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Dengue Vector Dynamics in India: Present and Future Multi-Model Suitability under SSP Scenarios Using a Machine Learning-Based Maximum Entropy Model

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Title Page

Dengue Vector Dynamics in India: Present and Future Multi-Model Suitability under SSP Scenarios Using a Machine Learning-Based Maximum Entropy Model.

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Dengue Vector Dynamics in India: Present and Future Multi-Model Suitability under SSP Scenarios Using a Machine Learning-Based Maximum Entropy Model.

Abstract

Dengue Fever has emerged as an alarming climate-sensitive disease in India in recent time. This study examines the present and future climatic suitability of dengue transmission using a species distribution modelling (MaxEnt). High-resolution bioclimatic data of CHELSA v2.1 dataset (~1 km resolution) and georeferenced occurrence data of *Aedes aegypti* from various sources are used. Particular attention is given to data quality through spatial thinning, multicollinearity removal, and correction for sampling bias to improve model robustness.

Future projections are generated using five General Circulation Models (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, UKESM1-0-LL) under three Shared Socioeconomic Pathways (SSP) (SSP126, SSP370, SSP585) across near (2011-2040), mid (2041-2070), and far-future (2071-2100) periods. The model has shown moderate predictive performance (AUC = 0.79, TSS = 0.53), while high Boyce Index (0.9) which is indicating strong ecological consistency in identifying suitable habitats.

The results are clearly showing that more than half of India is climatically suitable for dengue transmission. Western Ghats, eastern coastal regions, and the northeastern states have higher suitability. Future projections are showing that changes are likely to occur through spatial redistribution rather than uniform expansion, which includes a gradual northward shift and localized reductions in suitability under high-emission scenarios. A comparison with reported dengue incidence further shows that substantial transmission is occuring even in areas categorised as moderately suitable, which shows that the higher suitability alone does not fully determine disease burden. Overall, the study highlights that dengue risk in India is not only a future concern but an ongoing challenge.

Keywords: Dengue; MaxEnt, Suitability, Climte Change, CHELSA v2.1 Bioclim, Policy

1. Introduction

Dengue fever has become an increasingly important mosquito-borne public health concern, caused by four genetically related serotypes of the dengue virus (DENV-1 to DENV-4) which are transmitted by *Aedes aegypti* and *Aedes albopictus* mosquitoes (Roy and Bhattacharjee, 2021; Wu et al., 2022). Vector borne diseases are major health issue globally(Desjardins et al., 2020; Harris and Carter, 2019; Mishra et al., 2023) In recent time it has evolved as a main public health issue across tropical and subtropical areas. Dengue transmission is strongly influenced by environmental factors, particularly temperature and precipitation, which affect mosquito survival, breeding patterns, and viral replication. At the same time, socio-economic factors such as urbanization, population density, land-use change, and human mobility further shape the spatial distribution of the disease (Li et al., 2021; McMichael, 2015; Mishra et al., 2023a; Patz et al., 2014; Pinto et al., 2011; Roy and Bhattacharjee, 2021; Schmidt et al., 2011; Singh and Chaturvedi, 2024; Swain et al., 2020; Wu et al., 2022). As a result, dengue` is more often seen through the lens of environmental change and public health vulnerability (Moreira et al., 2022).

At the global level, dengue has spread drastically in last few decades (Bhatt et al., 2013). As per WHO estimates that nearly 4 billion world's population is now at risk and hundreds of millions of cases coming annually (World Health Organization, 2012). Historically it was concentrated in Southeast Asia and Latin America, but it has now expanded beyond its traditional geographic limits, with increasing cases from those regions that were previously considered less suitable, which also includes previously unaffected temperate zones (Gubler, 2008; Murray et al., 2013). This expansion is widely attributed to the aggregated effect of climate change, rapid urban growth, increased human mobility, and challenges in vector control (Abbasi, 2025a; Mishra and Sahu, 2022). Temperature plays a critical role by affecting the extrinsic incubation period of the virus, whereas rainfall patterns determine the of breeding places (Liu et al., 2017). This global expansion emphasis the need for spatial assessments of disease suitability and risk forecasting.

India has a complex setting for its transmission due to its diverse climatic regimes and dense population. It is now endemic across most parts of the country, with seasonal outbreaks commonly occurring during and after the monsoon (Chakravarti et al., 2012; Mutheneni et al., 2017; Prajapati et al., 2022; Rao et al., 2019). The country's diverse climatic zones, high population density, rapid and often unplanned urbanization, water storage practices, and socio-

economic disparities contribute significantly to the persistence and spread of the disease (Khan et al., 2014; Mani et al., 2021; Mishra et al., 2023; Singh and Chaturvedi, 2024). Recent years has seen surge in cases from peri-urban, rural, and even hilly regions that were previously considered low-risk, indicating a shift in ecological suitability of the vector (Chakravarti et al., 2012; Khan et al., 2014). Variations in temperature and rainfall patterns, along with changing land-use and infrastructure development, has further influenced transmission dynamics(Abbasi, 2025b; Mutheneni et al., 2017; Pinto et al., 2011). Despite continuous surveillance and control efforts, dengue is still a major burden on India's healthcare system, affecting productivity, economic stability, and public health resilience (Pilot et al., 2019).

Species distribution models (SDMs), especially Maximum Entropy (MaxEnt) approach, have been widely used to find species suitability using presence-only data(Elith et al., 2011; Phillips et al., 2009). These SDMs have provided valuable insights but several methodological challenges are still there which include spatial sampling bias in occurrence data(Fourcade et al., 2014; Phillips et al., 2009) redundancy among environmental predictors due to multicollinearity(Dormann et al., 2013), and inconsistencies arising from temporal mismatches between species records and climatic variables (Araújo and New, 2007). If these issues are not adequately addressed, can lead to biased or inflated estimates of species suitability.

In this context, the present study is using a rigorous and refined modelling framework that integrates high-resolution climate data from CHELSA v2.1 with carefully curated occurrence records of *Aedes aegypti*. The approach incorporates spatial thinning, bias correction, and a two-stage multicollinearity assessment, along with temporal alignment between occurrence and climate datasets. These steps are intended to improve the robustness and ecological relevance of the model outputs.

The study aims to (i) assess the current climatic suitability of dengue transmission across India, (ii) evaluate how suitability may change under different future climatic scenarios using multiple climate models, and (iii) examine the extent to which modelled suitability corresponds with observed dengue incidence patterns. By combining methodological rigor with multi-model projections along with addressing the above issues, this study seeks to find more realistic understanding of dengue risk in India and to support climate-informed public health planning.

2. Study Area

India is prone to several vector-borne diseases, particularly dengue and malaria, due to its vast geographical extent, climatic diversity, and dense population. It is located between 8°4′ and

37°6′ N latitude and 68°7′ and 97°25′ E longitude, and covers about 3.29 million km², making it the 7th largest country in the world (Fig. 1). Its population is exceeding 1.46 billion and has an average density of around 492 persons per km².

Climatically, India exhibits remarkable diversity. The southern and coastal regions experience a tropical monsoon climate with high temperatures and seasonal rainfall. The western part includes the arid and semi-arid Thar Desert region, characterized by low rainfall and high evapotranspiration. Northern India largely falls under a moist mesothermal climate, marked by hot summers, cool winters, and monsoon rains. The Himalayan and northeastern regions experience alpine and montane climates, with cooler temperatures and heavy orographic rainfall. Average annual rainfall ranges from 200 mm in Jaisalmer to over 11,000 mm in Meghalaya, while mean temperatures vary from below freezing in high-altitude regions to above 45°C in central and northwestern plains during summer. The Southwest Monsoon (June–September) plays a major role in dengue transmission by creating favourable breeding conditions for *Aedes aegypti* through increased moisture availability and stagnant water accumulation.

The wide climatic diversity and expanding dengue incidence across urban, peri-urban, and hilly regions make India an important region for assessing present and future climatic suitability of it.

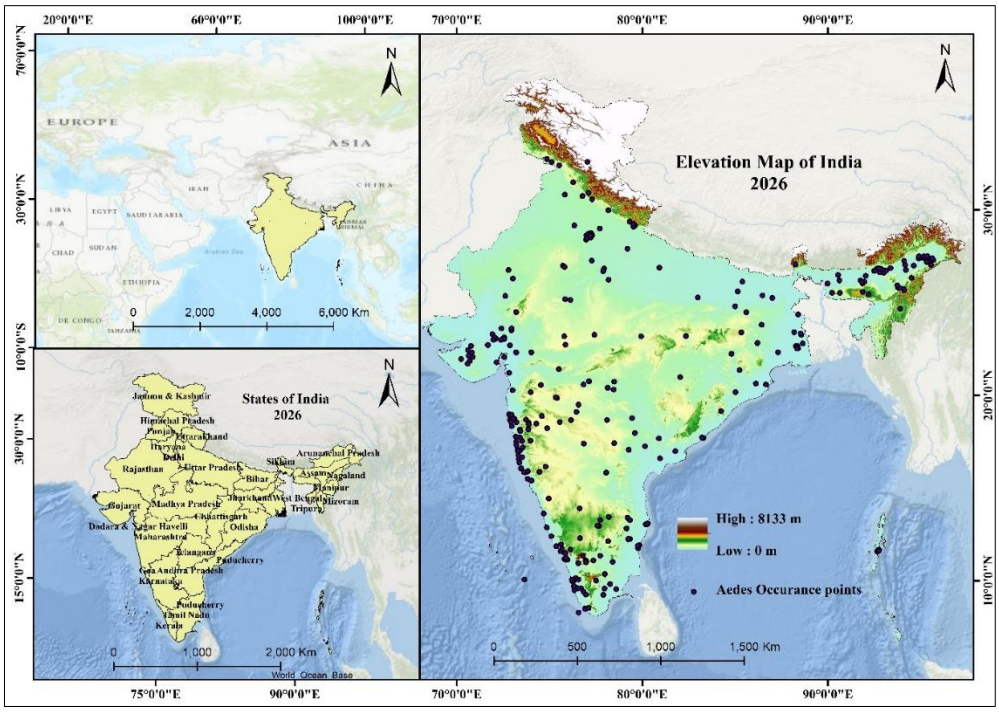


Fig 1. Map of study area.

3. Data sets and Methodology

3.1. Environmental Predictors

Bioclimatic variables are taken from the CHELSA v2.1 (Climatologies at High Resolution for the Earth's Land Surface Areas) with spatial resolution of 30 arc-seconds (~1 km at the equator). CHELSA data is selected because of its improved representation of topographic influences and precipitation patterns, particularly in climatically heterogeneous regions such as India (Karger et al., 2022).

Historical climate data corresponding to the period 1981–2010 were used as the baseline for present-day suitability assessment. Future climatic projections are downloaded for 5 General Circulation Models (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL) under three SSPs (SSP126, SSP370, and SSP585). Projections are analysed for three future periods: near future (2011–2040), mid-century (2041–2070), and far future (2071–2100) (Brun et al., 2022a; Brun et al., 2022b). To reduce uncertainty associated with individual climate models, multiple GCMs were incorporated to evaluate the consistency of projected suitability patterns across scenarios.

3.2. Species Occurrence Data and Pre-processing

Occurrence records of *Aedes aegypti*, are primarily compiled from the Global Biodiversity Information Facility (GBIF), including datasets derived from Kraemer et al (2015). Additional occurrence points were collected from Integrated Disease Surveillance Programme (IDSP) and peer-reviewed research articles from Scopus, Science direct and PubMed, only those studies were added that were having exact coordinates and date as well.

To maintain consistency between species occurrence and climatic baseline conditions, only records parallel to the bioclimatic datasets (1981–2010) are considered for model calibration. Species records which have missing coordinates and spatially ambiguous were excluded during preprocessing. Occurrence data was further cross-checked with historical dengue reporting patterns from the National Centre for Vector Borne Diseases Control (NCVBDC) to ensure broader geographic representation across India. This step was included to reduce excessive clustering of occurrence points in a few intensively sampled regions and include those areas which have higher cases but less samples in GBIF records to improve the ecological realism of the suitability model.

3.3 Data processing

Model Calibration and Bias Correction

Preprocessing of data was carried out to minimise sampling bias and enhance model reliability (Fig. 2). First, spatial thinning was applied to the occurrence dataset using a 5 km^2 filtering area to minimize spatial autocorrelation and overrepresentation of densely sampled locations. After thinning, the number of occurrence records was reduced substantially (from 860 to 468 records), resulting in a more spatially balanced dataset. To further account for uneven sampling intensity, a bias surface was generated using Kernel Density Estimation (KDE). The bias raster was used in model calibration to reduce the influence of clustered occurrence records and to improve the representation of environmentally suitable areas.

Multicollinearity among the 19 bioclimatic variables was assessed using a two-stage procedure. Initially, Pearson correlation analysis was performed to identify highly correlated variable pairs ($|r| > 0.75$) (Figure S1). Subsequently, Variance Inflation Factor (VIF) analysis was applied using a threshold of $VIF < 5$ (Table 1) to retain variables with lower redundancy. Variable selection was guided not only by statistical criteria but also by ecological relevance to dengue transmission dynamics. After testing all possible combinations, eight variables were identified as the upper limit, with only 60 unique eight-variable combinations meeting the statistical selection criteria.

These combinations were then subjected to an ecological curation process and 10 combinations were finalised (Table S1) among them 1 combination was selected that prioritized the monsoon-driven life cycle of the *Aedes* mosquito, and have higher AUC value (Figure S2)(Nakase et al., 2023). The final Primary Monsoon-Driven Suitability Model(Liu et al., 2020) incorporated mean diurnal temperature range (Bio02), isothermality (Bio03), maximum temperature of the warmest month (Bio05), precipitation of the wettest month (Bio13), precipitation of the driest month (Bio14), precipitation seasonality (Bio15), precipitation of the warmest quarter (Bio18), and precipitation of the coldest quarter (Bio19). These variables collectively represent thermal conditions, seasonal rainfall variability, and monsoonal moisture availability that are known to influence the survival and distribution of Aedes aegypti. This combination balance both temperature and rainfall factors and make suitability more realistic.

Table 1. Assessment of Redundancy among Bioclimatic Predictors via VIF Analysis

Variables	VIF
India_bio02	1.725951
India_bio03	1.8679
India_bio05	3.35378
India_bio13	4.137654
India_bio14	2.531639
India_bio15	4.006991
India_bio18	3.313524
India_bio19	1.897026

Predictive MaxEnt Modelling

Climatic suitability modelling for *Aedes aegypti* was carried out using the MaxEnt algorithm v3.4.4, which is widely applied in species distribution modelling for presence-only datasets. (Phillips et al., 2006, 2004; Phillips and Dudík, 2008). It does species distribution modelling using Bayes' theorem while constraining complexity to avoid overfitting(Elith et al., 2011b). The probability of species presence given environmental covariates is expressed in equation 1 as:

$$P(y = 1|x) = \frac{P(x|y=1)P(y=1)}{P(x)} \quad (1)$$

Where P(y = 1 | x) denotes the probability of species presence in given environmental conditions x, P(x | y = 1) represents environmental conditions at presence locations, P(y = 1) is the overall probability of occurrence, and P(x) describes the distribution of environmental conditions across the study area (background).However, $P(y = 1 \mid x)$cannot be directly estimated due to the absence of reliable absence data. To address this, MaxEnt shifts the problem to estimate the environmental signature of known occurrences, and contrasts it against background conditions(Phillips et al., 2004).This estimation is achieved by defining a Gibbs distribution over environmental space:

$$q_\lambda(x) = \frac{\exp\left(\sum_{i=1}^{n} \lambda_i f_i(x)\right)}{Z_\lambda} \quad (2)$$

where $f_i(x)$are feature functions derived from environmental predictors, λ_i are their weights, and $Z_\lambda$is a normalization constant.The optimal set of parameters $\lambda_i$is obtained by maximizing entropy, following the principle of Shannon entropy (eq. 3), which quantifies the degree of randomness, and the maximum entropy principle selects the least biased distribution consistent with known constraints (Phillips et al., 2006).

$$H(\hat{\pi}) = -\sum_{x \in X} \hat{\pi}(x) ln \hat{\pi}(x) \quad (3)$$

Here, $\pi$is the unknown true distribution over a finite set X, and $\hat{\pi}(x)$is its estimated probability for element $x \in X$, with probabilities summing to 1. The summation runs over all elements of X, and lndenotes the natural logarithm

Model calibration and tuning are performed using the ENMeval 2.0 package to reduce overfitting and improve model generalization. Different combinations of feature classes and regularization multiplier (RM) values were evaluated systematically. Feature class combinations included Linear (L), Linear-Quadratic (LQ), Hinge (H), Linear-Quadratic-Hinge (LQH), and Linear-Quadratic-Hinge-Product-Threshold (LQHPT), while RM values ranged from 0.5 to 4.0. Model selection was based on Akaike Information Criterion corrected for small sample size (AICc). The LQH feature combination with a regularization multiplier of 1 produced the best balance between model complexity and predictive performance and was therefore selected for final modelling.

The final model generated climatic suitability values varying from 0 to 1, where larger values indicate higher environmental suitability for *Aedes aegypti*. Suitability outputs were subsequently classified into unsuitable (<0.2467), moderately suitable(0.2467–0.5015) and highly suitable (>0.5015) categories using threshold values derived from the 10th percentile training presence threshold (<0.2467) and maximum training sensitivity plus specificity criterion (0.5015) (Hirzel et al., 2006). Unsuitable regions in map does not mean that *Aedes aegypti* cannot occur there it just means that probability of occurrence is low.

Additionally, linear regression analysis was also performed to examine the trend consistency of dengue accross India to asses its coming threat and importance of research on it. The coefficient of determination (R^2) was used to assess the extent to which climatic suitability corresponded with observed dengue case patterns (Figure S3).

3.4 Model Validation

The performance of this model is evaluated using three metrics which are Area Under the Receiver Operating Characteristic Curve (AUC), True Skill Statistic (TSS), and Boyce Index. AUC is used to assess the overall discriminatory ability of the model, while TSS provided an estimate of classification accuracy by considering both sensitivity and specificity. Presence-only models may sometimes produce inflated AUC values that why the Boyce Index was additionally calculated to evaluate the ecological reliability of predicted suitability patterns(Hirzel et al., 2006). The relative contribution of environmental variables is examined using Jackknife analysis and permutation importance. In addition, 10-fold cross-validation is performed to assess model robustness and reduce the influence of sampling variability.

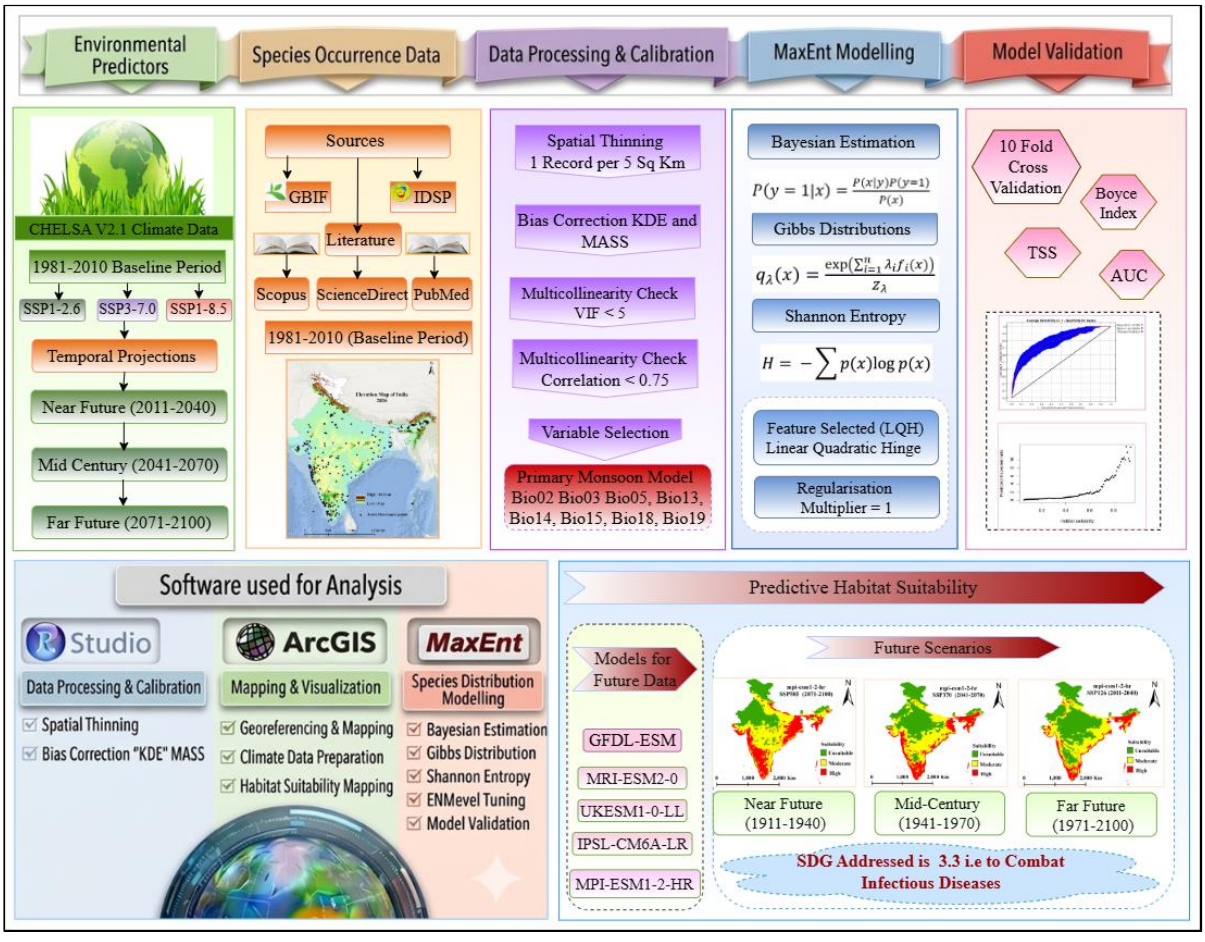


Fig. 2. Methodological flow work

4. Results and Discussion

4.1 Model performance

The model has shown satisfactory performance in predicting the climatic suitability of *Aedes aegypti* across India. The mean AUC value obtained from the 10-fold cross-validation is 0.79, indicating that the model was able to distinguish reasonably well between suitable and unsuitable environmental conditions (Figure S4; Figure S10). The TSS value of 0.53 also suggested moderate predictive ability. The Boyce Index value is comparatively high (0.90), indicating that the predicted suitability pattern was ecologically consistent with the observed occurrence distribution of the species (Figure S5).

Jackknife analysis is showing that Bio02 contributed the most unique information to the model, as its exclusion resulted in the largest reduction in training gain (Figure S6). In contrast, Bio05 has the highest gain when used independently, indicating strong standalone predictive ability. Precipitation-related variables have also shown relatively high gains when used alone, suggesting that both thermal variability and monsoonal precipitation play important roles in deciding the climatic suitability of *Aedes aegypti*. The Jackknife analyses based on AUC and test gain (Figure S7; Figure S8) displayed consistent trends which are confirming the dominant influence of thermal variability and peak monsoonal precipitation on the modelled distribution.

Among the selected predictors, Bio02 contributed most strongly to the model, followed by Bio03 and Bio13, indicating the dominant influence of temperature variability and wet-season precipitation on suitability patterns (Table 2). In comparison, Bio18 and Bio19 showed relatively smaller contributions to the final model output.

Table 2. Contribution and permutation importance of environmental predictors.

Variable	Percent contribution	Permutation importance
Bio02	44.3	28.1
Bio03	21.1	10.9
Bio13	12.9	29.3
Bio14	11.6	7.8
Bio18	5.1	3.8

Bio05	2.1	5
Bio15	1.9	11.5
Bio19	0.8	3.5

292

293 **4.2 Climatic Niche Responses of Aedes aegypti**

294 The response curves showed that the climatic suitability of *Aedes aegypti* in India is closely
295 linked with temperature stability and seasonal rainfall conditions (Fig. 3).

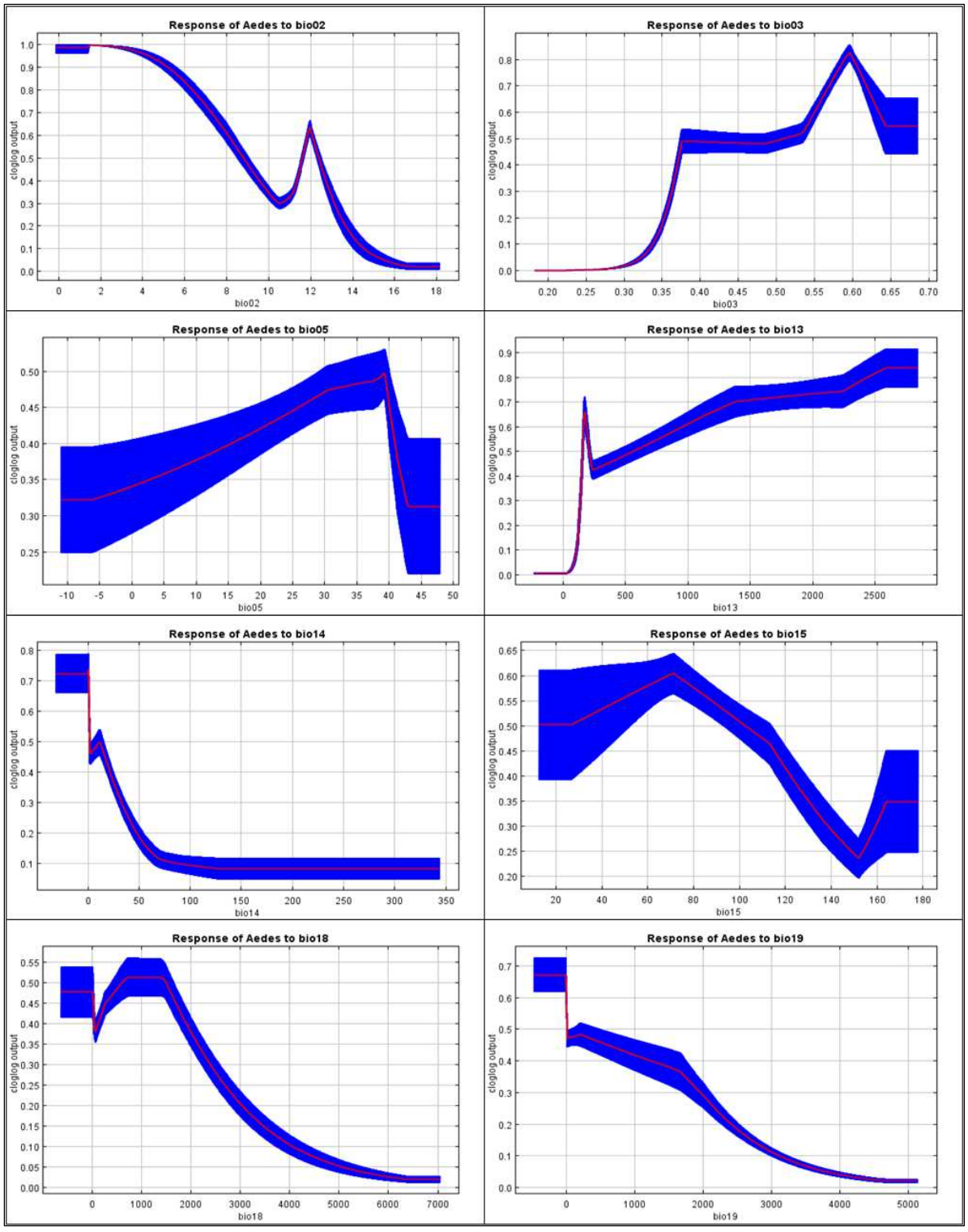


Fig.3. Climatic Response Curves of Dominant Predictors

Suitability remained highest (>0.90) under lower mean diurnal temperature range (Bio02 <4-6 °C) and declined progressively beyond ~12 °C, reaching <0.10 at 16–18 °C, which is suggesting that relatively stable thermal conditions favour vector survival (Ehelepola &

Ariyaratne, 2015). A positive relationship was also observed with isothermality (Bio03 <0.05 at ~25–30% to >0.75 at 55–60%), indicating that regions with less fluctuation in temperature are more suitable for the species. Maximum temperature of the warmest month (Bio05) has shown optimum suitability within an approximate range of 30–38°C, after which suitability gradually declined. This pattern suggests that extremely high temperatures may impose thermal stress on vector survival and persistence (Trejo et al., 2023 ; Wang et al., 2022).

In case of precipitation-related variables, suitability increased with higher precipitation during the wettest month (Bio13), from <0.05 at <50 mm to ~0.70–0.85 at 2000–2600 mm, reflecting the importance of monsoonal rainfall in supporting breeding habitats. However, suitability declined under extremely high rainfall conditions which is possibly due to the flushing of immature stages from breeding sites (Dieng et al., 2012; Koenraadt and Harrington, 2008). Precipitation seasonality (Bio15) indicated relatively higher suitability under moderate seasonal variability, whereas highly erratic rainfall conditions appeared less favourable.

Collectively, the response curves indicate that *Aedes aegypti* is favoured under warm and thermally stable conditions with moderate-to-high monsoonal rainfall, while excessive heat and highly variable precipitation conditions may reduce climatic suitability. Additionally univariate MaxEnt response curves (Figure S9) largely supported the dominant influence of BIO02 and BIO13, although some precipitation variables exhibited altered response shapes, indicating covariance effects within the full multivariate model.

4.3 Baseline Climatic Suitability (1980–2010)

The base period (1980–2010) is used as reference to suitability landscape against future projections for *Aedes aegypti* distribution. Approximately 43.41% of the country is classified as unsuitable (low suitable), while 38.10% and 18.49% fell under moderate and high suitability categories, respectively (Table S2).

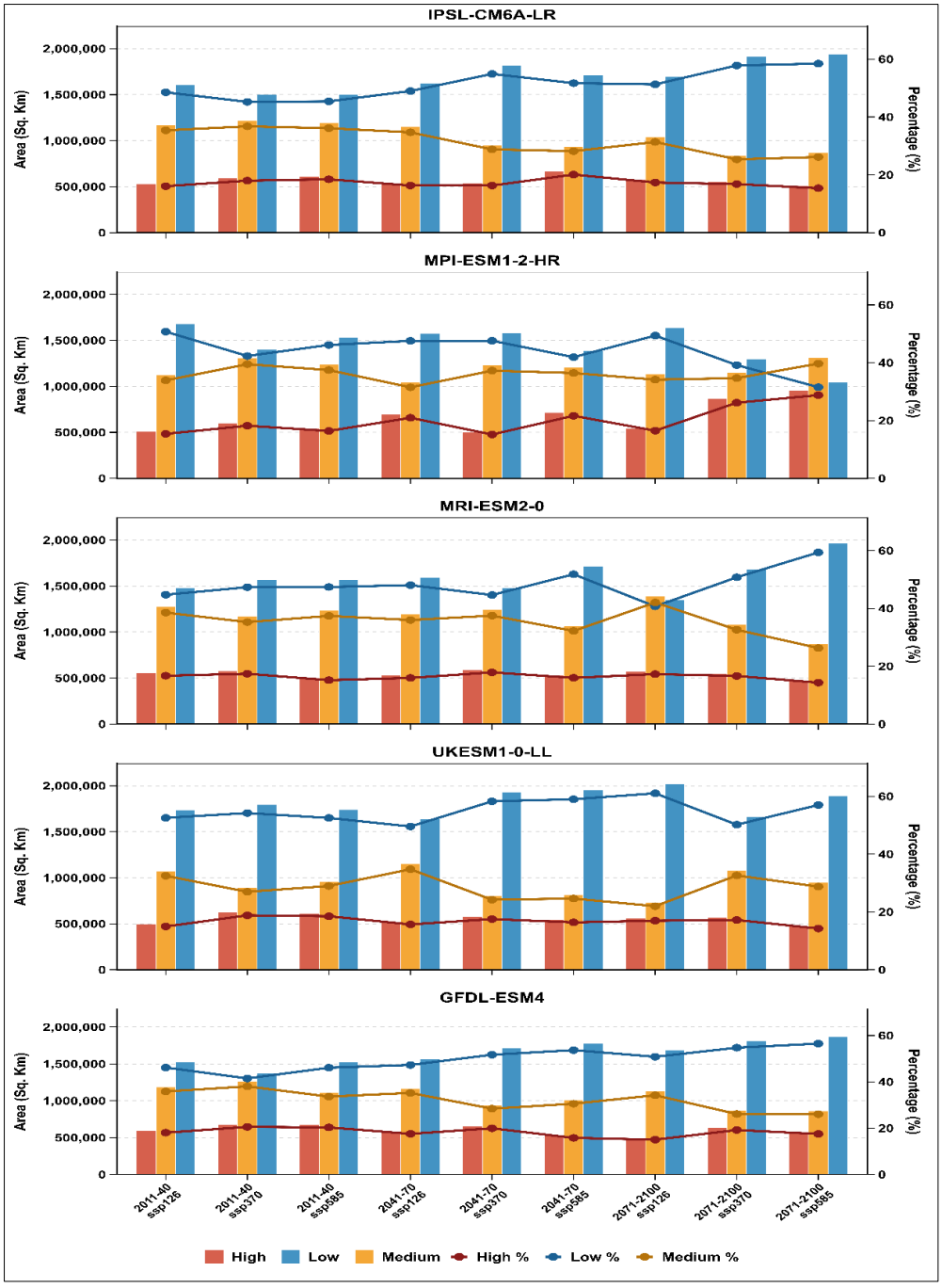
Spatially, highly suitable regions are concentrated along the Western Ghats, eastern coastal plains, and the northeastern states. These regions are characterized by warm temperatures, high humidity, and substantial monsoonal rainfall, which collectively support vector survival and breeding (Cardoso-Leite et al., 2014). In contrast, large parts of Rajasthan, central interior regions, and trans-Himalayan areas showed relatively lower suitability, likely due to extreme temperatures and limited moisture availability (Shah et al., 2022; Varamballi et al., 2024).

4.4 Future Climatic Suitability and Inter-model Variability

Future projections showed noticeable changes in the climatic suitability of *Aedes aegypti* across India under different SSP scenarios and climate models (Fig. 4–9, Table S2). However, the changes were not spatially uniform, and most projections indicated redistribution of suitable regions rather than continuous nationwide expansion.

Under SSP126, high suitability remained broadly comparable to the baseline (18.49%) across most models through the near- and mid-century, reflecting the limited climatic forcing under aggressive mitigation (Table S2). GFDL-ESM4 recorded the highest near-future high suitability under this scenario (18.04%), while MPI-ESM1-2-HR peaked at mid-century (20.95%), both marginally above baseline (Table S2). By 2071–2100, high suitability declined in most models, with UKESM1-0-LL recording the most pronounced contraction — unsuitable area expanding to 61.03% with moderate suitability falling to 22.00% (Fig.4), suggesting that under this model's climate sensitivity, aggressive mitigation could substantially reduce India's dengue suitability footprint by the end of the century. MRI-ESM2-0 diverged from this pattern, with moderate suitability expanding to 42.04% by the far-future - the highest moderate-zone proportion across the entire ensemble, indicating redistribution toward intermediate rather than high-risk habitat under constrained warming.

More pronounced changes emerged under the intermediate emissions pathway (SSP370). Several models projected expansion of moderate-to-high suitability zones during the mid- and late-century periods. Among the selected models, MPI-ESM1-2-HR showed the strongest increase in highly suitable area, reaching approximately 26.16% by the far-future period, accompanied by a reduction in unsuitable regions (Fig. 4 and Fig. 6). UKESM1-0-LL and GFDL-ESM4 also projected gradual expansion toward northern and northwestern India (Fig. 8 and Fig. 9), including parts of the sub-Himalayan belt and Indo-Gangetic Plain. These patterns indicate that intermediate warming conditions may increase climatic favourability for vector persistence in regions that are currently less suitable.



358 Fig 4. Quantitative Assessment of Climate-Driven Shifts in Suitability Zones (1980–2100)

Under the high-emissions fossil-fueled pathway (SSP585), the ensemble bifurcated sharply. IPSL-CM6A-LR, MRI-ESM2-0, and UKESM1-0-LL all showed a mid-century peak in high suitability followed by far-future contraction, with MRI-ESM2-0 and UKESM1-0-LL recording the lowest far-future high suitability values in the entire study at 14.33% and 14.27% respectively, accompanied by unsuitable area exceeding 59% in both models. This non-monotonic trajectory- expansion followed by contraction- is consistent with the thermal overshooting mechanism described by Zhang et al (2023), wherein sustained high emissions progressively push temperatures beyond the thermal ceiling of *Aedes aegypti*, eventually suppressing rather than enhancing suitability. MPI-ESM1-2-HR, however, showed the opposite trajectory under SSP585, with high suitability expanding progressively to 28.78% by 2071–2100 — the highest value recorded across the entire study — and unsuitable area

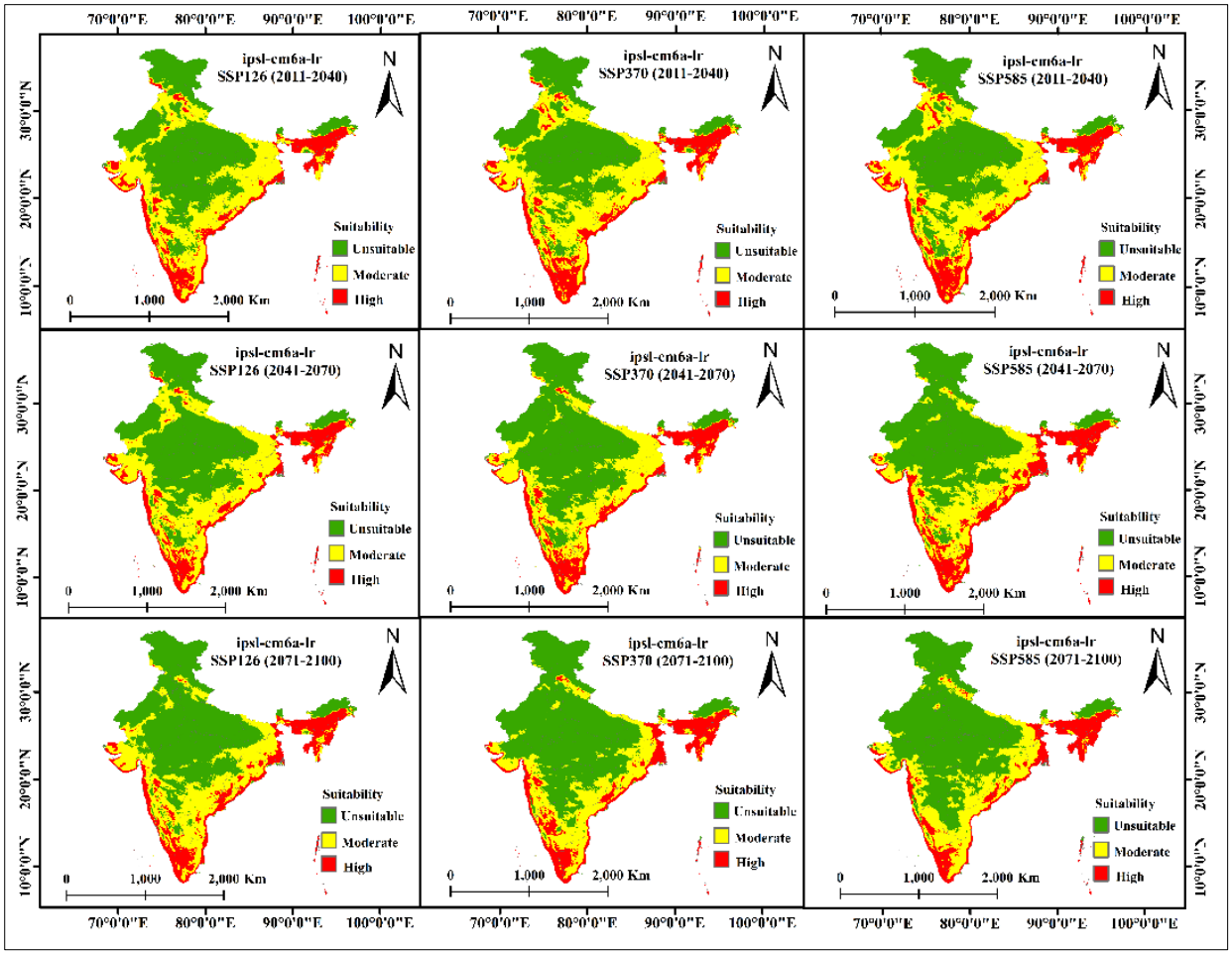


Fig. 5. Spatiotemporal projections of *Aedes aegypti* suitability in India (2011–2100) across SSP126, SSP370, and SSP585 scenarios under IPSL-CM6A-IR model.

contracting to just 31.53%, the lowest recorded. This divergence reflects fundamental differences in how these models represent South Asian monsoon intensification under high

forcing: MPI-ESM1-2-HR projects warming that remains within vector thermal optima alongside enhanced monsoon precipitation, while MRI-ESM2-0 and UKESM1-0-LL project absolute temperature increases that breach the species' upper thermal threshold. The resulting spread of 14.45 percentage points between the highest and lowest far-future high suitability estimates under SSP585 encapsulates the irreducible uncertainty in India's long-term dengue suitability trajectory under fossil-fuelled development.

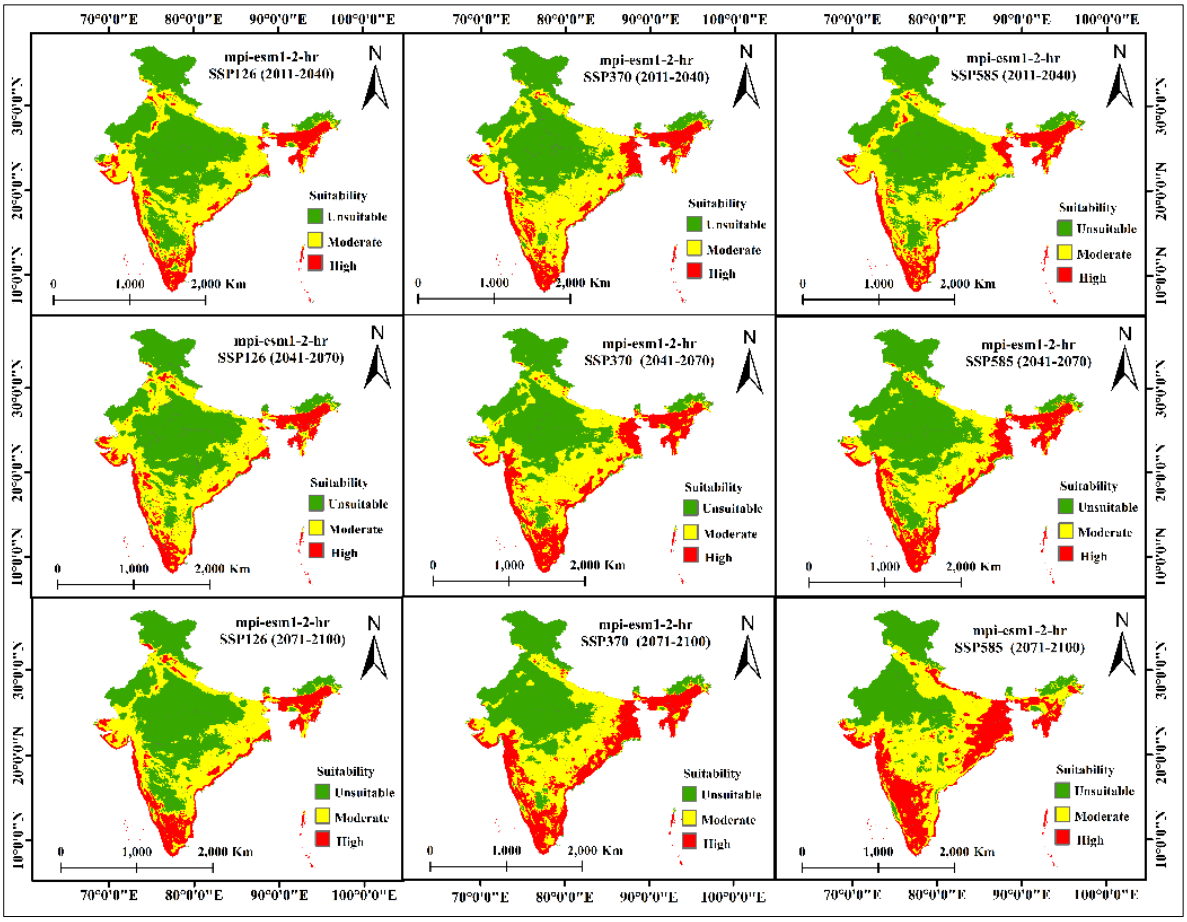


Fig. 6. Spatiotemporal projections of *Aedes aegypti* suitability in India (2011–2100) across SSP126, SSP370, and SSP585 scenarios under MPI-ESM-2-HR model.

A particularly notable finding is the reversal of the expected scenario ordering in the far-future. In three of five models- MRI-ESM2-0, UKESM1-0-LL, and IPSL-CM6A-LR- SSP585 produced lower high suitability than SSP370 or SSP126 by 2071–2100, directly contradicting the assumption that higher emissions uniformly translate to greater dengue risk. This pattern suggests that beyond certain thermal thresholds, further warming may reduce climatic suitability for *Aedes aegypti* rather than enhance it. The contrasting responses among models highlight the complexity of future dengue suitability projections and indicate that the

relationship between climate forcing and vector suitability is unlikely to be strictly linear under long-term warming scenarios.

Spatially, despite inter-model disagreement in magnitude, several patterns were consistent across all five GCMs and all three scenarios (Fig. 5-9). The northeastern states, Western Ghats corridor, and eastern coastal plains of Odisha and Andhra Pradesh retained high suitability throughout the century under all model-scenario combinations, identifying these as climatically stable transmission zones irrespective of emission pathway- a finding consistent with established vector ecological preferences for warm, humid, precipitation-rich environments (Shah et al., 2022; Varamballi et al., 2024). Along with this consistent northward displacement of the high-suitability envelope, with sub-Himalayan foothills of Uttarakhand, Himachal Pradesh, and the Punjab-Haryana belt showing progressive encroachment of moderate-to-high suitability from mid-century onward under SSP370 and SSP585. This is consistent with the latitudinal expansion of dengue vector ranges globally (Varamballi et al., 2024) and the altitudinal upslope shift of dengue climatic niche in Nepal, where the upper altitudinal limit of

suitability was projected to reach 1,400 m above sea level by 2070 under RCP 8.5 (Acharya et al., 2018).

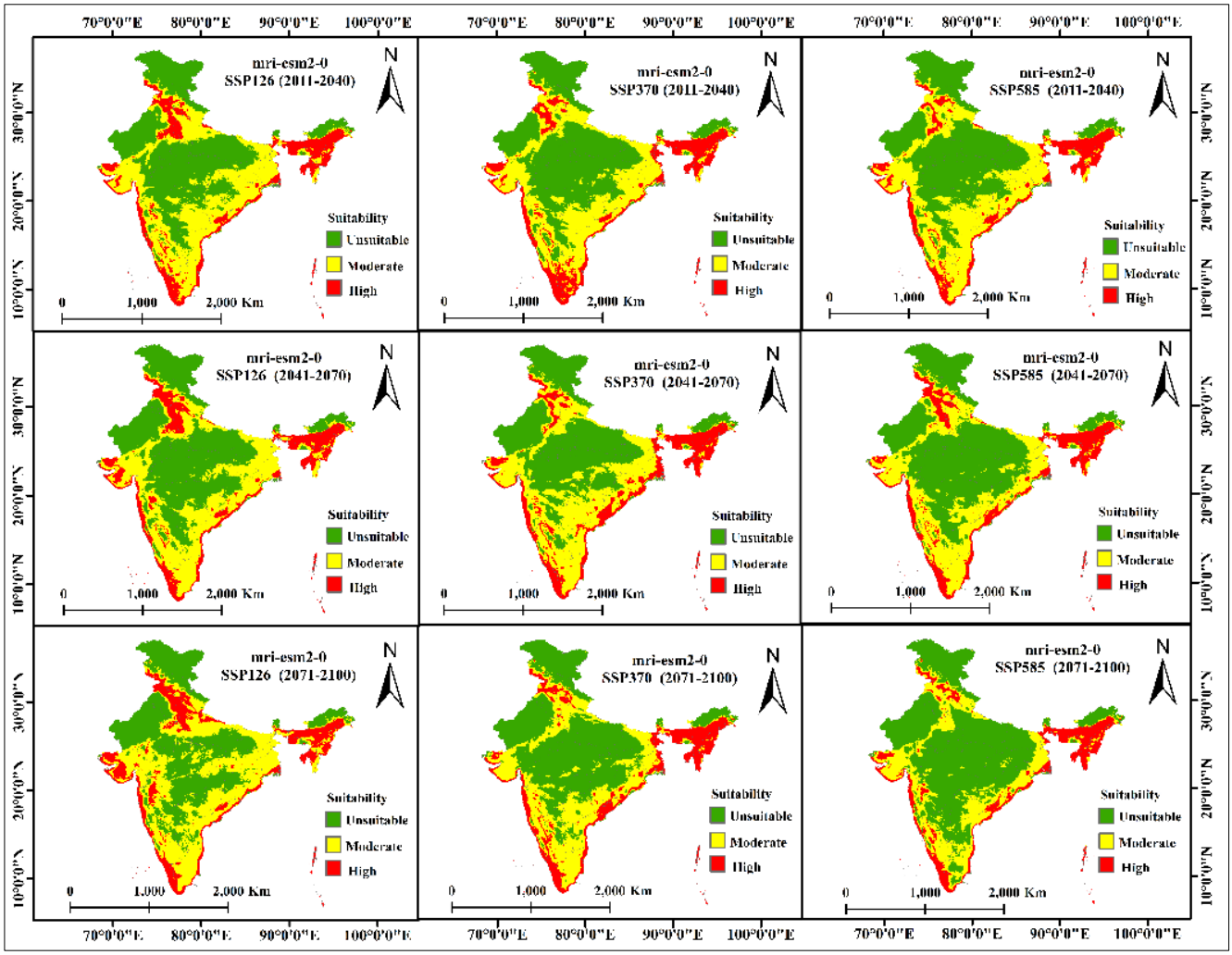


Fig. 7. Spatiotemporal projections of *Aedes aegypti* suitability in India (2011–2100) across SSP126, SSP370, and SSP585 scenarios under MRI-ESM2-0 model.

Interestingly, models are showing retraction of high suitability from the Deccan plateau-specifically the Karnataka plateau, Telangana interior, and parts of interior Tamil Nadu and Maharashtra - under SSP585 in the mid- to far-future, differing only in magnitude to moderate suitability. This is possiblily driven by maximum temperatures increasingly exceeding vector

thermal tolerance in this already hot interior and points to redistribution of dengue risk away from the interior toward coastal and northern margins.

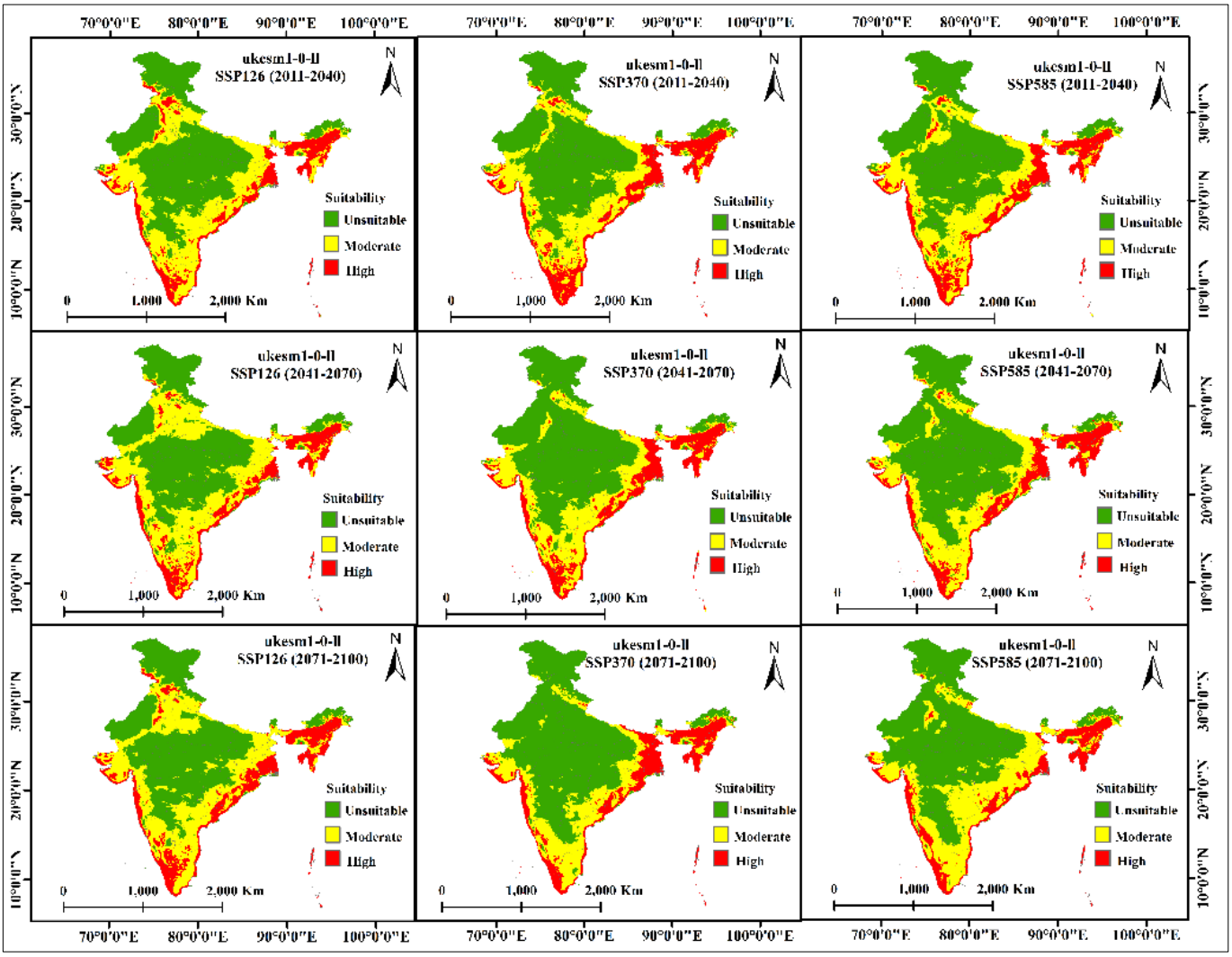
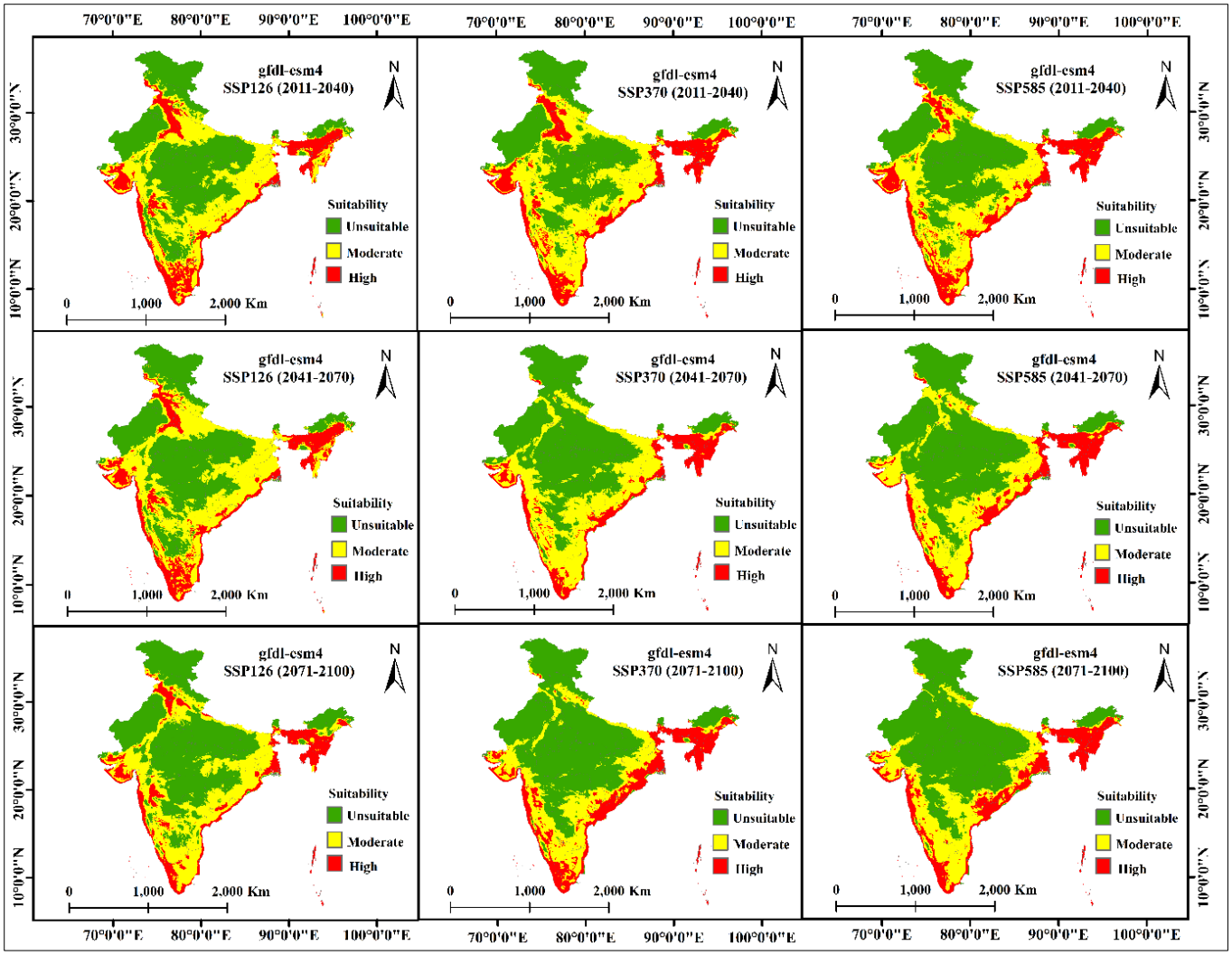


Fig. 8. Spatiotemporal projections of *Aedes aegypti* suitability in India (2011–2100) across SSP126, SSP370, and SSP585 scenarios under UKESM1-0- II model.

The greatest spatial disagreement among models concerned western Rajasthan and central India. MPI-ESM1-2-HR projected suitability gains in the Thar Desert fringe driven by projected monsoon intensification, whereas MRI-ESM2-0 and UKESM1-0-LL projected progressive unsuitability expansion into these same regions under SSP585 through extreme heating. Similarly, MPI-ESM1-2-HR showed expanding suitability across Madhya Pradesh, Chhattisgarh, and Jharkhand through the far-future (Varamballi et al., 2024), while IPSL-CM6A-LR and MRI-ESM2-0 projected the opposite, driven by divergent representations of precipitation seasonality over the central Indian plateau. Central India thus emerges as the zone of maximum model uncertainty for future dengue risk, where the direction of change remains genuinely unresolved across the ensemble.



425 Fig. 9. Spatiotemporal projections of *Aedes aegypti* suitability in India (2011–2100) across
426 SSP126, SSP370, and SSP585 scenarios under GFDL-ESM4 model.

427 **4.5 Dengue Incidence Trends and Suitability Cross-Validation**

428 Analysis of state-wise dengue incidence from 2001 to 2025 (Figure S3, Table S3) from
429 NCVBDC(https://ncvbdc.mohfw.gov.in/index4.php?lang=1&level=0&linkid=431&lid=3715)
430 reveals a strong and sustained upward trend at the national level (R^2=0.703), which is indicating
431 a consistent increase in dengue burden across India over the past two decades. Maharashtra
432 (R^2=0.748), Andhra Pradesh (R^2=0.688), Odisha (R^2=0.541), Rajasthan (R^2=0.548), and
433 Sikkim (R^2=0.542) has recorded the strongest temporal increases, while Arunachal Pradesh
434 (R^2=0.03), Lakshadweep (R^2=0.008), and Nagaland (R^2=0.104) has shown weak trends, which
435 is likely reflecting a combination of genuinely low transmission and chronic underreporting in
436 geographically remote areas. When these incidence trends are cross-referenced with modelled
437 suitability zones, a particularly important pattern emerges. States such as Rajasthan, Punjab (R^2
438 = 0.499), Uttar Pradesh (R^2 = 0.485), and Bihar (R^2 = 0.396), which are dominated largely by

low-to-moderate suitability conditions, still reported substantial and steadily increasing dengue cases over the study period. This suggests that high climatic suitability is not essential for sustained dengue transmission. Local factors such as rapid urban expansion, water storage practices, population density, and inadequate vector control can support active transmission even in regions that are only marginally suitable climatically(Li et al., 2021; Rahman et al., 2021; Schmidt et al., 2011). In contrast, states with persistently higher climatic suitability, including Karnataka ($R^2 = 0.498$), Kerala ($R^2 = 0.439$), and Maharashtra, generally recorded greater overall case intensity, indicating that climatic suitability may influence the magnitude of transmission more strongly than its mere occurrence.

These results have important insights for dengue risk management in India. Public health strategies focused exclusively on highly suitable climatic zones may overlook a critical share of the existing disease burden occurring in moderate suitability regions. Even under present climatic conditions, many of these areas already experience a heavy transmission pressure. This concern becomes more relevant in light of the SSP370 projections, which indicate sustained or expanding suitability across several already-affected regions of the country and this scenario is possibly more close to reality in future. The results therefore highlight the need for climate-sensitive public health planning that extends beyond traditional hotspot regions and prioritizes pre-monsoon preparedness, vector surveillance, elimination of artificial breeding habitats, and improved local-level control measures across both moderate- and high-suitability zones. Overall, the findings support immediate, climate-sensitive public health planning that integrates meteorological monitoring with localized vector control to reduce existing transmission risk.

4.6 Limitations of the Study

Although the study provides a detailed assessment of present and future climatic suitability for *Aedes aegypti* in India, several limitations should be acknowledged. First, the modelling framework primarily focuses on climatic controls and does not explicitly incorporate socio-economic, demographic, land-use, or urbanization-related variables that may influence dengue transmission at local scales. Factors such as population density, water storage behaviour, sanitation conditions, and vector control practices can substantially modify outbreak dynamics even within climatically less suitable regions.

Second, the analysis was based on the distribution of *Aedes aegypti* as a proxy for dengue suitability and did not explicitly account for the role of *Aedes albopictus*, which also contributes to dengue transmission in several parts of India, particularly across the northeastern states and sub-Himalayan belt (Hussain & Dhiman, 2022). Inclusion of both vector species may provide a more comprehensive understanding of future transmission risk.

The future projections are also subject to uncertainty associated with General Circulation Models and emission scenarios. Considerable differences among climate models, especially under SSP585 during the far-future period, indicate that long-term suitability patterns remain sensitive to projected warming intensity and precipitation variability. Finally, climatic suitability should not be interpreted as a direct estimate of dengue incidence. The occurrence and intensity of outbreaks are shaped by complex interactions among climate, vector ecology, human behaviour, healthcare access, and public health interventions. Therefore, the projected suitability patterns presented here should be interpreted as potential climatic favourability for vector persistence rather than direct forecasts of future disease burden.

5. Conclusion

The present study assessed the current and future climatic suitability of Aedes aegypti across India using a MaxEnt-based modelling framework integrated with high-resolution CHELSA climate data and multiple CMIP6 climate projections. This modelling approach has incorporated spatial thinning, bias correction, temporal matching of occurrence and climate data, and multicollinearity assessment to improve the reliability of suitability estimates. The results are showing that a large part of India is already climatically suitable for dengue vector, particularly across the Western Ghats, eastern coastal plains, and northeastern states.

Future projections are showing that climatic suitability for dengue is likely to undergo considerable spatial redistribution under changing climate conditions. While several models projected expansion of suitability toward northern and sub-Himalayan regions, others indicated declining suitability across parts of central and peninsular India under extreme warming scenarios. The contrasting responses among climate models highlight the importance of considering inter-model variability and suggest that the relationship between future warming and dengue suitability may not remain uniformly positive under all climatic conditions.

The comparison between modeled suitability and observed dengue incidence further showed that significant transmission can occur even within moderately suitable regions, indicating that

climatic suitability alone does not fully determine disease burden. Local environmental conditions, urbanization patterns, population density, and public health infrastructure also play important roles in shaping transmission dynamics.

Overall, the findings suggest that dengue risk in India should be viewed as an ongoing and spatially evolving public health challenge rather than only a future climate-related concern. Strengthening surveillance, vector management, and climate-informed public health planning across both high- and moderate-suitability regions will be important for reducing future dengue vulnerability under changing climatic conditions.

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Anil Kumar: Methodology and Data curation, Formal analysis and investigation, Visualization, Writing - original draft preparation, Writing - review and editing.

Ankita Chakraborty: Formal analysis and investigation, Visualization, Writing - review and editing.

Anisha Choudhury: Formal analysis and investigation, Visualization.

554 **Sonal Kumari:** Visualization, Writing - review and editing.

555 **Netrananda Sahu:** Formal analysis and investigation, Writing - review and editing.

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