

Supplementary Materials

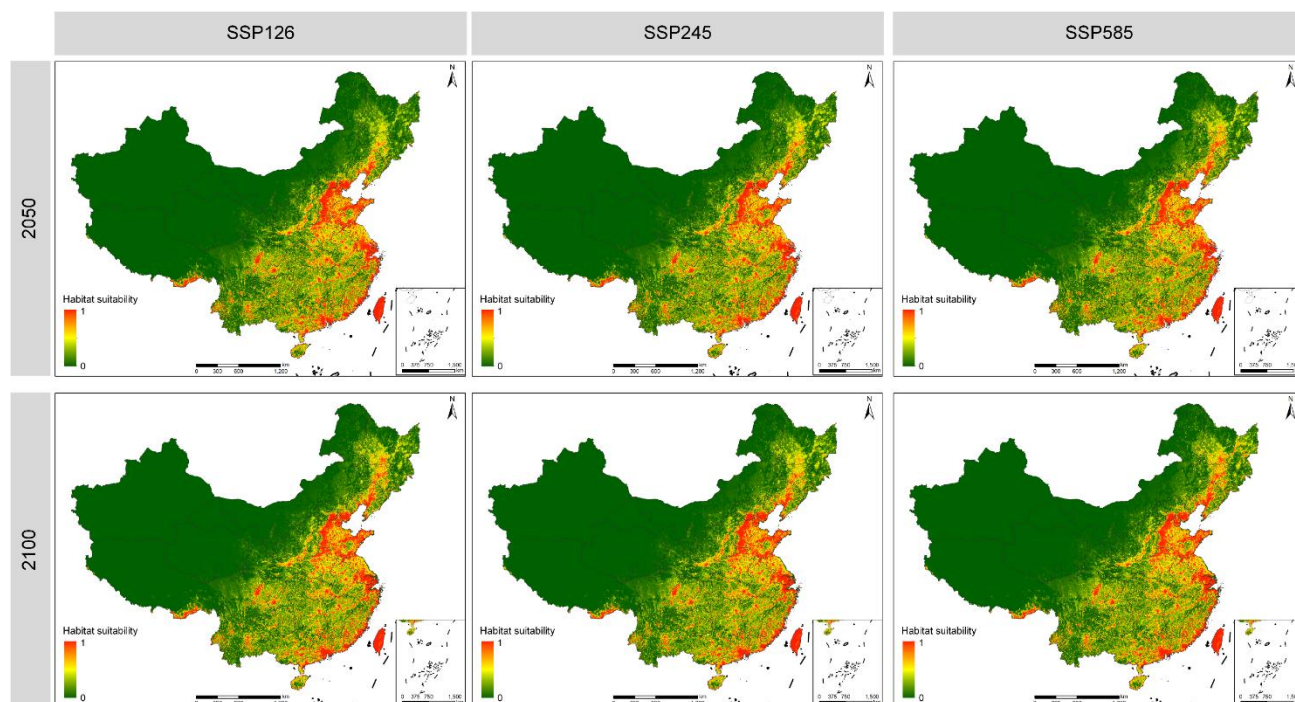
Climate and socioeconomic factors drive heterogeneous dengue risk escalation in the Chinese population

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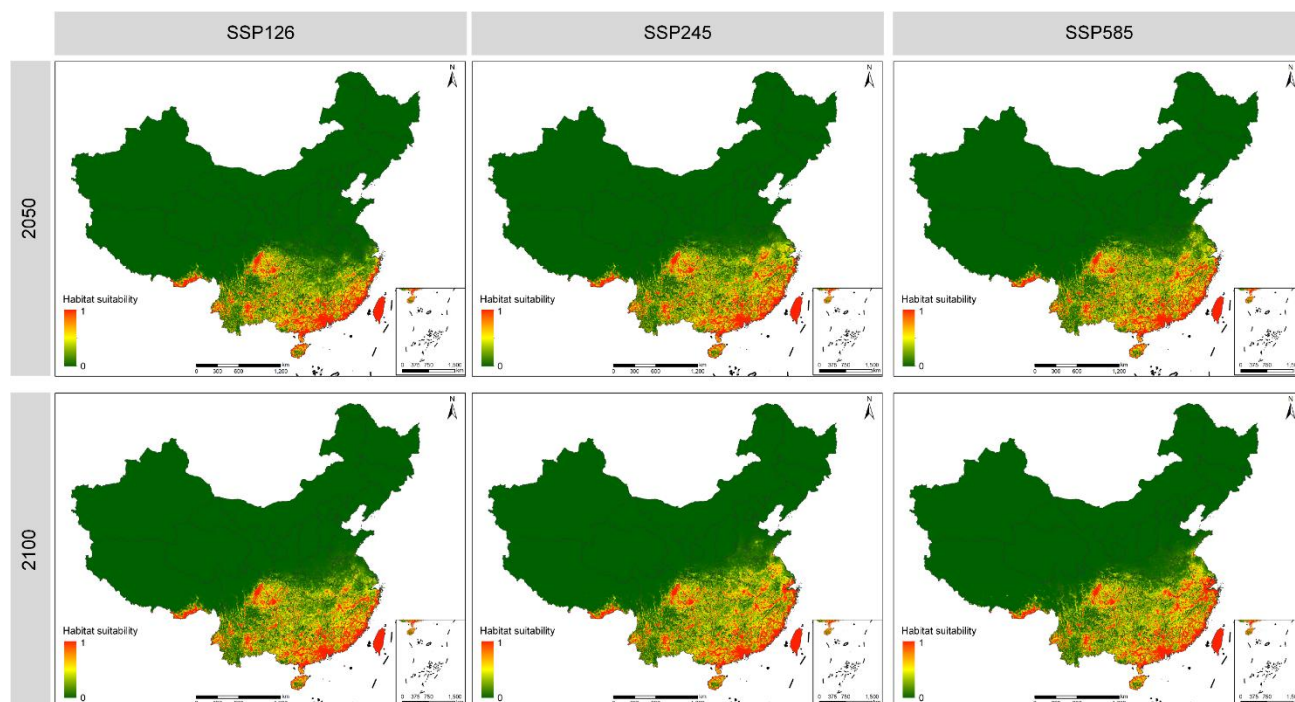
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Fig. S1. Habitat suitability for *Aedes albopictus* under different future scenarios.



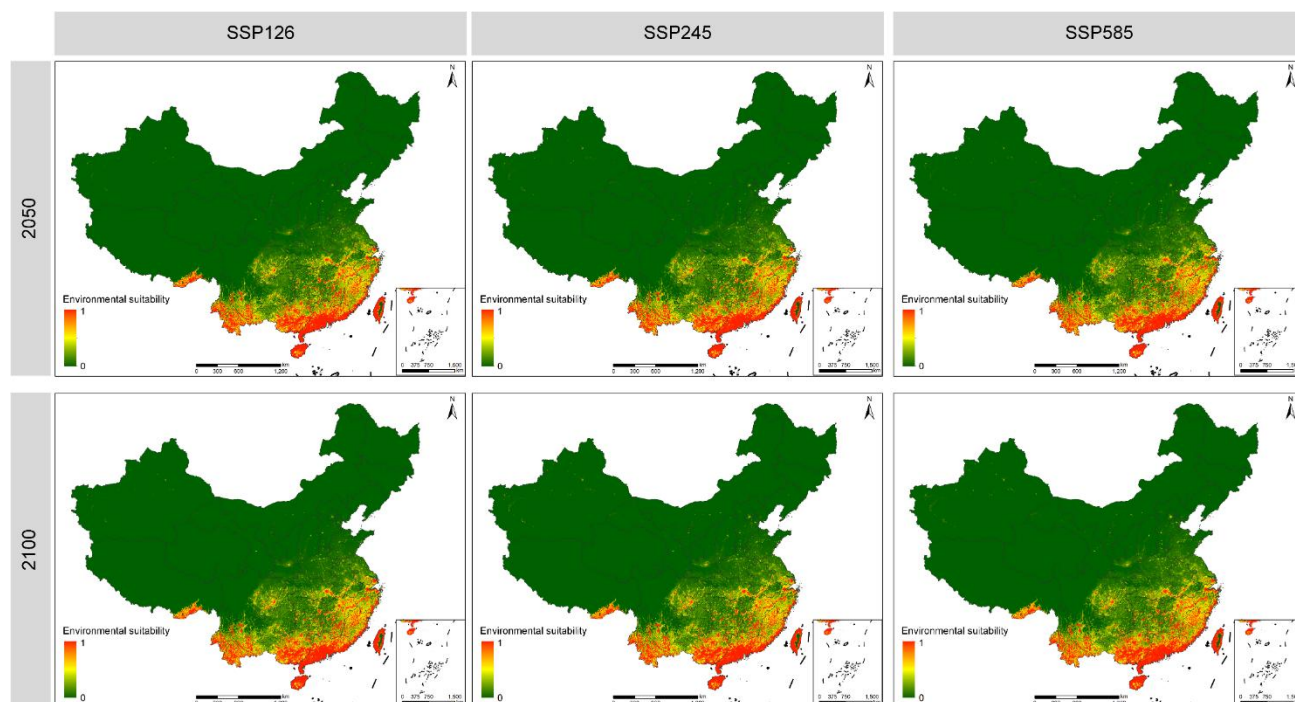
Note: Each future prediction (for 2050 and 2100) is based on three Shared Socioeconomic Pathways (SSPs)—narrative scenarios of societal development used by the Intergovernmental Panel on Climate Change (IPCC), which encompass different trajectories of greenhouse gas emissions and concentrations: SSP126, SSP245, and SSP585. The habitat suitability represents the probability that *Aedes albopictus* will occur. Habitat suitability index varied between 0 (unsuitable conditions) and 1 (highly suitable conditions).

Fig. S2. Habitat suitability for *Aedes aegypti* under different future scenarios.



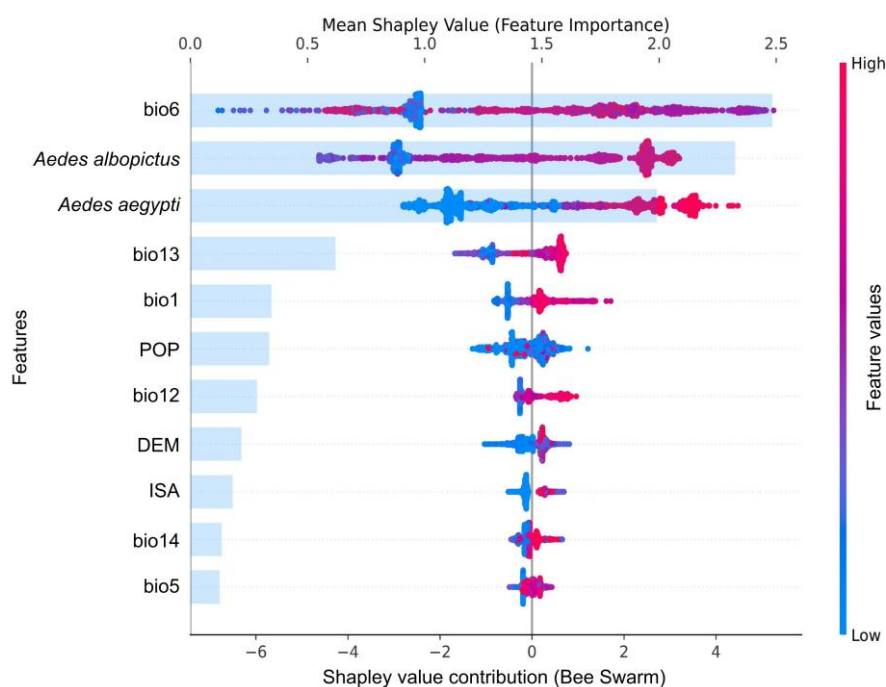
Note: Each future prediction (for 2050 and 2100) is based on three Shared Socioeconomic Pathways (SSPs)—narrative scenarios of societal development used by the Intergovernmental Panel on Climate Change (IPCC), which encompass different trajectories of greenhouse gas emissions and concentrations: SSP126, SSP245, and SSP585. The habitat suitability represents the probability that *Aedes aegypti* will occur. Habitat suitability index varied between 0 (unsuitable conditions) and 1 (highly suitable conditions).

Fig. S3. Dengue hazard under different future scenarios.



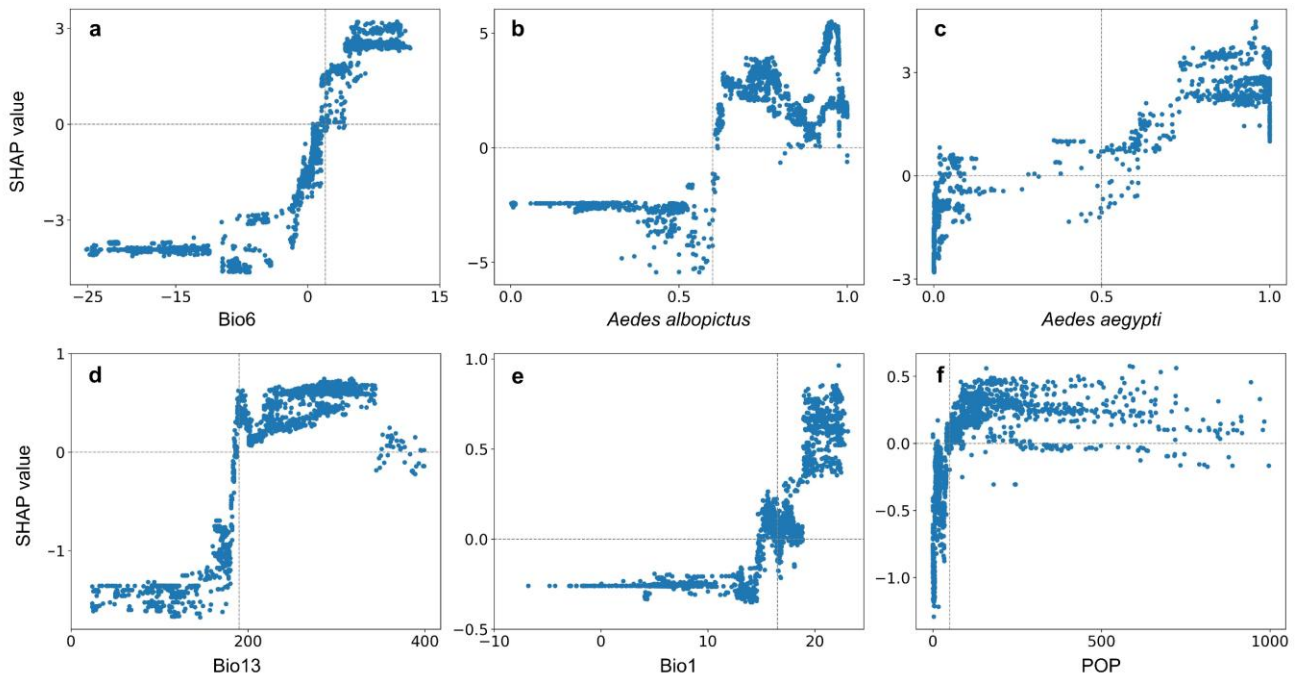
Note: Each future prediction (for 2050 and 2100) is based on three Shared Socioeconomic Pathways (SSPs)—narrative scenarios of societal development used by the Intergovernmental Panel on Climate Change (IPCC), which encompass different trajectories of greenhouse gas emissions and concentrations: SSP126, SSP245, and SSP585. The hazard value represents the probability that dengue will occur. Dengue hazard values varied between 0 (low hazard level) and 1 (high hazard level).

Fig.S4. Consolidated Shapley additive explanation (SHAP) value analysis for characterization of dengue suitability across China.



Note: Bar chart of the average magnitudes of SHAP values, highlighting the mean influence of each feature on the framework's output magnitude using the average absolute SHAP values. Abbreviation: minimum temperature of coldest month (bio6); habitat suitability of *Aedes albopictus* (*Aedes albopictus*); habitat suitability of *Aedes aegypti* (*Aedes aegypti*); precipitation of wettest month (bio13); annual mean temperature (bio1); population density (POP); annual precipitation (bio12); digital elevation model (DEM); impervious surface area (ISA); precipitation of driest month (bio14); and maximum temperature of warmest month (bio5).

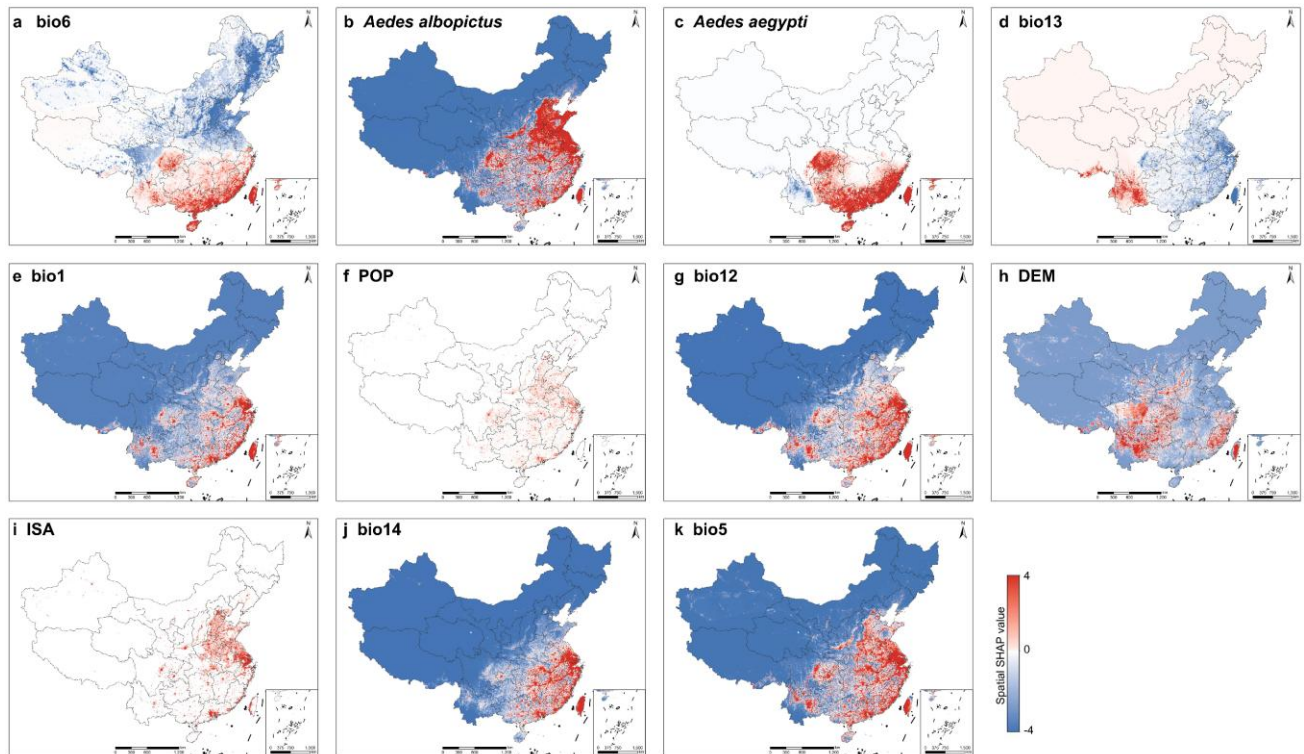
Fig. S5. Shapley additive explanation (SHAP) total effect value of the top 6 important variables based on the GNNWLR-SHAP model.



Note: The tipping point of bio6 (°C) (a), Habitat suitability of *Aedes albopictus* (b), Habitat suitability of *Aedes aegypti* (c), bio13 (mm) (d), bio1 (°C) (e), and POP (people·hm⁻²) (f) between negative and positive effect were marked by dotted line.

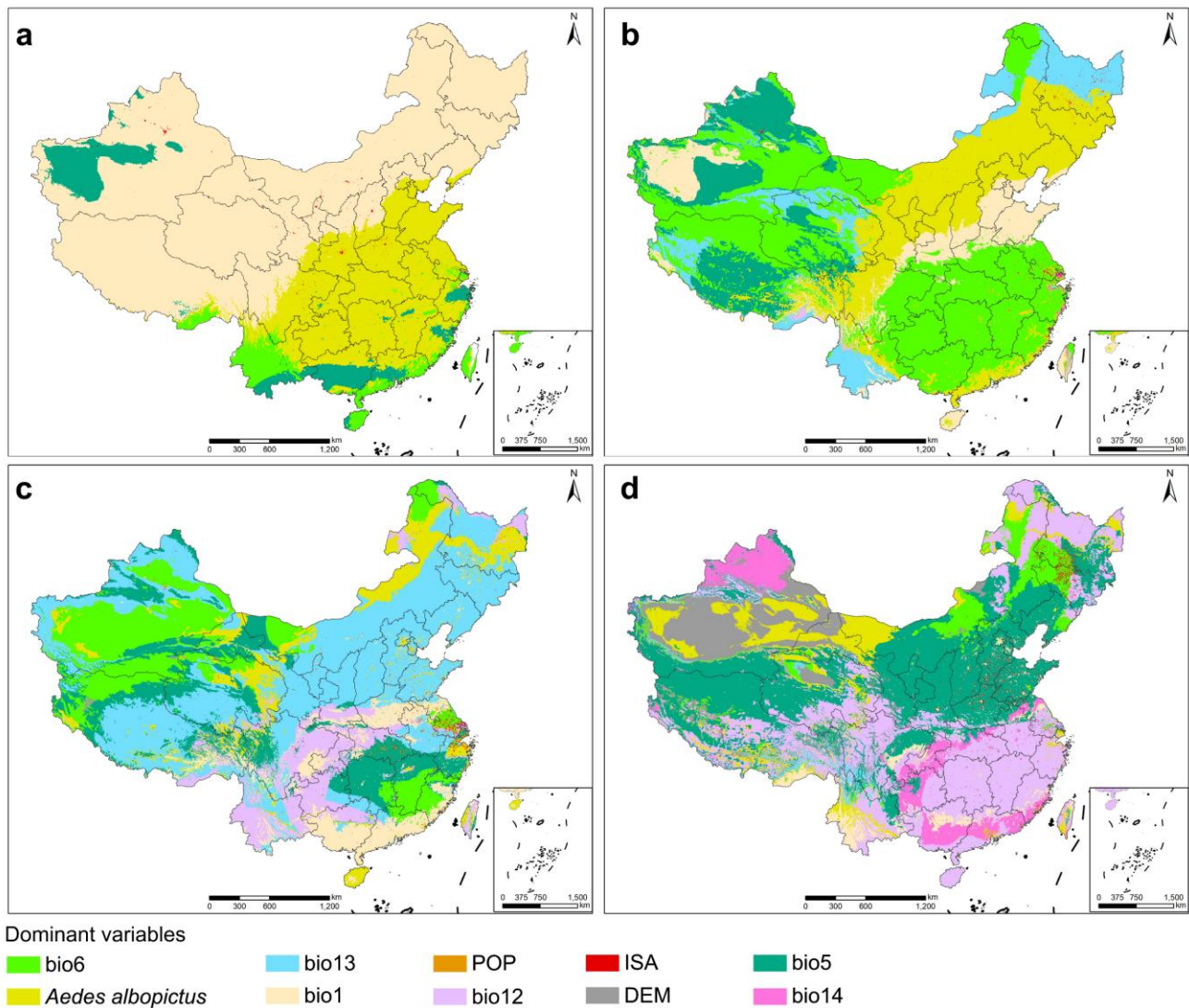
Abbreviation: GNNWLR-SHAP, Geographically Neural Network Weighted Logistic Regression-Shapley Additive Explanations.

Fig. S6. Spatial distribution maps of Shapley additive explanation (SHAP) values for all driving factors.



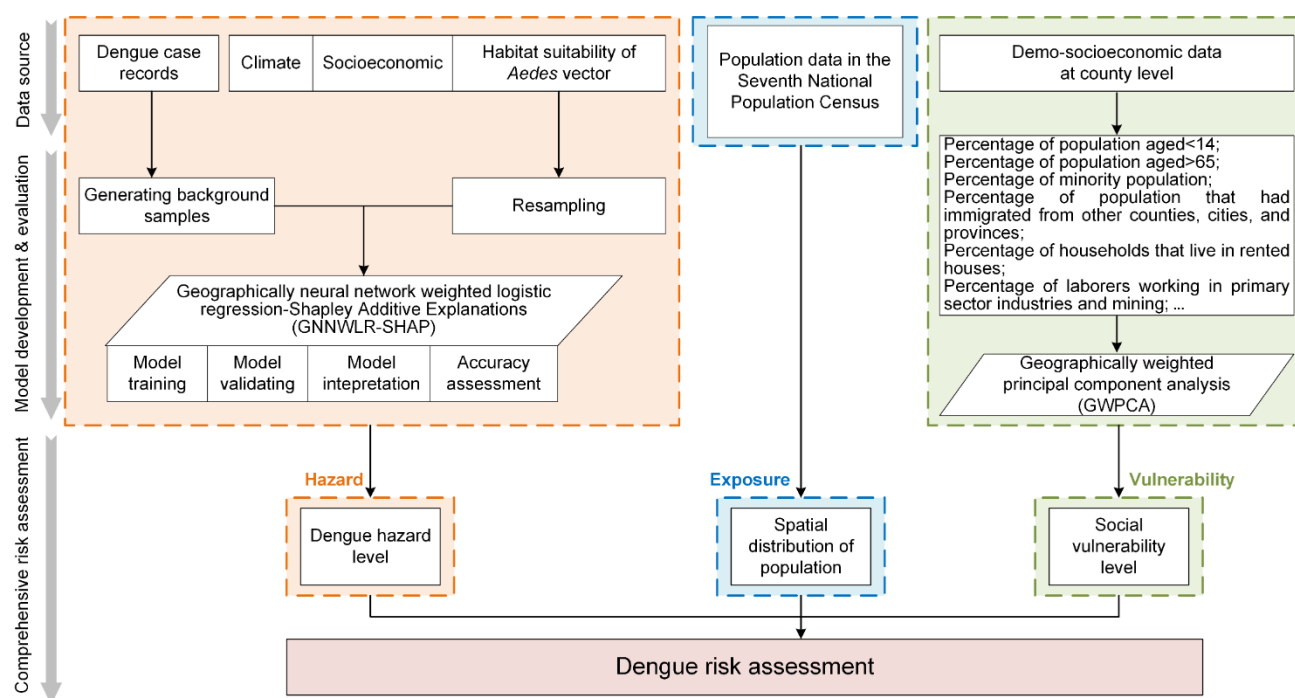
Abbreviation: (a) minimum temperature of coldest month (bio6); (b) habitat suitability of *Aedes albopictus*; (c) habitat suitability of *Aedes aegypti*; (d) precipitation of wettest month (bio13); (e) annual mean temperature (bio1); (f) population density (POP); (g) annual precipitation (bio12); (h) digital elevation model (DEM); (i) impervious surface area (ISA); (j) precipitation of driest month (bio14); and (k) maximum temperature of warmest month (bio5).

Fig. S7 Spatial distribution of the (a) first, (b) second, (c) third, and (d) fourth dominant factors.



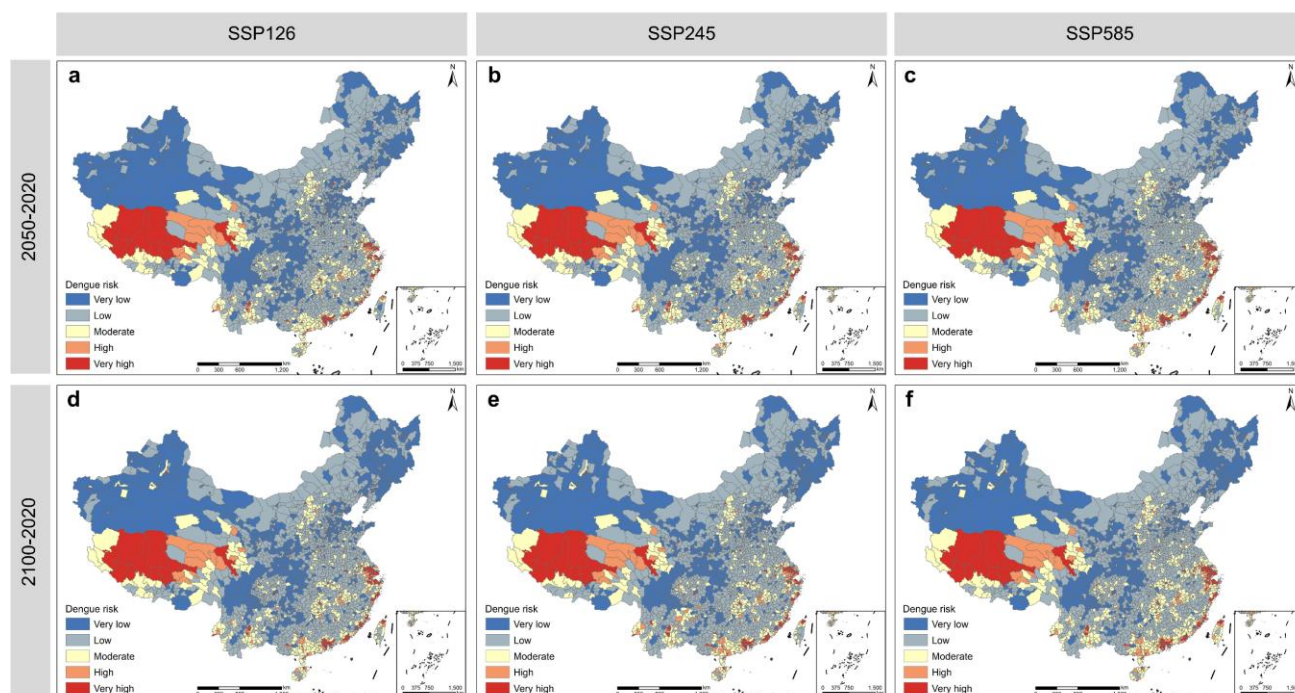
Abbreviation: minimum temperature of coldest month (bio6); habitat suitability of *Aedes aegypti*; precipitation of wettest month (bio13); annual mean temperature (bio1); population density (POP); annual precipitation (bio12); digital elevation model (DEM); impervious surface area (ISA); precipitation of driest month (bio14); and maximum temperature of warmest month (bio5).

Fig. S8. Dengue risk assessment framework.



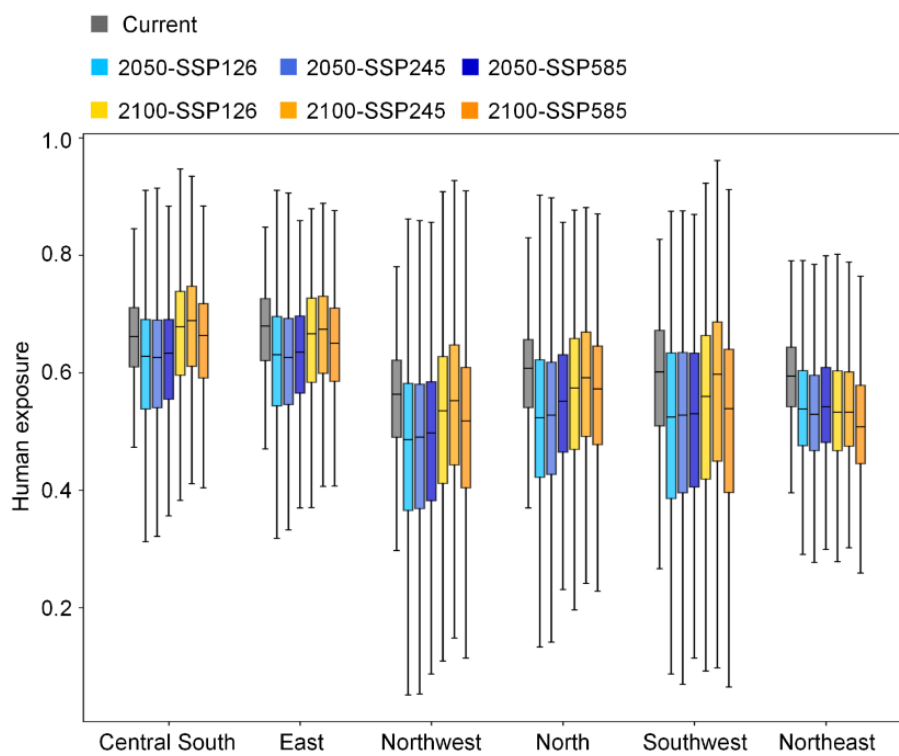
Firstly, various types of data are collected from multiple sources; secondly, the dengue hazard in China is estimated by GNNWLR-SHAP modelling based on surveillance data cooperating with climate, socioeconomic, and *Aedes* vector factors. Dengue hazard is a probability of dengue transmission between residents. Then, the dengue hazard and human exposure index are calculated at county level. The social vulnerability index for each county comes from the geographically weighted principal component analysis (GWPCA) results on demo-socioeconomic characteristics. In the third step, the components of dengue hazard, human exposure, and social vulnerability are integrated with equal weights for mapping the dengue risk in China. Finally, recommendations for the hot spots with dengue risk in China accordingly.

Fig. S9. Spatial distribution of dengue risk under different future scenarios.



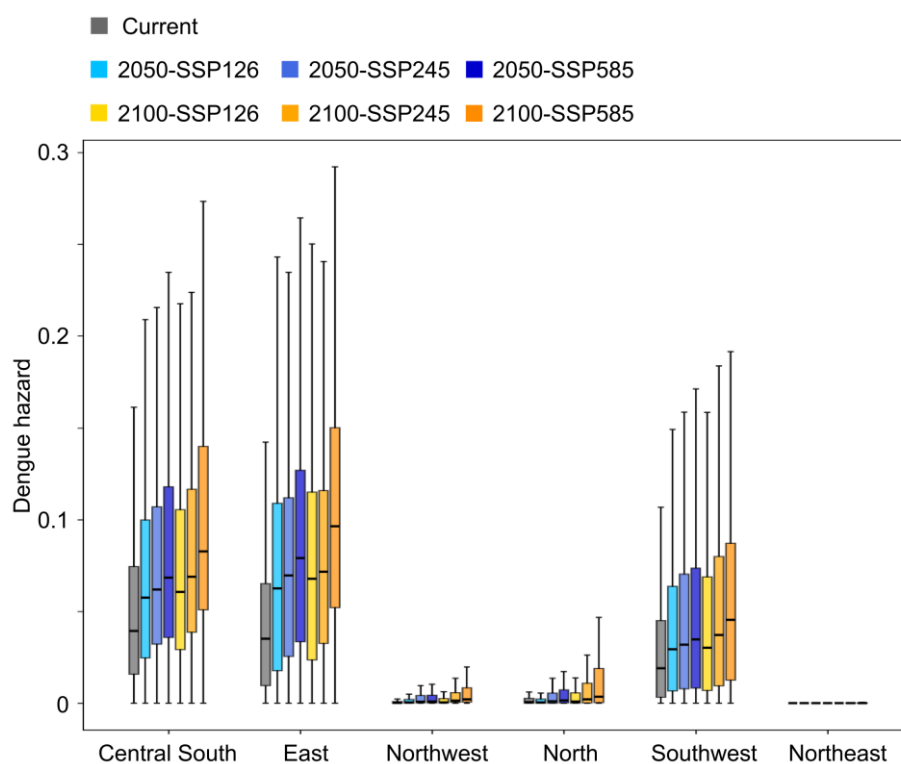
Note: Each future prediction (for 2050 and 2100) is based on three Shared Socioeconomic Pathways (SSPs)—narrative scenarios of societal development used by the Intergovernmental Panel on Climate Change (IPCC), which encompass different trajectories of greenhouse gas emissions and concentrations: SSP126, SSP245, and SSP585. The standardized dengue risk values are divided into five levels: Very high (0.80 to 1.00), High (0.60 to 0.80), Moderate (0.40 to 0.60), Low (0.20 to 0.40) and Very low (0.00 to 0.20).

Fig. S10. Boxplot of human exposure in each geographical division under current and different future scenarios.



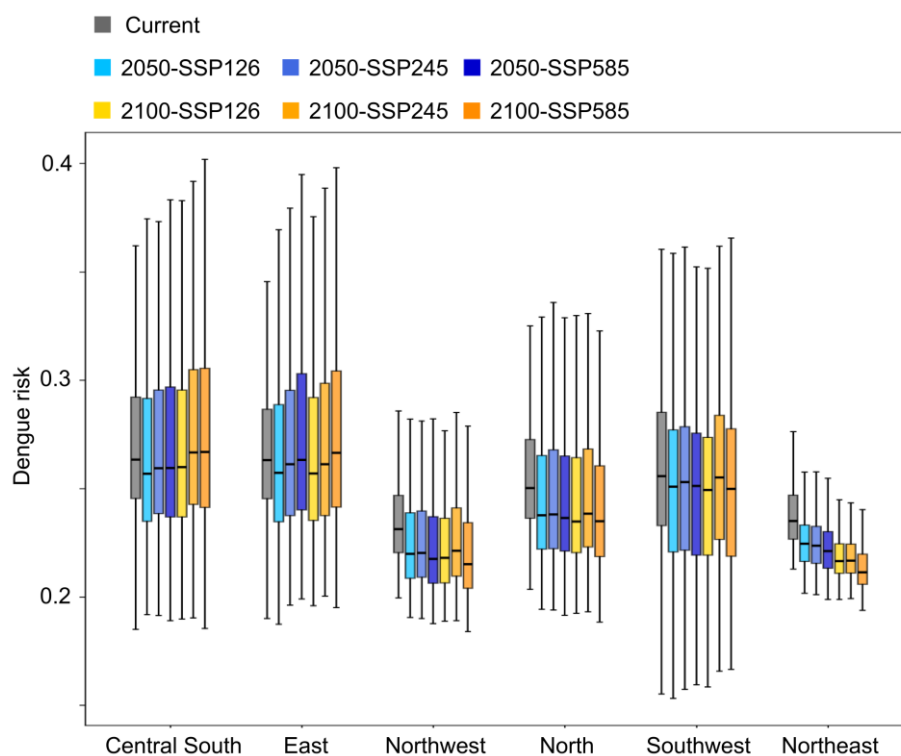
Note: Each future prediction (for 2050 and 2100) is based on three Shared Socioeconomic Pathways (SSPs)—narrative scenarios of societal development used by the Intergovernmental Panel on Climate Change (IPCC), which encompass different trajectories of greenhouse gas emissions and concentrations: SSP126, SSP245, and SSP585.

Fig. S11. Boxplot of dengue hazard in each geographical division under current and different future scenarios.



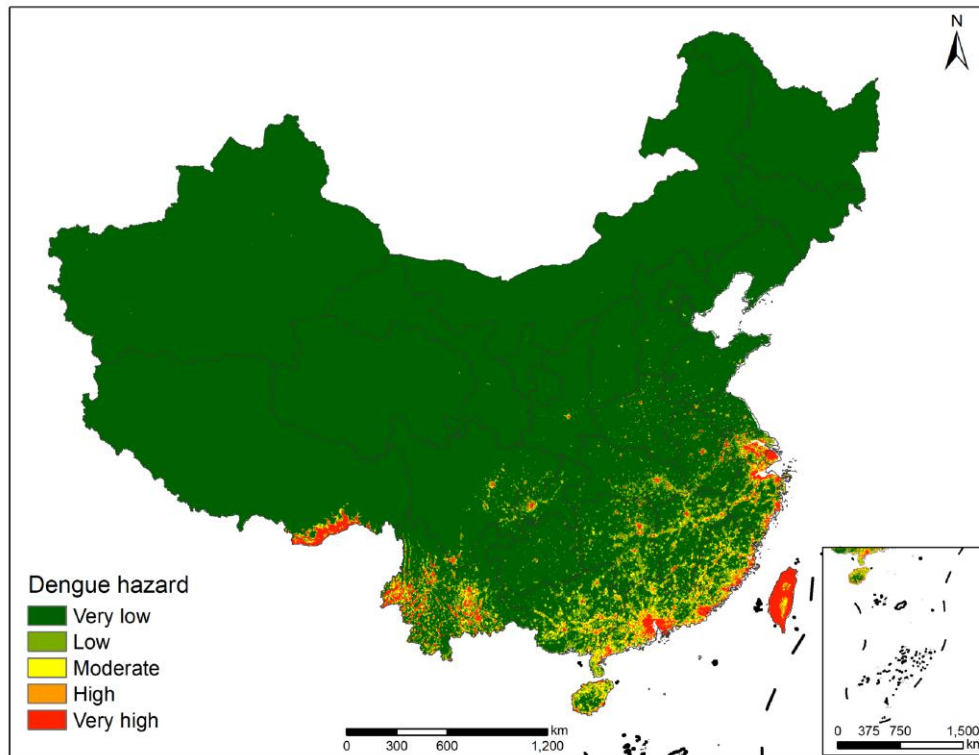
Note: Each future prediction (for 2050 and 2100) is based on three Shared Socioeconomic Pathways (SSPs)—narrative scenarios of societal development used by the Intergovernmental Panel on Climate Change (IPCC), which encompass different trajectories of greenhouse gas emissions and concentrations: SSP126, SSP245, and SSP585.

Fig. S12. Boxplot of dengue risk in each geographical division under current and different future scenarios.



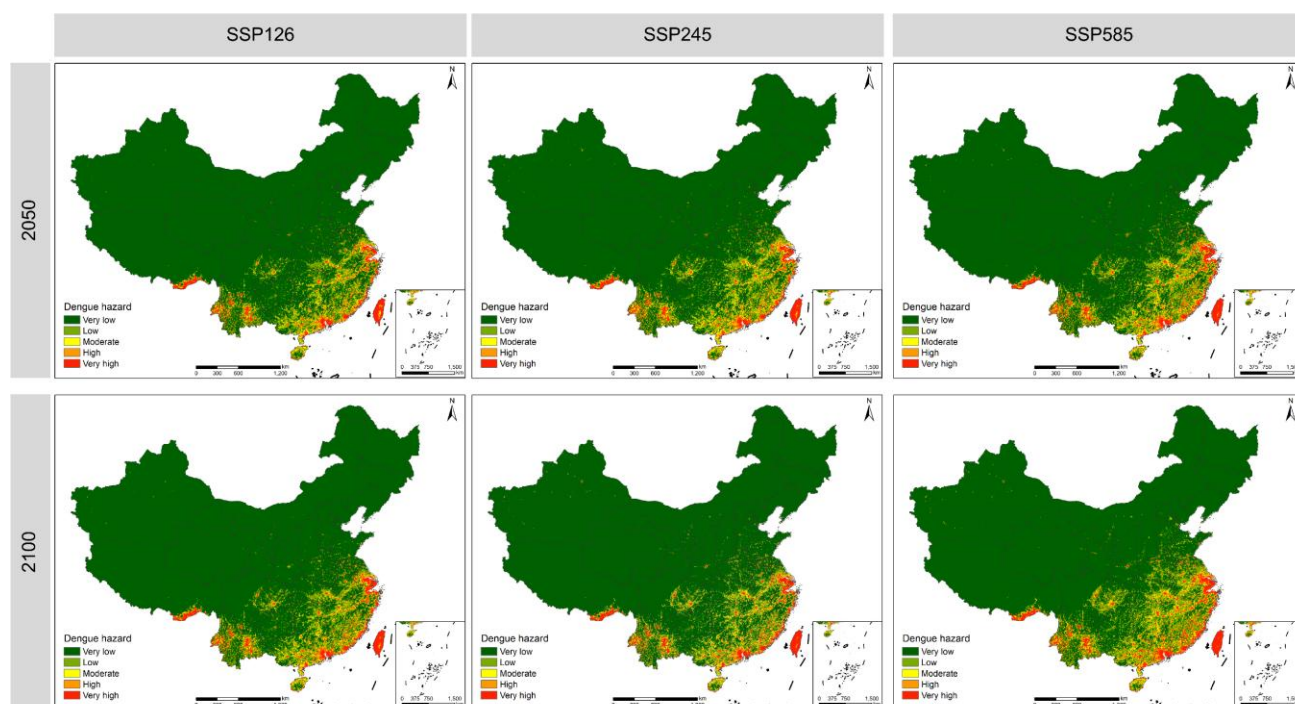
Note: Each future prediction (for 2050 and 2100) is based on three Shared Socioeconomic Pathways (SSPs)—narrative scenarios of societal development used by the Intergovernmental Panel on Climate Change (IPCC), which encompass different trajectories of greenhouse gas emissions and concentrations: SSP126, SSP245, and SSP585.

Fig. S13. Spatial distribution of dengue hazard levels at current period.



The dengue hazard values were divided into five levels: Very low (0.00 to 0.20), Low (0.20 to 0.40), Moderate (0.40 to 0.60), High (0.60 to 0.80), and Very high (0.80 to 1.00).

Fig. S14. Spatial distribution of dengue hazard levels at different future scenarios.



The dengue hazard is categorized into five levels from highest to lowest: very high, high, moderate, low, and very low. The regional evolution rules are defined as follows: Expansion regions: Regions transitioning from very low/low/moderate levels to high/very high levels, indicating an escalation in dengue hazard; Contraction areas: Regions shifting from high/very high/moderate levels to low/very low levels, reflecting a decline in dengue hazard; Stability regions: Regions where hazard levels remain unchanged.

Fig. S15. Map of six geographical divisions in China.

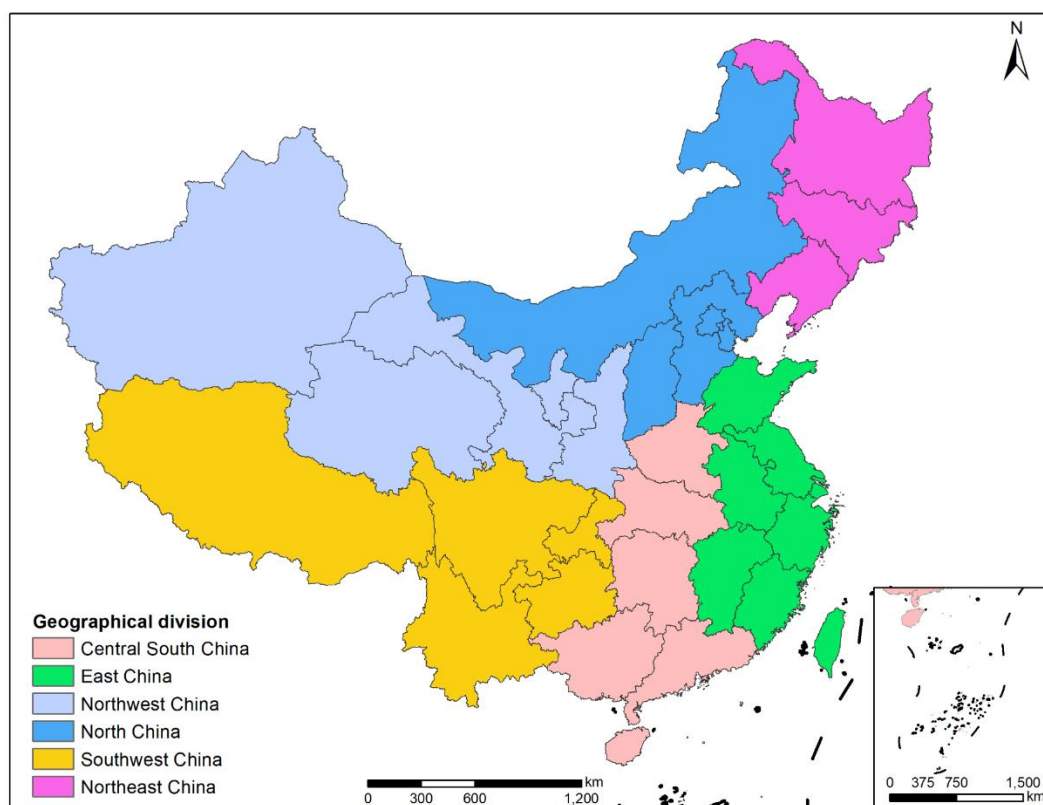
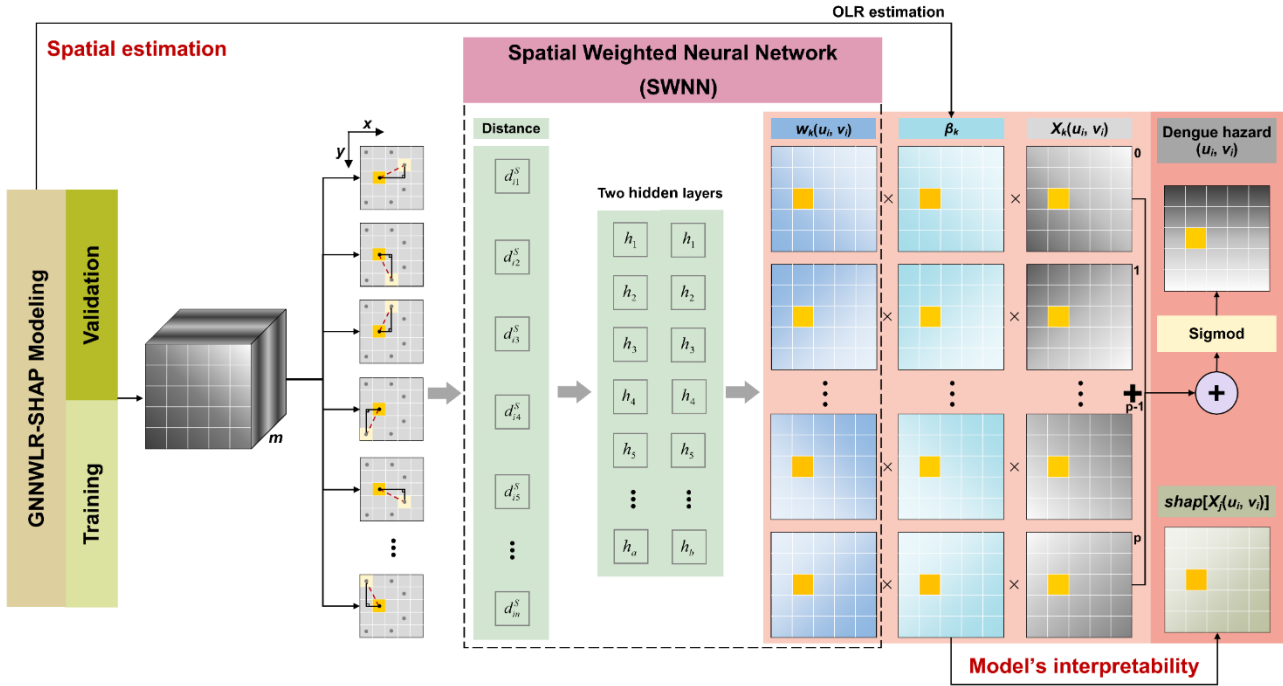


Fig. S16. The construction of the Geographically Neural Network Weighted Logistic Regression-Shapley Additive Explanations (GNNWLR-SHAP) model.



The GNNWLR-SHAP model integrates spatial patterns, neural networks, logistic regression, and SHAP theory for dengue hazard estimation. For each data point with spatial location and independent factors, spatial distances to training set points are computed, forming a vector input to a neural network that outputs spatial weights. These weights, combined with ordinary least squares coefficients and independent factors via dot multiplication, feed into logistic regression to estimate the regional dengue hazard. For interpretability, SHAP theory quantifies each factor's role by sequentially introducing features into the model's conditional expectation function, calculating induced variations, averaging across feature orderings to derive SHAP values. This enables accurate estimation and interpretable analysis of dengue hazard mechanisms.

Table S1. GNNWLR-SHAP model performance for five-fold cross-validation.

	AUC			ACC			Recall		
Habitat suitability of <i>Aedes albopictus</i>	Train	Valid	All Region	Train	Valid	All Region	Train	Valid	All Region
	0.834	0.825	0.836	0.861	0.851	0.827	0.852	0.826	0.866
Habitat suitability of <i>Aedes aegypti</i>	Train	Valid	All Region	Train	Valid	All Region	Train	Valid	All Region
	0.849	0.836	0.851	0.859	0.852	0.846	0.831	0.822	0.854
Dengue hazard	Train	Valid	All Region	Train	Valid	All Region	Train	Valid	All Region
	0.854	0.824	0.863	0.843	0.831	0.825	0.852	0.841	0.868

Abbreviation: GNNWLR-SHAP, Geographically Neural Network Weighted Logistic Regression-Shapley Additive Explanations. AUC, area under the receiver operating characteristic curve; ACC, Accuracy.

Table S2. Mean dengue hazard for each province under different future scenarios.

Province	Mean dengue hazard (different scenarios)						
	Current	2050-SSP126	2050-SSP245	2050-SSP585	2100-SSP126	2100-SSP245	2100-SSP585
Heilongjiang	0.0001	0.0001	0.0001	0.0002	0.0004	0.0002	0.0003
Jilin	0.0006	0.0005	0.0009	0.0011	0.0007	0.0005	0.0006
Qinghai	0.004	0.02	0.03	0.03	0.01	0.02	0.02
Liaoning	0.005	0.003	0.01	0.01	0.005	0.01	0.01
Inner Mongolia	0.006	0.03	0.04	0.05	0.03	0.03	0.03
Xinjiang	0.01	0.03	0.12	0.15	0.05	0.06	0.08
Gansu	0.04	0.05	0.07	0.12	0.05	0.08	0.08
Hebei	0.04	0.04	0.05	0.07	0.02	0.03	0.04
Shanxi	0.04	0.04	0.05	0.05	0.04	0.04	0.05
Beijing	0.02	0.04	0.05	0.07	0.02	0.03	0.05
Ningxia	0.03	0.11	0.15	0.18	0.09	0.12	0.13
Tibet	0.05	0.06	0.07	0.10	0.06	0.06	0.08
Tianjin	0.03	0.04	0.08	0.12	0.05	0.07	0.08
Shandong	0.06	0.11	0.15	0.22	0.12	0.16	0.23
Shannxi	0.10	0.12	0.15	0.18	0.12	0.16	0.19
Sichuan	0.18	0.23	0.25	0.30	0.22	0.24	0.25
Henan	0.18	0.24	0.32	0.36	0.26	0.34	0.38
Jiangsu	0.32	0.35	0.38	0.42	0.38	0.42	0.46
Anhui	0.33	0.38	0.42	0.45	0.39	0.43	0.48
Hubei	0.33	0.39	0.46	0.47	0.42	0.47	0.49
Guizhou	0.35	0.40	0.47	0.49	0.46	0.48	0.50
Chongqing	0.37	0.41	0.49	0.51	0.48	0.49	0.53
Hunan	0.39	0.43	0.51	0.53	0.51	0.55	0.58
Zhejiang	0.42	0.45	0.52	0.58	0.53	0.58	0.60
Jiangxi	0.45	0.50	0.53	0.59	0.55	0.60	0.62
Guangxi	0.48	0.52	0.56	0.61	0.55	0.62	0.64

Fujian	0.52	0.58	0.60	0.63	0.60	0.65	0.68
Guangdong	0.58	0.60	0.62	0.68	0.62	0.68	0.72
Shanghai	0.62	0.68	0.70	0.72	0.70	0.72	0.78
Yunnan	0.64	0.70	0.73	0.75	0.72	0.75	0.79
Hainan	0.65	0.71	0.72	0.76	0.73	0.76	0.78
Taiwan	0.82	0.86	0.86	0.91	0.82	0.85	0.92

Table S3. Social vulnerability characteristics for the top 5 counties by dengue risk in each geographical division.

County	A	B	C	D	E	F	G	H	I	J	K	L	M
Dongguan	10466625	13.12	3.54	9.14	79.38	74.73	0.66	0.61	98.96	90.23	99.74	95.38	37.64
Baoan	4476554	13.72	2.19	8.35	87.28	84.90	0.63	0.14	99.46	89.20	99.69	90.27	33.46
Zhongshan	4418060	15.69	5.98	7.63	62.60	53.60	1.08	1.85	99.08	92.44	99.70	97.02	44.28
Longgang	3742991	12.99	6.11	4.81	81.16	77.54	0.73	1.22	108.68	107.45	109.73	105.99	28.94
Longhua	1654276	23.27	8.75	1.17	9.89	1.03	3.89	6.04	87.25	90.46	90.80	90.81	16.58
Pudong	5681512	10.48	14.99	1.47	59.89	39.26	1.53	0.78	98.69	94.83	96.81	92.09	44.80
Huangpu	662030	8.67	18.48	2.36	59.33	52.39	0.71	0.02	99.99	87.21	84.34	82.71	28.28
Yangpu	1242548	8.84	21.85	1.63	47.77	24.85	0.85	0.10	99.55	98.44	97.10	97.73	35.41
Hongkou	2653489	12.49	16.12	2.01	75.50	45.79	1.68	0.26	113.78	111.75	111.07	110.55	53.92
Jingan	975707	9.31	21.97	1.47	47.67	28.27	0.89	0.11	97.70	97.71	97.71	96.94	33.77
Dari	2046737	14.97	7.67	0.95	54.93	37.20	0.40	0.45	84.27	80.84	88.89	83.27	40.35
Maduo	34496	27.38	5.71	92.15	58.76	3.72	45.59	76.23	2.90	22.79	62.45	5.23	45.93
Qumalai	57159	27.43	6.07	93.17	10.20	2.80	28.02	69.79	25.26	36.14	72.97	7.34	23.39
Lianhu	1019102	14.55	12.06	3.49	53.53	23.14	0.53	0.60	97.92	97.23	97.81	95.30	36.07
Xincheng	617986	13.35	13.63	1.71	53.33	20.93	0.66	0.21	98.26	98.17	98.06	96.25	32.00
Hunyuan	75757	15.08	19.76	0.08	35.08	6.75	4.66	59.30	56.17	64.74	78.21	35.82	20.89
Haidian	3133469	11.84	13.06	4.99	54.08	39.55	0.52	0.36	94.46	92.56	93.11	93.11	51.00
Pianguan	73382	13.58	18.77	0.07	33.88	9.64	4.71	38.68	44.09	44.38	76.25	31.18	21.86
Xicheng	355000	11.65	12.58	3.04	41.89	19.94	0.58	0.90	76.75	75.26	75.20	73.62	37.30
Dongcheng	1106214	11.42	14.54	5.18	32.30	27.82	0.43	0.19	77.40	73.45	67.71	74.22	39.16
Yuzhong	441455	16.24	7.59	61.94	11.92	7.22	13.63	56.71	74.05	76.07	59.85	66.48	19.62
Bange	160262	25.34	10.74	106.20	19.34	10.85	13.18	77.14	110.50	116.42	84.78	82.33	25.49
Dangxiong	87291	28.77	8.45	110.80	13.31	8.50	13.68	67.73	92.83	100.43	92.83	98.38	22.55
Gaize	353720	23.09	10.20	98.01	25.38	13.35	16.49	81.47	111.95	113.87	108.25	114.92	55.00
Anduo	144693	26.57	8.78	94.49	29.85	13.37	14.64	81.31	115.75	114.66	80.92	109.90	37.75
Shahekou	670310	10.79	18.59	3.09	38.34	16.01	0.72	1.99	98.84	99.46	99.66	97.34	35.17
Jinzhou	1335935	13.14	16.41	10.48	51.97	13.49	1.69	3.68	98.90	100.88	100.53	95.00	39.41

Ganjinzi	782628	12.52	18.06	9.24	49.92	16.40	1.55	1.67	99.97	100.72	100.79	98.82	38.27
Linghai	17301	7.55	18.96	2.85	18.84	4.41	1.17	65.10	90.05	70.65	71.16	45.47	10.20
Zhuanghe	877287	10.75	15.37	7.22	43.84	9.85	1.04	0.78	97.86	98.23	97.68	94.61	37.89

Note: A, Population number; B, Percentage of population aged<14; C, Percentage of population aged>65; D, Percentage of minority population (non-Han groups in China); E, Percentage of population that had immigrated from other counties, cities, and provinces; F, Percentage of households that live in rented houses; G, Illiteracy rate of population 15 years or older; H, Percentage of laborers working in primary sector industries and mining; I, Percentage of households with tap water in their houses; J, Percentage of households with a kitchen in their houses; K, Percentage of households with a lavatory in their houses; L, Percentage of households with bathing facilities in their houses; M, Percentage of owning family cars.

Table S4. Top 5 counties by dengue exposure risk and their hazard-exposure-vulnerability patterns in each geographical division.

County	Dengue hazard	Human exposure	Social vulnerability	Sum	Division
Dongguan	0.49	1.00	0.43	1.92	Central South
Baoan	0.55	0.43	0.43	1.40	Central South
Zhongshan	0.40	0.42	0.42	1.25	Central South
Longgang	0.41	0.40	0.42	1.22	Central South
Longhua	0.45	0.24	0.43	1.12	Central South
Pudong	0.54	0.54	0.42	1.50	East
Huangpu	0.92	0.06	0.46	1.44	East
Yangpu	0.90	0.12	0.41	1.42	East
Hongkou	0.88	0.07	0.42	1.37	East
Jingan	0.83	0.09	0.41	1.32	East
Dari	0.00	0.00	0.88	0.88	Southwest
Maduo	0.00	0.00	0.87	0.87	Southwest
Qumalai	0.00	0.00	0.83	0.84	Southwest
Lianhu	0.16	0.09	0.42	0.67	Southwest
Xincheng	0.16	0.06	0.43	0.65	Southwest
Hunyuan	0.00	0.02	0.76	0.79	Northwest
Haidian	0.02	0.30	0.44	0.76	Northwest
Pianguan	0.00	0.01	0.70	0.71	Northwest
Xicheng	0.14	0.11	0.46	0.71	Northwest
Dongcheng	0.16	0.07	0.47	0.69	Northwest
Yuzhong	0.61	0.06	0.40	1.07	North
Bange	0.01	0.00	1.00	1.02	North
Dangxiong	0.00	0.00	0.97	0.98	North
Gaize	0.00	0.00	0.96	0.96	North
Anduo	0.00	0.00	0.94	0.95	North
Shahekou	0.26	0.07	0.40	0.73	Northeast
Jinzhou	0.00	0.15	0.42	0.58	Northeast
Ganjinzi	0.01	0.15	0.41	0.58	Northeast
Linghai	0.00	0.04	0.52	0.57	Northeast
Zhuanghe	0.00	0.07	0.48	0.55	Northeast

Table S5 Key features of different SSP scenarios and their relevance to dengue hazard.

Scenario	Core characteristics	Relevance to dengue hazard
SSP126 (Sustainable Development Scenario)	Greenhouse gas emissions: Peak around 2030, then rapidly decline, and achieve net zero emissions by 2100; Socioeconomic priorities: Sustainable development, low-carbon energy transformation, improvement of environmental protection, and balanced regional development; Climate policy: Strengthen global cooperation in mitigating climate change and adopt strict emission reduction measures.	Low greenhouse gas emissions slow down global warming, limiting the northward expansion of Aedes vector habitats. Moderate urbanization and improved public health infrastructure further constrain dengue transmission potential.
SSP245 (Middle-of-the-Road Scenario)	Greenhouse gas emissions: Peak around 2040, then gradually decrease, and net zero emissions cannot be achieved by 2100; Socioeconomic priorities: Moderate economic growth, balanced energy structure (fossil fuels and renewable energy), and gradual progress in climate policies; Climate policy: Moderate global cooperation and targeted emission reduction measures.	Moderate climate warming leads to a moderate expansion of Aedes vector habitats. Stable urbanization and gradual improvement in public health capacity result in a moderate increase in dengue hazard.
SSP585 (Fossil-Fueled Development)	Greenhouse gas emissions: Continue to rise throughout the 21st century without significant emission reduction measures implemented;	Rapid climate warming significantly expands Aedes vector habitats, especially northward to temperate regions. Rapid, unplanned urbanization increases breeding sites for Aedes vector.

Scenario)	Socioeconomic priorities: high-intensity economic development relying on fossil fuels, rapid urbanization, and weak environmental constraints; Climate policy: Minimize global cooperation in mitigating climate change and prioritize economic growth over emissions reduction.	
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Table S6. Data source of predictor factors.

Group	Predictor factors	Source
Climate	Annual mean temperature (bio1)	https://worldclim.org/
	Maximum temperature of warmest month (bio5)	https://worldclim.org/
	Minimum temperature of coldest month (bio6)	https://worldclim.org/
	Annual precipitation (bio12)	https://worldclim.org/
	Precipitation of wettest month (bio13)	https://worldclim.org/
	Precipitation of driest month (bio14)	https://worldclim.org/
Socioeconomic	Population density (POP)	figshare.24916140.v1
	Impervious surface area (ISA)	https://data.ess.tsinghua.edu.cn/
Topography	Digital elevation model (DEM)	https://www.gscloud.cn
<i>Aedes</i> vector	Habitat suitability of <i>Aedes albopictus</i>	Predicted in this study
	Habitat suitability of <i>Aedes aegypti</i>	Predicted in this study

Supplementary Note 1: The details of data cleaning, and integration for *Aedes* vector occurrence data

The key procedures for data cleaning and integration of *Aedes aegypti* and *Aedes albopictus* occurrence records in China focusing on spatial standardization and technical validation to ensure data accuracy and reliability (Table S8). Data cleaning aimed to eliminate duplicates, correct errors, and ensure spatial/temporal consistency., with core operations concentrated in spatial/temporal standardization and technical validation. Spatial standardization aimed to refine spatial precision, remove redundant records, and ensure all occurrences align with China. Duplicates were systematically identified and excluded across three data sources: previously collated databases (doi:10.5061/dryad.47v3c9, doi.org/10.1186/s40249-023-01083-245, and doi.org/10.1016/j.scitotenv.2019.01.30146), literature-derived data, and Global Biodiversity Information Facility (GBIF) records. A record was defined as a duplicate if it met all three criteria: (i) Consistency in species identity (confirmed as either *Aedes aegypti* or *Aedes albopictus*); (ii) Spatial overlap within a 5 km × 5 km grid cell; (iii) Matching original data source. Temporal standardization aimed to avoid overrepresentation from repeated annual surveys, only one record per unique location (5 km × 5 km grid or polygon centroid) per calendar year was retained. Cross-year records (spanning multiple years) were split into individual annual records. Multiple records from the same location and year were aggregated into one entry.

Technical validation focused on two core aspects: (i) Land/water screening: A 5 km × 5 km global land-water raster was used to filter out records erroneously placed in water bodies, removing 5 *Aedes aegypti* and 14 *Aedes albopictus* records. (ii) Climate suitability cross-validation: Records were cross-checked against temperature-based *Aedes* population persistence models (Brady et al., 2014), which predict survival based on adult longevity and gonotrophic cycle length. Records outside

the model's predicted suitable range were manually verified to ensure accuracy.

After spatial standardization and technical validation, all remaining valid records were integrated into a unified dataset with consistent formatting. Core fields included: species identity (*Aedes aegypti* or *Aedes albopictus*), geographic coordinates (WGS1984), data source. The dataset was exported as a comma-delimited (CSV) file and a shapefile (for spatial analysis).

Table S7 Literature inclusion and exclusion criteria.

Criteria	Requirement	Result
Title/Abstract filtering		
1. <i>Aedes</i> vector	Whether the title and abstract indicate the inclusion of <i>Aedes</i> vectors (i.e., <i>Aedes albopictus</i> or <i>Aedes aegypti</i>)?	If it meets the requirements, proceed to step 2; otherwise, it will be excluded
2. Field survey	Whether the title and abstract suggest that the study is based on a field survey in China?	If it meets the requirements, proceed to step 3; otherwise, it will be excluded
3. Non review	Whether the title and abstract suggest that the literature is not a review study?	If it meets the requirements, perform full text screening; otherwise, it will be excluded
Full text screening		
1. Key elements	(i) Contains <i>Aedes albopictus</i> or <i>Aedes aegypti</i> ; (ii) Field surveys of the natural	If it meets the requirements, proceed to step 2; otherwise, it will be excluded

	environment, not laboratory studies; (iii) Not a review study; (iv) Not a pesticide, test method, drug or vaccine test; (v) Not part of molecular biology research	
2. Detection method	(i) Collect mosquito samples for testing; (ii) Clear methods for detecting and identifying mosquito species;	If it meets the requirements, proceed to step 3; otherwise, it will be excluded
3. Geographic information	(i) Clarify the province, city, and county where the mosquito investigation site is located; (ii) Precise location or latitude and longitude coordinates	If it meets the requirements, data entry and extraction will be carried out; otherwise, it will be excluded

Supplementary Note 2: Rationale for selecting the specific driving factors

For climate factors, annual mean temperature (bio1) was included because it directly regulates the metabolic rate and development cycle of *Aedes* vectors, with optimal temperatures (25–30°C) accelerating larval growth and adult reproduction (Brady et al., 2014). Maximum temperature of the warmest month (bio5) reflects heat stress thresholds—temperatures exceeding 35°C can reduce *Aedes* survival and virus replication efficiency (Kraemer et al., 2019). Minimum temperature of the coldest month (bio6) is critical for determining overwintering survival of *Aedes albopictus* and *Aedes aegypti*, as prolonged exposure to temperatures below 10°C can suppress vector populations (Kraemer et al., 2019). Annual precipitation (bio12), Precipitation of the wettest month (bio13), and Precipitation of the driest month (bio14) were selected because they shape the availability of larval habitats (e.g., water-filled containers), with moderate rainfall promoting habitat formation while extreme droughts or floods may limit breeding sites (Hales et al., 2002; Rogers et al., 2006). Socioeconomic variables included Population density (POP) and Impervious surface area (ISA). Higher population density increases opportunities for *Aedes* vectors to feed on humans, amplifying virus transmission (Hales et al., 2002). Impervious surface area, as a proxy for urbanization, correlates with artificial water storage (e.g., discarded containers in cities) that serve as key larval habitats for *Aedes* vectors (Weaver et al., 2013). The digital elevation model (DEM) was chosen as a topographic variable because elevation influences local temperature and precipitation patterns—higher elevations often have cooler temperatures that may restrict *Aedes* survival and dengue transmission (Hnusuwan et al., 2020). Finally, Habitat suitability of *Aedes albopictus* and *Aedes aegypti* were core predictors, as these two species are the primary vectors of dengue virus in China; their habitat suitability directly determines the spatial potential for virus transmission (Kraemer et al., 2015). Due to correlations exist among these factors, the Pearson correlation coefficient (r) was

used to test the multicollinearity of environmental factors. For two factors with high correlations ($r \geq \pm 0.8$), only one was selected and used for further modeling (Cao et al., 2023).

Supplementary Note 3: Relative uncertainty of dengue hazard under different future scenarios

Quantifying uncertainty in dengue hazard prediction holds core supporting significance for both the scientific rigor of the research and the practical value of public health applications. From a scientific perspective, it dispels the misleading nature of single precise values—by defining the 95% confidence interval and the contributions of different components (e.g., variations in GNNWLR-SHAP models, fluctuations in habitat suitability of *Aedes* vector, and differences among 17 global climate models (GCMs)), it clearly outlines the credible boundaries of prediction results. This approach acknowledges the inherent variability in future climate, *Aedes* vector spread, and dengue transmission, avoiding biases in conclusions caused by over-simplifying complex ecological processes. From a decision-making and practical perspective, such uncertainty analysis provides more actionable evidence for public health policymakers: the range of risk fluctuations under different SSP scenarios enables them to anticipate prevention and control pressures under various development pathways and formulate resilient strategies. Furthermore, transparent uncertainty reporting enhances the reproducibility of the research and its recognition across institutions, providing a reliable scientific basis for global or regional joint prevention and control of mosquito-borne infectious diseases and avoiding misallocation of prevention resources or inadequate responses caused by concealing uncertainty.

In this study, we implemented a comprehensive framework to quantify prediction uncertainty, ensuring results are characterized by their credible range rather than overstated precision. Our objective was to generate nine final prediction maps, corresponding to dengue suitability in 2024,

2050, and 2100 under each of the three Shared Socioeconomic Pathways (i.e., SSP126, SSP245, SSP585). Each map was constructed from 100 ensemble predictions, with random sampling (with replacement) applied across seven critical components of the analysis to fully propagate uncertainties from their sources through to the final output. These components included: 100 independently fitted GNNWLR-SHAP models to account for model fitting variability; 100 predicted future distributions each for *Aedes aegypti* and *Aedes albopictus* to capture uncertainty in vector range shifts; and projections from 17 global climate models (GCMs) for temperature suitability, minimum monthly precipitation, maximum monthly precipitation, and relative humidity to address climate projection discrepancies. This approach ensured uncertainties from model parameterization, vector habitat modeling, and climate forecasting were comprehensively integrated into each ensemble prediction (Fig. S17). The 100 predictions for each SSP-time combination were then summarized using the mean (representing central tendency) and 95% confidence interval, providing a transparent and robust characterization of dengue hazard prediction reliability under future climate and socioeconomic scenarios.

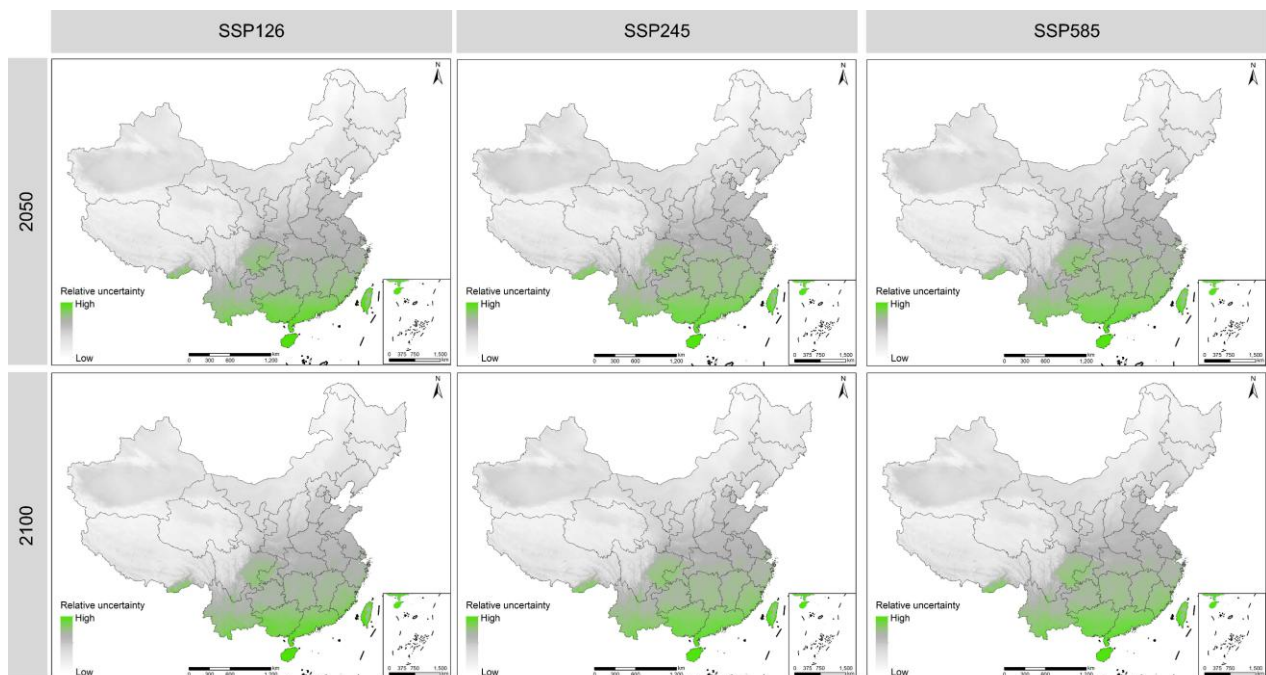


Fig. S17. Relative uncertainty of dengue hazard under different future scenarios.

Note: Each future prediction (for 2050 and 2100) is based on three Shared Socioeconomic Pathways (SSPs)—narrative scenarios of societal development used by the Intergovernmental Panel on Climate Change (IPCC), which encompass different trajectories of greenhouse gas emissions and concentrations: SSP126, SSP245, and SSP585. Areas in white have low relative uncertainty, while areas in green have high relative uncertainty.

Supplementary Note 4: Incorporating human mobility for dengue hazard modeling

Human mobility modelling The core dataset integrates domestic and international human mobility data to capture the full importation-diffusion cycle of dengue. The core domestic dataset is Baidu's largest location-based service (LBS) positioning data from China, covering GPS trajectory information of users in 2024 (Fig. S18). After validation, it is used to infer inter-regional population mobility characteristics, including stopover locations, cross-regional commuting frequency, and long-distance travel routes. To quantify international import risk, we supplemented the 2024 global air transport dataset from the International Civil Aviation Organization (ICAO, <https://www.icao.int/>) (Fig. S19), filtering routes linking dengue-endemic regions to China's gateway cities and weighting passenger volumes by the dengue risk (https://github.com/ahyoung-lim/Arbo_riskmaps_public) (Fig. S20) of departure regions to generate risk-weighted international travel flux (Lim et al., 2025). Supplementary data include gridded population density data and administrative division boundary vectors (<http://www.gadm.org>), which support calculations of inter-regional distances (domestic and international), adjacency relationships, and mobility intensity standardization.

Multi-scale models are constructed to quantify the role of domestic-international linked mobility in driving dengue transmission across scenarios: **Gravity Model**: Covers two scales—domestic scale uses the formula "population size of origin $\times$ population size of destination / distance²" to reflect megacity attraction; international scale adapts to the formula "population of endemic region $\times$ its dengue probability $\times$ population size of destination / international distance²" to capture long-distance import risk. **Radiation Model**: Incorporates the pathway from endemic regions to gateway cities and then to domestic intermediate regions to fit stopover behaviors during international travel, capturing indirect transmission via transit mobility. **Adjacency Network Model**: Treats gateway cities as primary importation nodes, quantifying high-frequency mobility between gateways and adjacent

domestic regions to adapt to local clustered transmission triggered by imported cases. **Great-Circle Distance Model:** Calculates geographical distances between (i) endemic region centroids and gateway city centroids, and (ii) domestic region centroids, serving as a basic parameter to quantify spatial barriers for both domestic and international transmission.

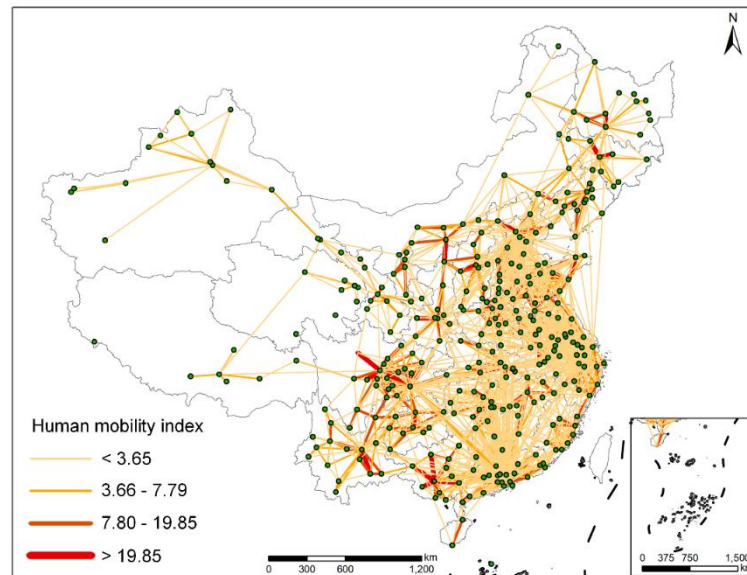


Fig. S18. The human mobility of e-scooter trips in the study area (The darker the color, the higher the number of trips).

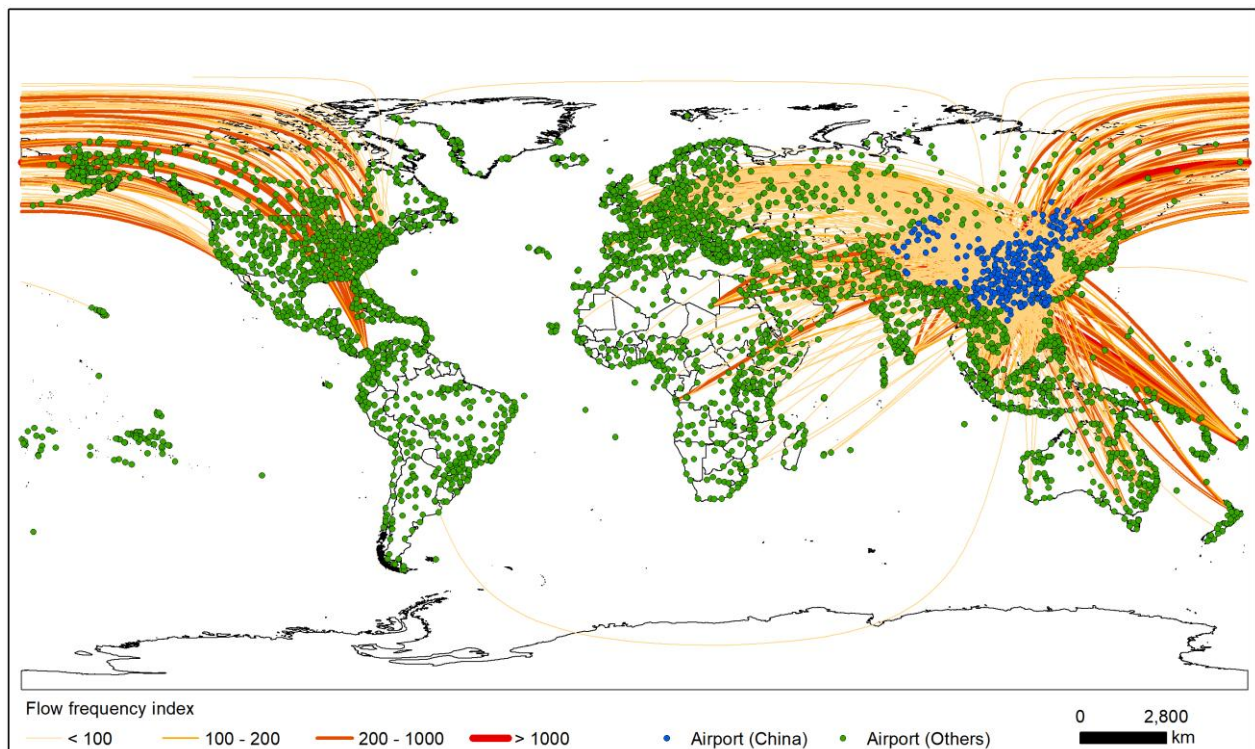


Fig. S19. The international travel flows in the world (The darker the color, the higher the number of trips).

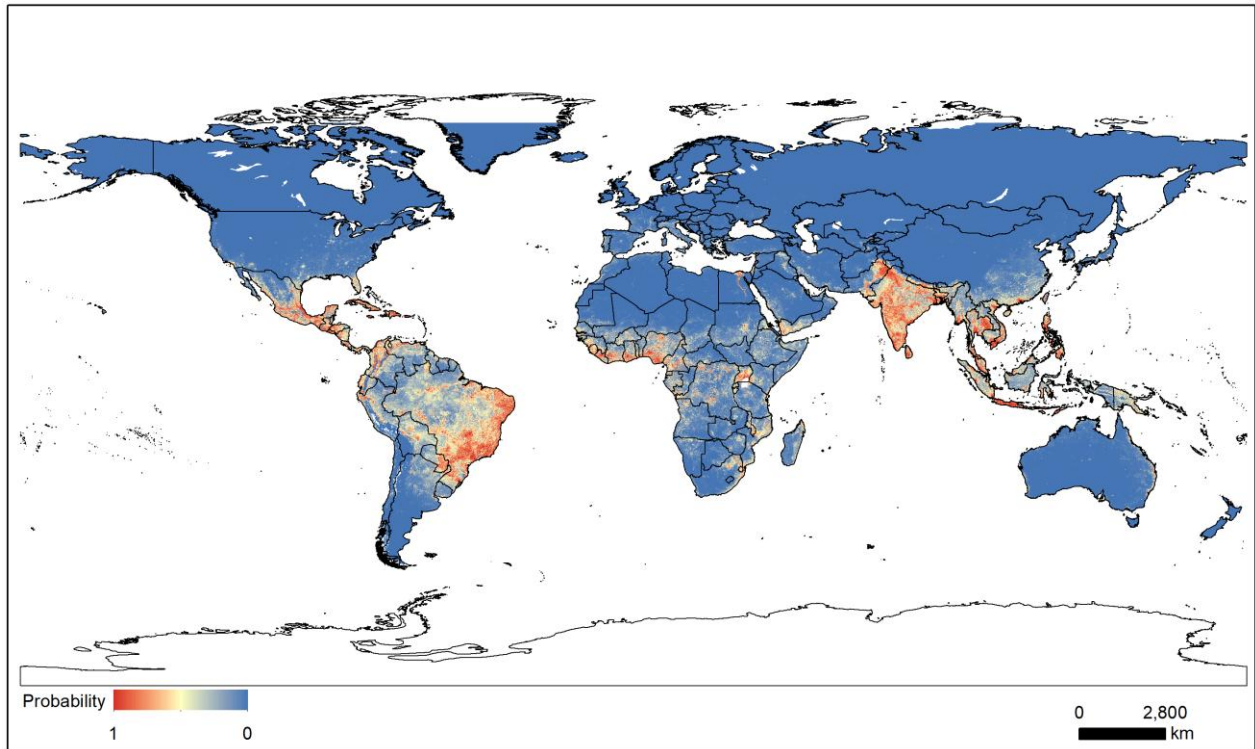


Fig. S20. The potential probability of dengue case in the world.

Dengue transmission modelling Let $x_j(t)$ be the dengue transmission status of district j at time t (that is, a binary variable taking the value 1 if dengue transmission occurred at that time, and 0 otherwise). Given the nature of the collected dataset (primarily consisting of confirmed dengue case reports and transmission chain tracing records), we assumed that all data points represented established dengue transmission in the district (rather than isolated imported cases). Thus, we further assumed continuous dengue transmission risk in the district between the first and last reported transmission events. To characterize the probability that district j will experience dengue transmission at time t , we used a standard logistic model:

$$\log \text{it} \left\{ P \left[x_j(t) = 1 \mid x_j(t-1) = 0 \right] \right\} = \beta_0 + \sum_{k=1}^n \beta_k Y_{j,t}^{(k)}$$

where $Y_{j,t}^{(k)}$ corresponds to the value of explanatory variable k in district j at time t . Explanatory variables included in this analysis were the predicted dengue hazard and connectivity between infested and non-infested districts (that is, probability of transmission of dengue). Separate metrics of connectivity were defined for each human movement model. From each human movement model, a connectivity matrix $A_{ij}^{(k)}$ was calculated for each location i and j . A corresponding covariate for the occupation model was then computed to represent the global force of importation, exerted from all other infested districts to j : $Y_{j,t}^{(k)} = \sum_i A_{ij}^{(k)} x_i(t-1)$.

Supplementary Note 5: Estimating relative surveillance capability to correct sampling bias in dengue case records

High-hazard clusters like the Yangtze River Delta and Pearl River Delta (e.g., Shanghai, Shenzhen, Guangzhou) exhibit not only high human exposure and social vulnerability but also exceptionally robust surveillance systems. For instance, Shenzhen and Shanghai have established real-time dengue case reporting platforms, high-capacity nucleic acid detection laboratories, and active mosquito surveillance during peak transmission seasons. These strengths lead to more comprehensive case capture, often resulting in higher reported cases that may overestimate the actual transmission risk if not corrected. In contrast, some underdeveloped regions in central and western China (e.g., rural areas of Sichuan, Gansu) face challenges such as passive reporting-dominated systems and limited access to diagnostic resources, leading to significant underreporting and potential underestimation of hidden risks. The heterogeneity of surveillance intensity and reporting practices has led to substantial sampling bias in dengue case record data. The relative surveillance capability we focus on here specifically refers to the long-term average probability that an individual with dengue in China will seek medical care, be accurately diagnosed, and have their case officially reported. Its value ranges from 0 (no effective surveillance capacity) to 1 (optimal surveillance capacity), directly quantifying the heterogeneity of dengue case reporting across Chinese provinces.

To address the above limitations, our research methodology framework involves the development of two independent models: a surveillance model and a dengue hazard model (i.e., GNNWLR-SHAP model). Among them, the surveillance model aims to capture within-country differences in the long-term average probability that individuals infected with acute viruses seek medical treatment, receive accurate diagnosis, and are publicly reported. It should be noted that

such estimates may not correlate with the ability to detect unfamiliar emerging diseases, but will represent long-term differences in surveillance capacity once locally circulating diseases have been appropriately characterized. Subsequently, the predictions of this surveillance model are used as an offset term in the dengue hazard model, thereby allowing the dengue hazard model to attribute the spatial variations in dengue occurrence data solely to the drivers of transmission risk.

Specifically, we used a down sampled random forest (RF) approach that balances the presence and background points at a 1:1 ratio, as RF model has shown to outperform many other machine-learning approaches for the modelling of presence-only data across a range of examples. The surveillance model formula is as follows, with covariates listed in the same order as in Table S7.

$$occ_{RF-i} \sim \text{Bernoulli}[P(occ_{RF-i})]$$

$$\text{logit}[P(occ_{RF-i})] = f(GDP_i, GDP_{county-i},$$

$$Urban_i, travel_{health-i},$$

$$travel_{cities-i}, physician_i, govern_i)$$

where $\text{logit}[P(occ_{RF-i})]$ is the location-specific probability that a record i is a dengue occurrence record, rather than a background point, and function f denotes the non-linear and interacting function of all covariates at the same spatial location as dengue occurrence record i .

The target factors for covariate selection drive the entire surveillance workflow. Including the following available covariates: (i) gross domestic product (GDP) (5×5 km resolution and aggregated county level); (ii) urbanization; (iii) travel time to health facilities by walk; (iv) travel time to cities; (v) physicians' density; and (vi) government effectiveness (Table S7). All covariates were standardized to ensure comparability. Thirdly, the model training and verification uses 100 times of spatial block cross validation to avoid excessive optimism of spatial autocorrelation data. The down sampling RF model achieved high predictive performance (AUC = 0.96). The final output is a relative monitoring capability score grid of 5×5 km in China, with high values (≈ 1) concentrated in East China and low

values (<0.3) concentrated in rural and resource poor areas (Fig. S21).

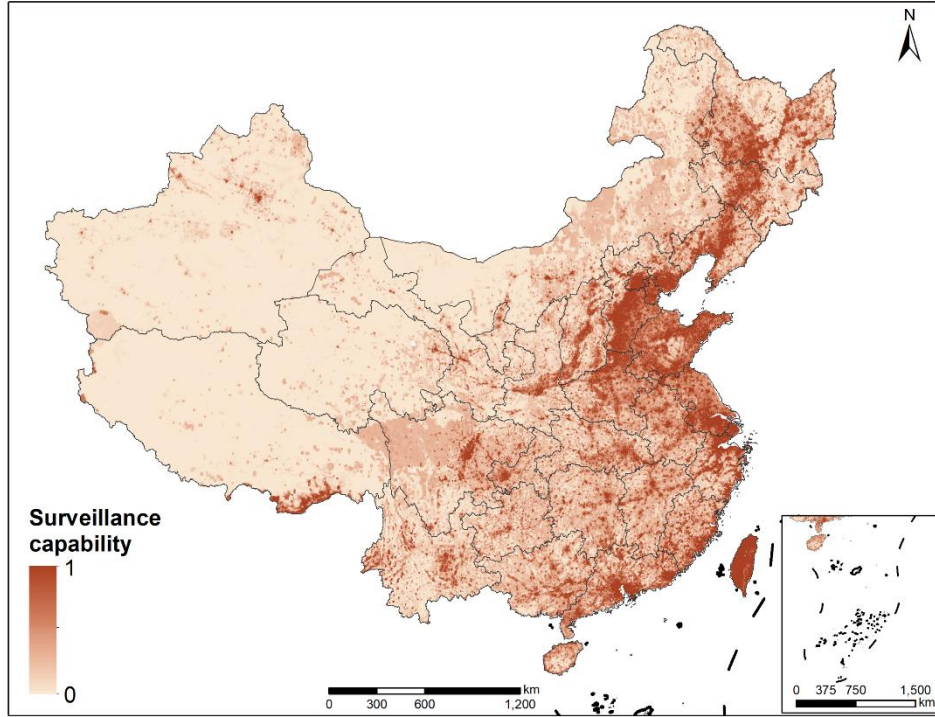


Fig. S21. Model-predicted relative surveillance capability for dengue case records.

The overall formula for the dengue hazard model, calibrated using predictions from the surveillance model as an offset term, is as follows:

$$\begin{aligned} \text{logit}[P(\text{occ}_{\text{GNNWLR-SHAP-}i})] = f(\text{dengue}_i, \\ \text{bio6}_i, \text{Aedes vector}_i, \\ \text{bio13}_i, \text{bio1}_i, \text{POP}_i, \text{bio12}_i, \\ \text{DEM}_i, \text{ISA}_i, \text{bio14}_i, \text{bio5}_i) + \\ \text{logit}[P(\text{occ}_{\text{RF-}i})] \end{aligned}$$

where $\text{logit}[P(\text{occ}_{\text{RF-}i})]$ is an offset term. The use of a modelled offset for spatial sampling bias enables us to explicitly map the estimated spatial variation in reporting rates. The two-stage approach separates the modelling of surveillance and disease processes. This minimizes the potential for overlap in the effects of covariates that influence both surveillance and disease dynamics, which is particularly important for the dengue hazard.

Table S8. Covariates included in the surveillance model.

Covariate	Abbreviation	Years covered	Original spatial resolution	Data source
Gross Domestic Product	<i>GDP</i> and <i>GDP_{county}</i>	2009-2019	1 km and county level	Chen et al., 2022
Proportion of urban land	<i>Urban</i>	2010 and 2020	1 km	Gao et al., 2020
Travel time to healthcare facilities (walking)	<i>travel_{health}</i>	2020	1 km	Weiss et al., 2020
Travel time to cities (>50,000 people, any travel mode)	<i>travel_{cities}</i>	2015	1 km	Weiss et al., 2020
Physicians density	<i>physician</i>	2010-2018	National	Nguyen et al., 2023
Government effectiveness	<i>govern</i>	2013-2020	National	Kaufmann, D. & Kraay, 2023

Supplementary Note 6: Field validation of the GNNWLR-SHAP model for dengue hazard prediction

To strengthen the scientific rigor and predictive reliability of the GNNWLR-SHAP model, we conducted dedicated field validation in Shenzhen City, a major international port and typical high-incidence dengue region in southern China. We formally collaborated with the Shenzhen Center for Disease Control and Prevention (Shenzhen CDC) to obtain de-identified confirmed dengue case records for 2024 (Fig. S22). These records included fine-grained spatial coordinates (street and community level), diagnosis dates, residential locations, and incubation-period travel histories, forming a robust ground-truth dataset for spatial matching and model evaluation.

We further assembled a standardized multi-source dataset tailored for Shenzhen to support rigorous validation: bioclimatic variables (e.g., annual mean temperature, monthly precipitation extremes, minimum temperature of the coldest month) from the China Meteorological Data Service Center; habitat suitability layers for *Aedes albopictus* and *Aedes aegypti* from ecological monitoring networks; geographic base data (digital elevation model, impervious surface area, gridded population density, and administrative boundaries) from the Geospatial Data Cloud; and domestic–international human mobility indicators developed in this study (Fig. S23 and Table S6).

Using this integrated dataset, we performed comprehensive validation covering five core dimensions: model predictive performance (Table S9); spatial congruence between observed 2024 case locations and modeled dengue hazard; consolidated SHAP analysis for quantifying driver contributions; fine-scale spatial SHAP maps for all key factors; and spatial heterogeneity of the top four dominant drivers across Shenzhen (Figs. S24-S26). This field-based validation, grounded in official surveillance data and harmonized geospatial information, verifies that the GNNWLR-SHAP model reliably captures fine-scale spatial patterns and driving mechanisms of dengue hazard. The results confirm the model's strong regional applicability, spatial accuracy, and robustness, markedly

improving the overall methodological rigor of this study.

Table S9. GNNWLR-SHAP model performance for five-fold cross-validation in Shenzhen.

	AUC			ACC			Recall		
Dengue hazard	Train	Valid	All	Train	Valid	All	Train	Valid	All
	0.886	0.893	0.888	0.811	0.819	0.824	0.812	0.802	0.823

Abbreviation: GNNWLR-SHAP, Geographically Neural Network Weighted Logistic Regression-Shapley Additive Explanations. AUC, area under the receiver operating characteristic curve; ACC, Accuracy.

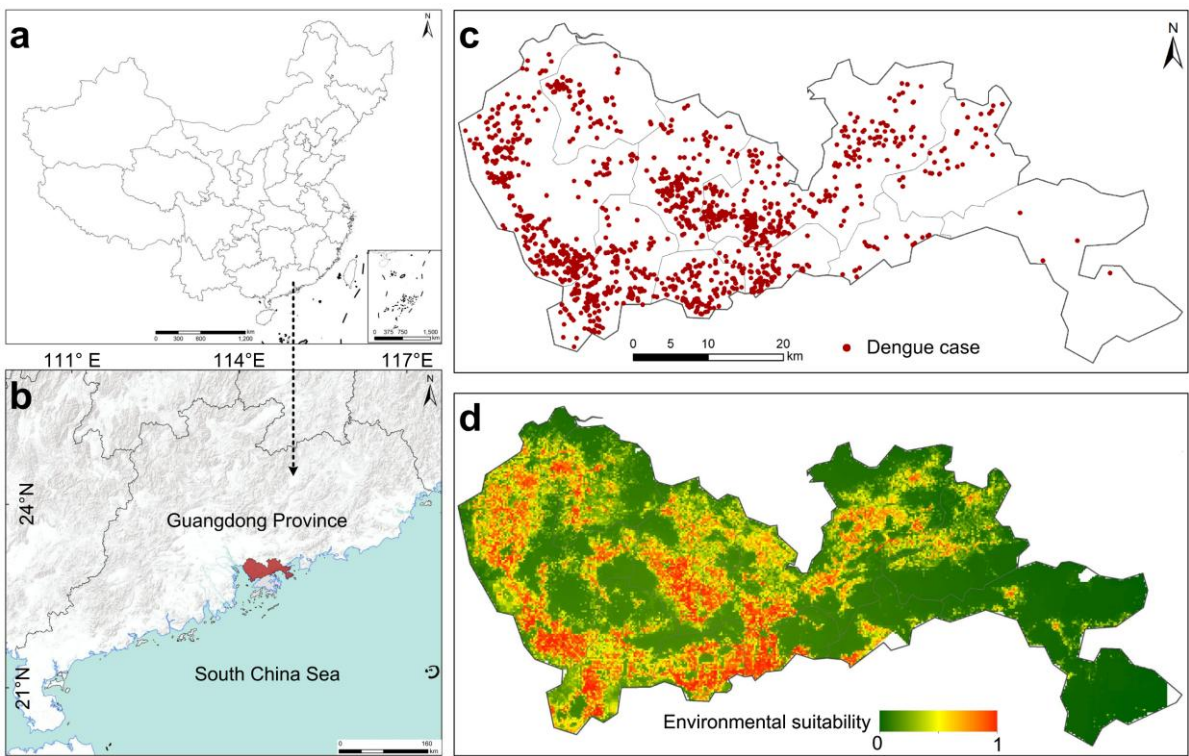


Fig. S22. **a, b**, Location of Shenzhen City in China. **c**, Spatial distributions of dengue case records in Shenzhen in 2024. **d**, Estimated dengue hazard during 2024 in Shenzhen.

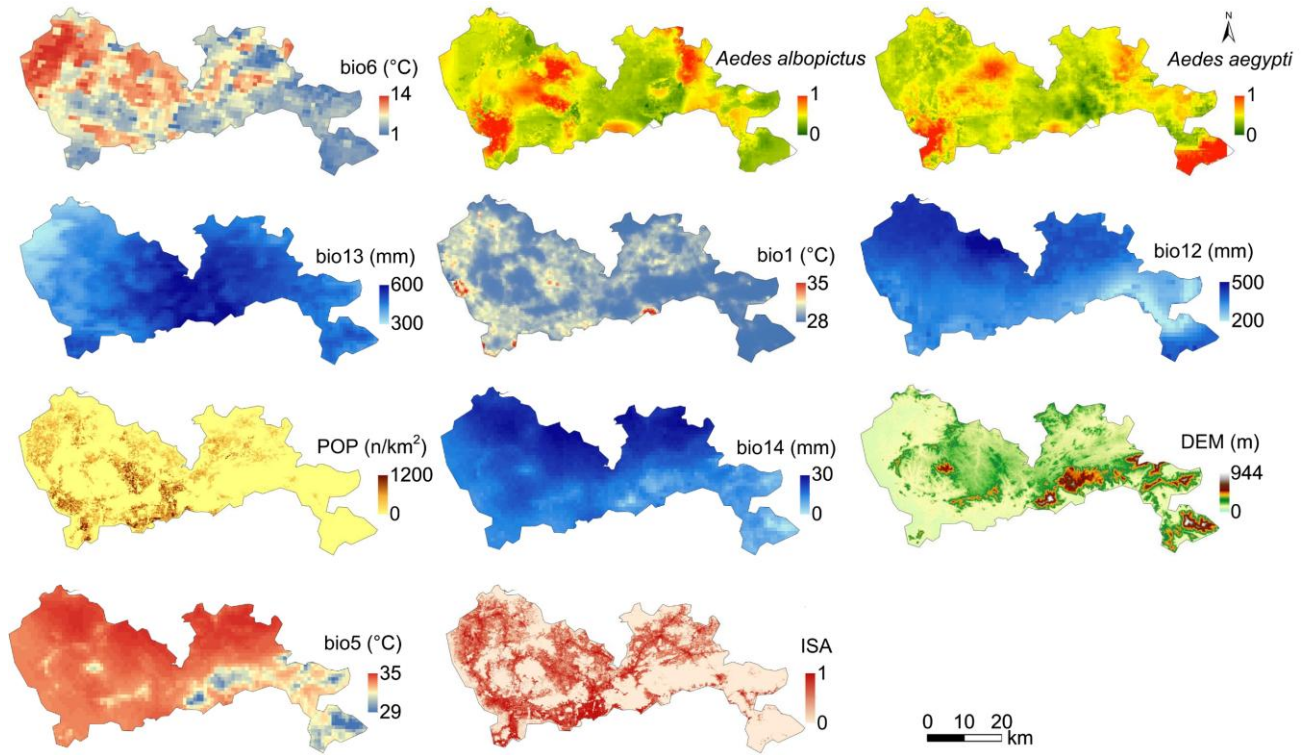


Fig. S23. Spatial distribution of these influence factors in Shenzhen.

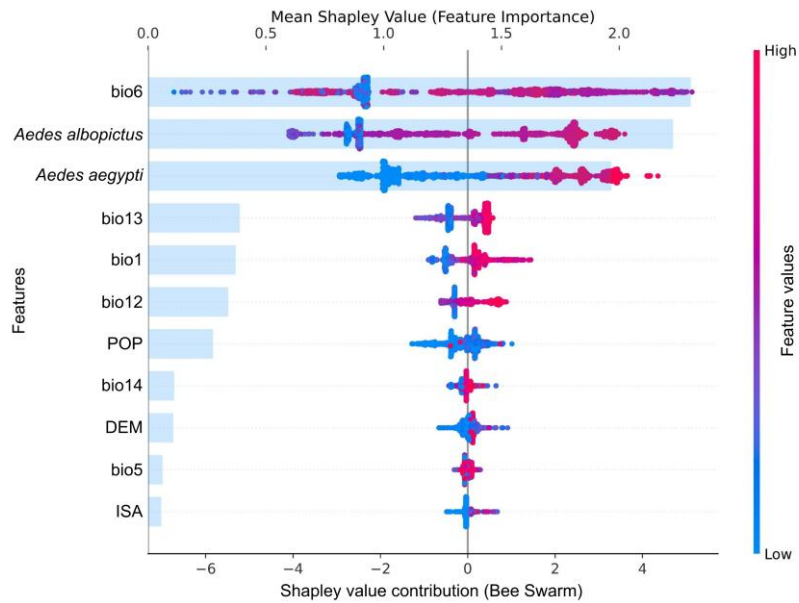


Fig. S24. Consolidated Shapley additive explanation (SHAP) value analysis for characterization of dengue suitability across Shenzhen.

Note: Bar chart of the average magnitudes of SHAP values, highlighting the mean influence of each feature on the framework's output magnitude using the average absolute SHAP values. Abbreviation:

minimum temperature of coldest month (bio6); habitat suitability of *Aedes albopictus* (*Aedes albopictus*); habitat suitability of *Aedes aegypti* (*Aedes aegypti*); precipitation of wettest month (bio13); annual mean temperature (bio1); population density (POP); annual precipitation (bio12); digital elevation model (DEM); impervious surface area (ISA); precipitation of driest month (bio14); and maximum temperature of warmest month (bio5).

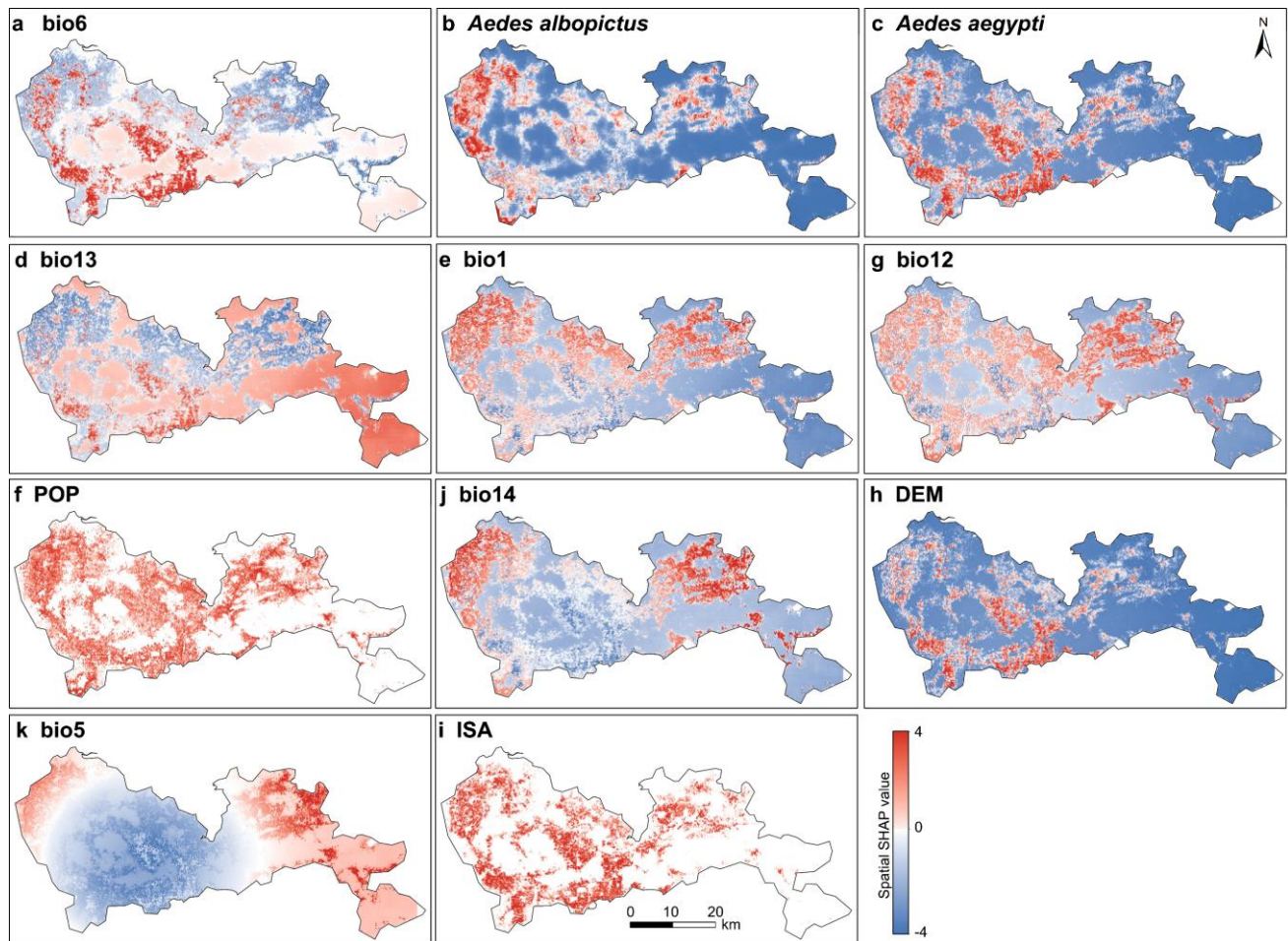


Fig. S25. Spatial distribution maps of Shapley additive explanation (SHAP) values for all driving factors in Shenzhen.

Abbreviation: (a) minimum temperature of coldest month (bio6); (b) habitat suitability of *Aedes albopictus*; (c) habitat suitability of *Aedes aegypti*; (d) precipitation of wettest month (bio13); (e) annual mean temperature (bio1); (f) population density (POP); (g) annual precipitation (bio12); (h) digital elevation model (DEM); (i) impervious surface area (ISA); (j) precipitation of driest month

(bio14); and (k) maximum temperature of warmest month (bio5).

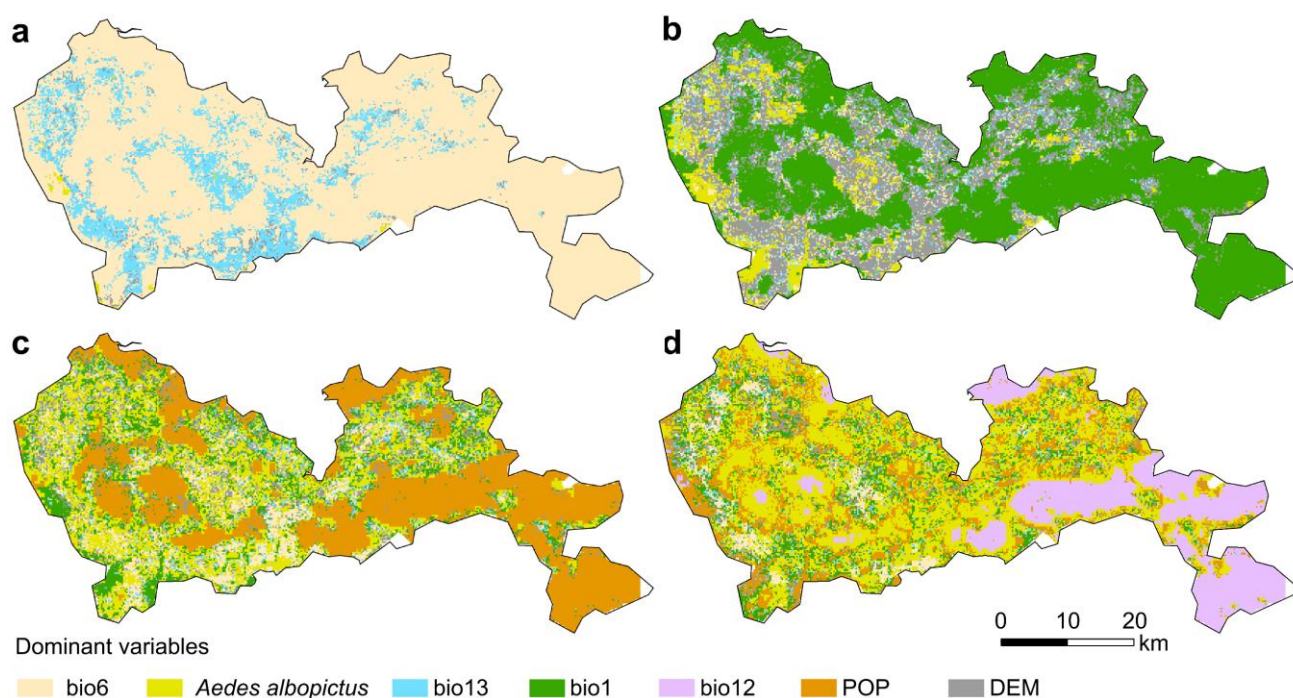


Fig. S26. Spatial distribution of the (a) first, (b) second, (c) third, and (d) fourth dominant factors in Shenzhen.

Abbreviation: minimum temperature of coldest month (bio6); habitat suitability of *Aedes aegypti*; precipitation of wettest month (bio13); annual mean temperature (bio1); annual precipitation (bio12); population density (POP); digital elevation model (DEM)."

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