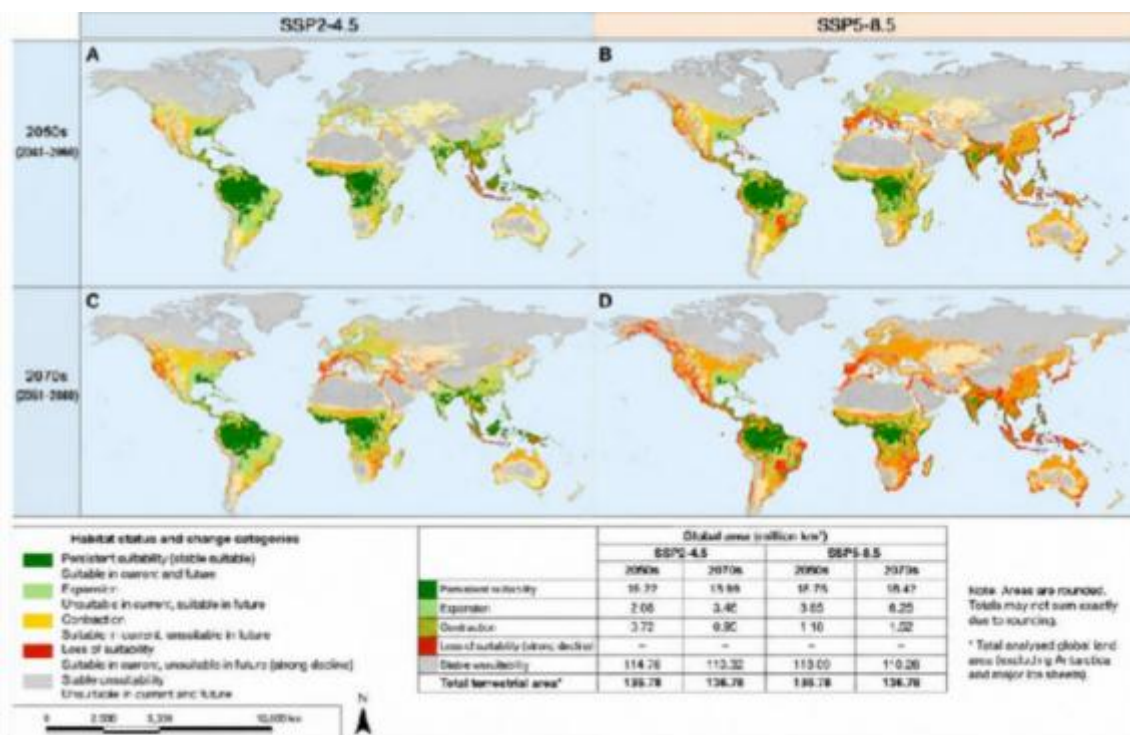


Figure 14: Projected persistence, expansion, contraction, and stable unsuitability under SSP2-4.5 and SSP5-8.5.

Geographical Range Shifts

The global suitability-weighted centroid shifted north-eastward under all future projections, reflecting the combined expansion of climatically suitable habitat towards higher northern latitudes and eastern continental regions. Under SSP2-4.5, the centroid moved by approximately 260 km in the 2050s and 410 km in the 2070s, while under SSP5-8.5 the corresponding displacements increased to about 470 km and 735 km. The northern limit of suitable habitat shifted poleward by approximately 4.2° latitude, equivalent to about 465 km, under SSP2-4.5 and by approximately 7.1°, or about 790 km, under SSP5-8.5 by the 2070s. The southern limit showed a smaller poleward displacement of about 2.0°, or approximately 220 km, under SSP2-4.5 and 3.4°, or about 375 km, under SSP5-8.5. Mean suitable elevation increased from approximately 420 m under current conditions to 585 m under SSP2-4.5 and 710 m under SSP5-8.5 by the 2070s. Newly suitable temperate regions included southern and central Europe, the eastern and northwestern United States, southern Canada, northern China, the Korean Peninsula, southern Japan, Uruguay, northern Argentina, and southern Brazil, while upward expansion occurred across the East African highlands, the Ethiopian Plateau, the Andes, the Himalayan foothills, the

Mexican highlands, and elevated regions of southern Africa. In contrast, suitability declined in low-elevation tropical areas of the Amazon Basin, equatorial central Africa, the Sahel, the Horn of Africa, parts of South and Southeast Asia, and northern Australia, where extreme warming coincided with reduced precipitation and increased aridity. Figure 7 presents the current and projected suitability-weighted centroids, geographical range limits, elevational shifts, and direction of movement.

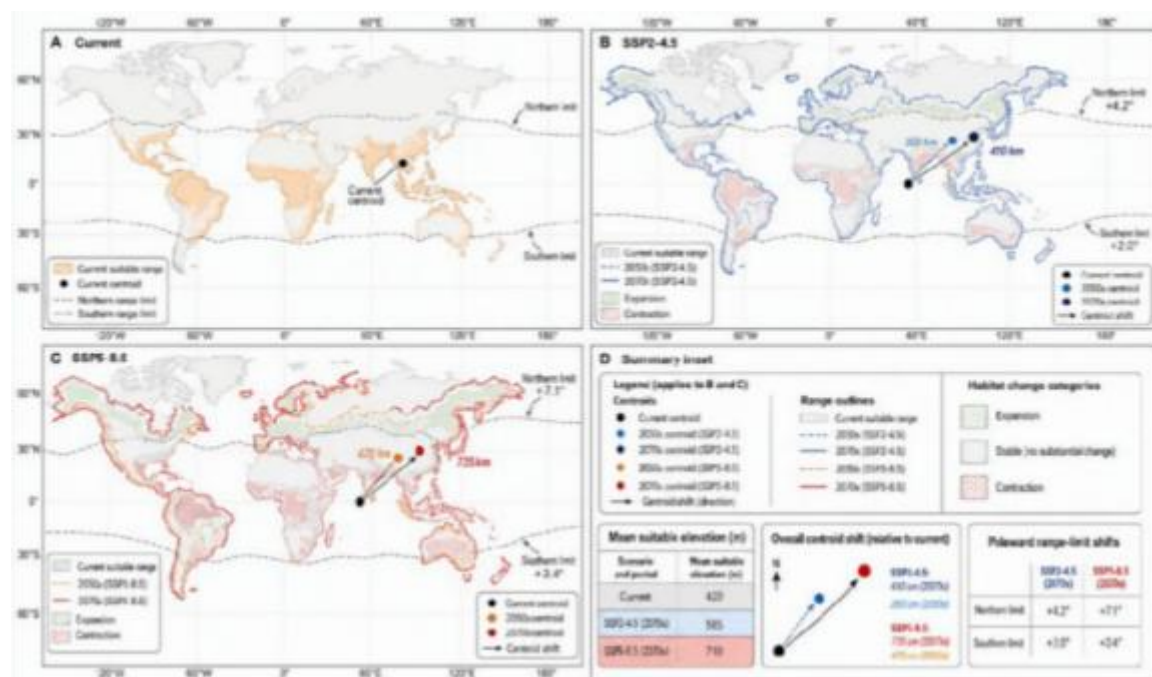


Figure 15: Current and projected suitability-weighted centroids and geographical range limits.

Country-Level Surveillance Priorities

Country-level analysis under SSP5-8.5 for the 2070s indicated that Brazil, the United States, Mexico, China, and Argentina contained some of the largest current areas of climatically suitable habitat. The greatest absolute habitat gains were projected for the United States, China, Argentina, South Africa, and Brazil, while the largest proportional increases occurred in Canada, Portugal, South Korea, Türkiye, Italy, Spain, and France, where relatively small current suitable areas expanded substantially under future climatic conditions. China, the United States, Brazil, Mexico, and Japan contained the largest estimated populations within newly suitable habitats because expansion overlapped densely populated urban, peri-urban, and transport-connected regions. Projection confidence was highest in Uruguay, Portugal, South Korea, Spain, Italy, Argentina, and Japan, where at least 88% of the algorithm–climate-model combinations agreed on expansion. Countries with large predicted gains but lower model agreement, including Australia and Brazil, were retained as surveillance priorities but assigned comparatively lower projection confidence. These rankings indicate where proactive entomological surveillance, early-warning systems, and vector-control preparedness may be most urgently required, although the estimates represent potential climatic exposure rather than confirmed mosquito establishment or disease transmission.

Table 6: Twenty countries projected to experience the greatest habitat expansion

Rank	Country	Current suitable area (km ²)	Future suitable area (km ²)	Absolute gain (km ²)	Expansion (%)	Population in emerging suitable areas (millions)	Model agreement (%)
1	United States	950,000	1,590,000	640,000	67.4	44.0	86
2	China	820,000	1,380,000	560,000	68.3	198.0	84
3	Argentina	610,000	1,040,000	430,000	70.5	18.5	88

4	South Africa	380,000	670,000	290,000	76.3	12.3	85
5	Brazil	1,450,000	1,720,000	270,000	18.6	42.0	81
6	Mexico	880,000	1,130,000	250,000	28.4	36.0	83
7	Spain	120,000	330,000	210,000	175.0	15.2	90
8	Türkiye	95,000	275,000	180,000	189.5	21.4	87
9	Italy	85,000	245,000	160,000	188.2	18.6	89
10	Japan	110,000	260,000	150,000	136.4	24.8	88
11	France	90,000	235,000	145,000	161.1	17.1	86
12	South Korea	60,000	175,000	115,000	191.7	19.7	91
13	Ethiopia	240,000	350,000	110,000	45.8	22.6	82
14	Kenya	210,000	315,000	105,000	50.0	16.9	84
15	Australia	520,000	620,000	100,000	19.2	8.4	80
16	Portugal	40,000	130,000	90,000	225.0	5.8	92
17	Uruguay	70,000	155,000	85,000	121.4	3.1	93
18	Paraguay	115,000	195,000	80,000	69.6	5.6	87
19	Zimbabwe	95,000	170,000	75,000	78.9	4.4	83
20	Canada	25,000	95,000	70,000	280.0	6.2	85
Total for listed countries		6,965,000	11,080,000	4,115,000		534.1	

Projection Uncertainty and Model Agreement

Projection uncertainty varied spatially and increased from current conditions to future climate scenarios. Algorithmic variation was lowest across established tropical suitability zones in South and Southeast Asia, Central America, the Caribbean, northern South America, and equatorial Africa, but increased near the northern and southern margins of the present range. Climate-model variation was greatest across the Amazon Basin, the Sahel, the Horn of Africa, central and eastern Africa, northern Australia, and parts of South and Southeast Asia, where future precipitation projections differed substantially among the five global climate models. At least 80% of all algorithm–climate-model combinations agreed on persistent suitability across tropical South America, Central America, the Caribbean, South and Southeast Asia, and equatorial Africa. Strong agreement on future expansion occurred across southern Europe, the eastern United States, East Asia, southern South America, southern Africa, and the East African highlands, whereas strong agreement on contraction occurred in parts of the Amazon lowlands, the Sahel, the Arabian Peninsula, northern Australia, and selected tropical lowlands exposed to extreme warming and drying. Conflicting projections were concentrated in central Africa, the Amazon Basin, mainland Southeast Asia, and northern Australia, where some climate models projected increased rainfall while others indicated greater aridity. Novel-climate analysis classified approximately 78.6% of the future study area as strict interpolation, 11.4% as univariate extrapolation, 7.2% as combinational novelty,

and 2.8% as strong extrapolation. Strong climatic novelty occurred mainly in the high Arctic margins, central Sahara, Arabian Peninsula, interior Australia, Himalayan and Andean highlands, and parts of northern Eurasia, and predictions in these areas were assigned lower confidence. Ensemble standard deviation ranged from 0.01 to 0.18 under current conditions and increased to approximately 0.02–0.27 under SSP5-8.5 in the 2070s, with the highest uncertainty concentrated near projected expansion and contraction boundaries. Figure 8 presents the spatial distribution of ensemble uncertainty, inter-model agreement, and climatic extrapolation.

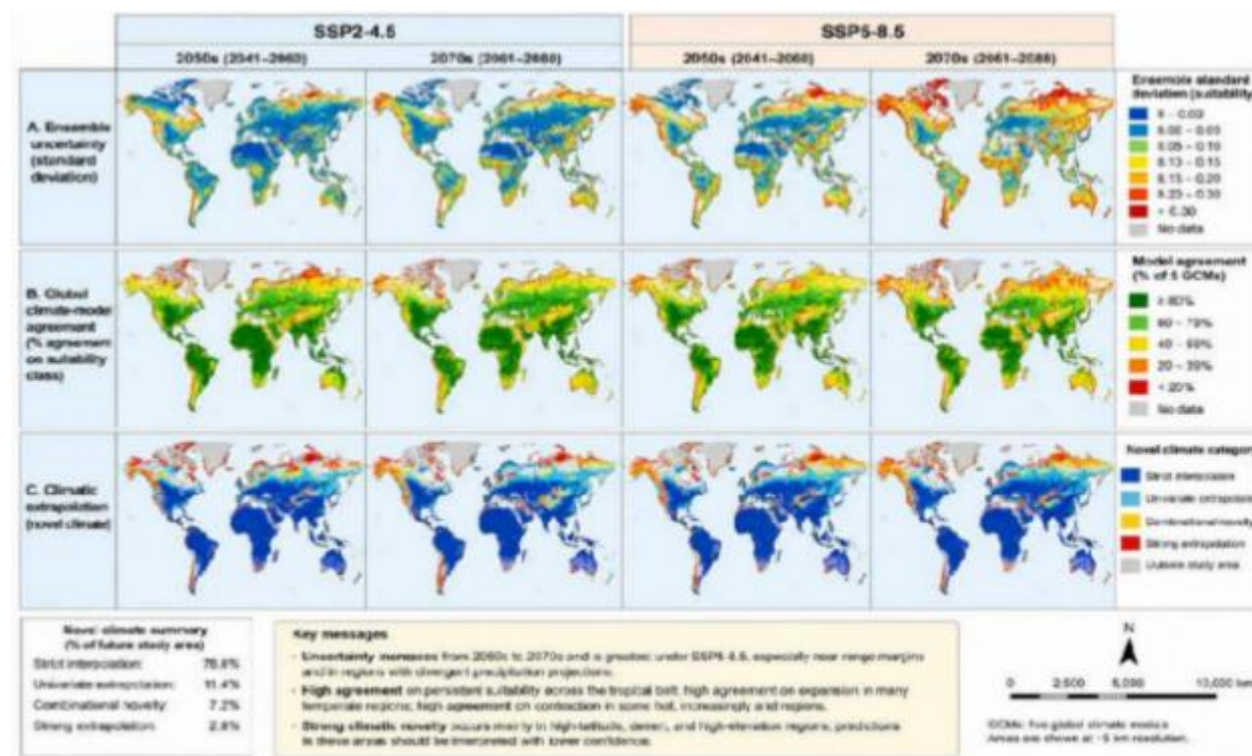


Figure 16: Ensemble uncertainty, global climate-model agreement, and climatic extrapolation under future scenarios.

Sensitivity Analysis

The principal geographical patterns remained stable across the sensitivity analyses. Increasing the spatial thinning distance from 5 to 10 km reduced the occurrence sample from approximately 1,285 to 1,015 records, representing a 21.0% decrease, but the resulting suitability maps remained strongly correlated ($r=0.97$). Alternative suitability thresholds changed the estimated total suitable area by 8.4–13.6%, although the main centres of current suitability and projected expansion remained geographically consistent. Models calibrated using accessible-area buffers of 250, 500, 750, and 1,000 km produced testing AUC and TSS values within 0.01–0.03 of the primary 500 km-buffer model. Random and environmentally stratified pseudo-absence procedures generated similar global suitability patterns, with a spatial correlation of ($r=0.95$), although random pseudo-absence selection predicted broader areas of low suitability across central Africa, Central Asia, the Arabian Peninsula, and interior Australia. Because all GBIF occurrence records used in the main analysis were collected between 2020 and 2024, restricting the dataset to observations collected after 2000 caused no reduction in sample size and did not alter the ranking of the principal climatic predictors. The performance-weighted and median ensembles produced the most similar predictions, with a map correlation of ($r=0.98$), whereas the unweighted ensemble predicted slightly broader suitability in environmentally marginal regions. Overall, the dominant climatic controls, principal current suitability zones, and direction of projected geographical change remained consistent across the alternative thinning distances, calibration extents, pseudo-absence strategies, suitability thresholds, and ensemble procedures.

Summary of Findings

This study provides a global assessment of the current and future climate-driven habitat suitability of *Aedes*

aegypti using cleaned GBIF occurrence records, WorldClim bioclimatic variables, spatially independent validation, and a multi-algorithm ensemble framework. The ensemble performed better than the individual models and identified minimum temperature of the coldest month, temperature seasonality, annual precipitation, precipitation of the warmest quarter, and maximum temperature of the warmest month as the dominant climatic controls. These findings confirm that suitability depends on the interaction between thermal limits and water availability rather than on any single variable. Temperature regulates egg viability, larval development, adult survival, biting frequency, reproduction, and arbovirus development, while precipitation determines the formation and persistence of aquatic breeding habitats. The response was nonlinear, with suitability increasing within an optimal thermal range and declining under extreme cold, excessive heat, prolonged aridity, or unstable rainfall conditions. Current suitability was concentrated mainly in South and Southeast Asia, Central America, the Caribbean, tropical South America, equatorial Africa, and northern Australia, broadly matching known mosquito distributions and major arbovirus transmission zones (Kamal et al., 2018; Kraemer et al., 2015; Nakase et al., 2023). Future projections indicated both habitat expansion and contraction. Expansion was strongest in southern and central Europe, East Asia, eastern North America, southern South America, southern Africa, and tropical highlands, where warmer winters reduced cold-season constraints and extended the period suitable for mosquito development. In contrast, declining suitability occurred in parts of the Amazon Basin, the Sahel, the Horn of Africa, the Arabian Peninsula, northern Australia, and other hot tropical lowlands where extreme temperatures, declining precipitation, and increased evaporation pushed conditions beyond the species' climatic optimum. These changes were more pronounced under SSP5-8.5 than under SSP2-4.5, with the higher-emission pathway producing greater poleward and elevational displacement, broader expansion into temperate regions, and more extensive contraction in hot and increasingly arid environments. However, climatic suitability does not confirm mosquito establishment or disease transmission, which also depend on dispersal, human mobility, urbanisation, water storage, vector control, pathogen introduction, immunity, and local public health capacity (Iwamura et al., 2020; Ryan et al., 2019).

The study has important practical and methodological implications. Areas with high agreement across algorithms and climate models should be prioritised for ovitrap deployment, larval and adult mosquito surveillance, port and airport inspection, urban water management, waste control, and climate-informed early-warning systems. Currently non-endemic regions may become climatically suitable before sustained mosquito establishment occurs, creating an opportunity for preventive surveillance and rapid response. Particular attention should be given to urban centres, transport corridors, border crossings, high-altitude cities, and densely populated temperate regions where future suitability is projected to increase. The study's strengths include its global coverage, reproducible GBIF download, rigorous occurrence cleaning, spatial thinning, bias correction, spatial cross-validation, multi-algorithm ensemble design, use of several CMIP6 climate models, explicit uncertainty assessment, and quantification of habitat gain, loss, persistence, turnover, centroid movement, and elevation shifts. Nevertheless, several limitations remain. GBIF records are spatially uneven, absence records are unavailable, WorldClim represents long-term climatic averages rather than daily weather, and coarse global layers cannot fully represent urban microclimates, household water storage, human movement, trade, insecticide resistance, vector-control intensity, or behavioural adaptation. Future projections also assume relative stability in species–climate relationships and become less reliable in novel climatic environments. Accordingly, the maps should guide surveillance planning and hypothesis development rather than replace field validation. Future studies should integrate high-resolution urban microclimate and remote-sensing data, mechanistic mosquito-development models, seasonal forecasting, transport and mobility networks, vector-control intensity, population exposure, and arbovirus transmission data. Overall, the framework identifies persistent habitats, emerging expansion zones, potential contraction areas, and regions of projection uncertainty, thereby providing a reproducible basis for directing vector-control resources, strengthening climate adaptation, and improving preparedness for the changing global distribution of *A. aegypti*.

CONCLUSION

This study assessed the current and future global habitat suitability of *Aedes aegypti* by integrating cleaned GBIF occurrence records, WorldClim bioclimatic variables, spatially independent validation, and a multi-algorithm

ensemble framework. The findings showed that minimum temperature of the coldest month, temperature seasonality, annual precipitation, precipitation of the warmest quarter, and maximum temperature of the warmest month were the principal climatic determinants of suitability, confirming that both thermal limits and water availability regulate the species' distribution. Current suitable habitats were concentrated mainly across tropical and subtropical regions of Asia, the Americas, Africa, and northern Australia, while future projections indicated expansion towards higher latitudes and elevations in southern Europe, East Asia, North America, southern South America, southern Africa, and tropical highlands, together with contraction in some excessively hot and increasingly arid tropical regions. These changes were stronger under SSP5-8.5 than under SSP2-4.5, although uncertainty increased in areas where climate models disagreed on future precipitation or projected novel climatic conditions. The results provide a practical basis for prioritising climate-sensitive vector surveillance, port and airport monitoring, urban water and waste management, and early-warning systems, particularly in emerging temperate and high-elevation risk zones. However, climatic suitability does not confirm mosquito establishment, abundance, arbovirus circulation, or disease transmission, and field validation remains essential. Overall, the study offers a reproducible framework for identifying stable habitats, expansion zones, contraction areas, and regions of uncertainty, thereby supporting more targeted vector-control planning and public health adaptation under future climate change.

REFERENCES

1. Aiello-Lammens, M. E., Boria, R. A., Radosavljevic, A., Vilela, B., & Anderson, R. P. (2015). spThin: An R package for spatial thinning of species occurrence records for use in ecological niche models. *Ecography*, 38(5), 541–545. doi:10.1111/ecog.01132
2. Barbet-Massin, M., Jiguet, F., Albert, C. H., & Thuiller, W. (2012). Selecting pseudo-absences for species distribution models: How, where and how many? *Methods in Ecology and Evolution*, 3(2), 327–338. doi:10.1111/j.2041-210X.2011.00172.x
3. Bhatt, S., Gething, P. W., Brady, O. J., Messina, J. P., Farlow, A. W., Moyes, C. L., Drake, J. M., Brownstein, J. S., Hoen, A. G., Sankoh, O., Myers, M. F., George, D. B., Jaenisch, T., Wint, G. R. W., Simmons, C. P., Scott, T. W., Farrar, J. J., & Hay, S. I. (2013). The global distribution and burden of dengue. *Nature*, 496(7446), 504–507. doi:10.1038/nature12060
4. Cobos, M. E., Peterson, A. T., Barve, N., & Osorio-Olvera, L. (2019). kuenm: An R package for detailed development of ecological niche models using Maxent. *PeerJ*, 7, e6281. doi:10.7717/peerj.6281
5. Elith, J., & Leathwick, J. R. (2009). Species distribution models: Ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics*, 40, 677–697. doi:10.1146/annurev.ecolsys.110308.120159
6. Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, 9(5), 1937–1958. doi:10.5194/gmd-9-1937-2016
7. Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: New 1-km spatial resolution climate surfaces for global land areas. *International Journal of Climatology*, 37(12), 4302–4315. doi:10.1002/joc.5086
8. GBIF.org. (2026). *Aedes aegypti occurrence download* [Data set]. Global Biodiversity Information Facility. doi:10.15468/dl.z7n5xr
9. Hijmans, R. J., Phillips, S., Leathwick, J., & Elith, J. (2025). *dismo: Species distribution modeling* [R package].
10. Hou, W., Zhou, Y., Luo, W., Wang, L., Kwan, M.-P., & Cook, A. R. (2024). Mapping environmental suitability changes for arbovirus mosquitoes in Southeast Asia: 1960–2020. *iScience*, 27(8), 110498. doi:10.1016/j.isci.2024.110498
11. Intergovernmental Panel on Climate Change. (2023). *Climate change 2023: Synthesis report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (H. Lee & J. Romero, Eds.). IPCC. doi:10.59327/IPCC/AR6-9789291691647
12. Iwamura, T., Guzman-Holst, A., & Murray, K. A. (2020). Accelerating invasion potential of disease vector *Aedes aegypti* under climate change. *Nature Communications*, 11, 2130. doi:10.1038/s41467-020-16010-4
13. Kamal, M., Kenawy, M. A., Rady, M. H., Khaled, A. S., & Samy, A. M. (2018). Mapping the global potential distributions of two arboviral vectors *Aedes aegypti* and *Aedes albopictus* under changing

- climate. *PLOS ONE*, 13(12), e0210122. doi:10.1371/journal.pone.0210122
14. Kraemer, M. U. G., Sinka, M. E., Duda, K. A., Mylne, A. Q. N., Shearer, F. M., Barker, C. M., Moore, C. G., Carvalho, R. G., Coelho, G. E., Van Bortel, W., Hendrickx, G., Schaffner, F., Elyazar, I. R. F., Teng, H.-J., Brady, O. J., Messina, J. P., Pigott, D. M., Scott, T. W., Smith, D. L., Wint, G. R. W., Golding, N., & Hay, S. I. (2015). The global distribution of the arbovirus vectors *Aedes aegypti* and *Aedes albopictus*. *eLife*, 4, e08347. doi:10.7554/eLife.08347
15. Lim, A., Shearer, F. M., Sewalk, K., Pigott, D. M., Clarke, J., Ghouse, A., Judge, C., Kang, H., Messina, J. P., Kraemer, M. U. G., Gaythorpe, K. A. M., de Souza, W. M., Nsoesie, E. O., Celone, M., Faria, N., Ryan, S. J., Rabe, I. B., Rojas, D. P., Hay, S. I., Brownstein, J. S., Golding, N., & Brady, O. J. (2025). The overlapping global distribution of dengue, chikungunya, Zika and yellow fever. *Nature Communications*, 16, 3418. doi:10.1038/s41467-025-58609-5
16. Majeed, S., Akram, W., Sufyan, M., Abbasi, A., Riaz, S., Faisal, S., Binyameen, M., Bashir, M. I., Hassan, S., Zafar, S., Kucher, O., Piven, E. A., & Kucher, O. D. (2025). Climate change: A major factor in the spread of *Aedes aegypti* (Diptera: Culicidae) and its associated dengue virus. *Insects*, 16(5), 513. doi:10.3390/insects16050513
17. Muscarella, R., Galante, P. J., Soley-Guardia, M., Boria, R. A., Kass, J. M., Uriarte, M., & Anderson, R. P. (2014). ENMeval: An R package for conducting spatially independent evaluations and estimating optimal model complexity for Maxent ecological niche models. *Methods in Ecology and Evolution*, 5(11), 1198–1205. doi:10.1111/2041-210X.12261
18. Nakase, T., Giovanetti, M., Obolski, U., & Lourenço, J. (2023). Global transmission suitability maps for dengue virus transmitted by *Aedes aegypti* from 1981 to 2019. *Scientific Data*, 10, 275. doi:10.1038/s41597-023-02170-7
19. Nakase, T., Giovanetti, M., Obolski, U., & Lourenço, J. (2024). Population at risk of dengue virus transmission has increased due to coupled climate factors and population growth. *Communications Earth & Environment*, 5, 475. doi:10.1038/s43247-024-01639-6.
20. Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling*, 190(3–4), 231–259. doi:10.1016/j.ecolmodel.2005.03.026
21. Portilla Cabrera, C. V., & Selvaraj, J. J. (2020). Geographic shifts in the bioclimatic suitability for *Aedes aegypti* under climate change scenarios in Colombia. *Heliyon*, 6(1), e03101. doi:10.1016/j.heliyon.2019.e03101
22. Roberts, D. R., Bahn, V., Ciuti, S., Boyce, M. S., Elith, J., Guillera-Arroita, G., Hauenstein, S., Lahoz-Monfort, J. J., Schröder, B., Thuiller, W., Warton, D. I., Wintle, B. A., Hartig, F., & Dormann, C. F. (2017). Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography*, 40(8), 913–929. doi:10.1111/ecog.02881
23. Ryan, S. J., Carlson, C. J., Mordecai, E. A., & Johnson, L. R. (2019). Global expansion and redistribution of *Aedes*-borne virus transmission risk with climate change. *PLOS Neglected Tropical Diseases*, 13(3), e0007213. doi:10.1371/journal.pntd.0007213
24. Sintayehu, D. W., Tassie, N., & de Boer, W. F. (2020). Present and future climatic suitability for dengue fever in Africa. *Infection Ecology & Epidemiology*, 10(1), 1782042. doi:10.1080/20008686.2020.1782042
25. Thuiller, W., Georges, D., Engler, R., & Breiner, F. (2024). *biomod2: Ensemble platform for species distribution modeling* [R package].
26. Valavi, R., Elith, J., Lahoz-Monfort, J. J., & Guillera-Arroita, G. (2019). blockCV: An R package for generating spatially or environmentally separated folds for k-fold cross-validation of species distribution models. *Methods in Ecology and Evolution*, 10(2), 225–232. doi:10.1111/2041-210X.13107
27. Vergara, A. J., Valqui-Reina, S. V., Cieza-Tarrillo, D., Ocaña-Zúñiga, C. L., Hernández, R., Chapa-Gonza, S. R., Aquñivin-Silva, E. A., Fernández-Jeri, A. B., & dos Santos, A. R. (2025). Current and future spatial distribution of *Aedes aegypti* in Peru based on topoclimatic analysis and climate change scenarios. *Insects*, 16(5), 487. doi:10.3390/insects16050487
28. World Health Organization. (2024, May 30). *Dengue: Global situation*. Disease Outbreak News.