

Flood Vulnerability Assessment of Immovable Cultural Heritage in Beijing's Ecological Conservation Area Across Climate Scenarios

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Abstract

Climate change is increasing the frequency of extreme precipitation events, making flooding a major natural threat to immovable cultural heritage. Focusing on seven study districts associated with Beijing's Ecological Conservation Area, this study developed a flood vulnerability assessment framework based on the Vulnerability Scoping Diagram (VSD), incorporating exposure, sensitivity, and adaptive capacity. GIS-based spatial analysis was integrated with flood-prone-area data derived from the Soil Conservation Service Curve Number (SCS-CN) method to calculate the relative flood vulnerability index (R) for 1969 georeferenced heritage assessment points under a baseline and three future Shared Socioeconomic Pathway scenarios: SSP1-1.9, SSP2-4.5, and SSP5-8.5. Mean R was 0.101 under the baseline and increased to 0.123, 0.126, and 0.120 under the three future scenarios, respectively. The number of points with high or very high vulnerability increased from 192 to 271–294. Higher R values were concentrated mainly in mountainous and riverine areas, with relatively high district-level means in Pinggu, Yanqing, Huairou, and Miyun. City- and county-level protected heritage had the highest mean R values under the future scenarios, whereas the large number of undesignated heritage points resulted in substantial cumulative management pressure. All 57 heritage points damaged by flooding in July 2025 were located in these four districts. The Gubeikou Town Wall Site and Shangying Castle Site showed large increases in R and also sustained flood damage, providing retrospective spatial-consistency evidence for the assessment. The framework provides a practical approach for regional flood vulnerability screening and conservation prioritization of immovable cultural heritage.

1. Introduction

Climate change is altering the environmental conditions surrounding cultural heritage and reshaping its risk landscape [1, 2]. Sea-level rise, changing precipitation regimes, and more frequent extreme events are exposing heritage assets to increasingly complex climate-related stresses [3, 4]. Changes in the frequency and intensity of extreme precipitation have made flooding a major climate-related threat to immovable cultural heritage [5, 6]. Because these assets remain exposed in situ and cannot be relocated, variations in their materials and structural forms strongly influence their vulnerability to hazards [7, 8]. Prolonged inundation, hydraulic scour, and foundation softening can cause structural damage and irreversible losses of historical information and heritage value [9]. Identifying flood vulnerability at individual heritage points, characterizing its spatial heterogeneity, and assessing its potential evolution under future climate scenarios are therefore essential for spatially differentiated conservation and climate adaptation [10–12].

Existing approaches to flood risk assessment for immovable cultural heritage can be grouped broadly into three categories. First, statistical approaches use historical disaster records, including flood frequency, inundation depth, and observed damage, to develop empirical functions, damage curves, or probabilistic models [13, 14]. Second, hydrological and hydrodynamic scenario-simulation approaches represent flood-generating and propagation processes. The SCS-CN method estimates surface runoff under different rainfall conditions and is suitable for regional screening in data-scarce settings [15, 16], whereas HEC-RAS and FLO-2D can simulate flood propagation, flow velocity, and inundation depth when suitable terrain, channel, and boundary-condition data are available [17–19]. Third, multidimensional indicator-based approaches commonly integrate hazard, exposure, and vulnerability indicators with remote sensing and GIS to derive composite indices for individual heritage points or assessment units [20–22]. Indicator weights may be obtained through the analytic hierarchy process, entropy weighting, or combined subjective–objective weighting, although the robustness of weighting schemes and the scarcity of external validation remain persistent limitations [21, 23]. Because indicator-based approaches can represent the flood environment, heritage attributes, and spatial heterogeneity simultaneously, they are widely used for regional-scale cultural heritage screening [10, 11]. Nevertheless, most studies still emphasize the flood environment, spatial exposure, and intrinsic heritage characteristics [10, 12, 21], while management conditions, emergency accessibility, and resource-mobilization capacity remain insufficiently quantified as components of adaptive capacity [24–26]. Although some studies have used Shared Socioeconomic Pathways

(SSPs) to investigate future climate risk, they have focused mainly on changes in hazard and have rarely compared heritage vulnerability systematically across scenarios [27, 28]. Moreover, most assessments address individual assets, specific heritage sites, or conventional administrative regions [29–31]. Systematic assessments of large heritage inventories across megacities or other extensive contiguous areas remain limited, indicating a need for scalable frameworks that retain heritage-specific characteristics [32].

Beijing is a world-renowned historic city with a high concentration of cultural heritage [33]. Several recent extreme precipitation events have intensified flood-related pressures on its heritage assets. Although drainage management and infrastructure resilience have been strengthened in the central urban area [34], heritage points in the Ecological Conservation Area are more numerous and dispersed, the terrain is more rugged, drainage and flood-control infrastructure is comparatively limited, and adaptive capacity is generally lower. These characteristics make cultural heritage in this area particularly susceptible to flooding and underscore the practical importance of a regional vulnerability assessment.

Against this background, this study evaluates 1969 georeferenced heritage assessment points in Beijing's Ecological Conservation Area using a regional flood vulnerability framework based on the VSD. Exposure was characterized using potential flood-prone-area datasets for different return periods developed by Jia et al. with a GIS-based SCS-CN method [16, 28]. Future conditions were represented by the CMIP6 SSP1-1.9, SSP2-4.5, and SSP5-8.5 scenarios [35]. By integrating exposure, sensitivity, and adaptive capacity, the study compares relative flood vulnerability and its spatial variation between the baseline and future scenarios and examines differences among protection levels and management conditions. The objective is to provide a regional screening approach for spatially dispersed cultural heritage in the ecological conservation area of a megacity and to support conservation prioritization and climate adaptation. The framework may also inform assessments in ecological conservation areas of other heritage-rich megacities.

2. Study Area

Beijing lies in northern China, at the northern margin of the North China Plain. Mountains and hills dominate the west, north, and northeast, and the terrain descends toward the southeastern plains. The Yongding, Chaobai, North Canal, and Juma rivers form a characteristic mountain–plain transitional watershed system. More than half of the city's annual precipitation occurs in summer, when rainfall is typically short-lived, intense, and highly variable. Extreme rainstorms have occurred more frequently in recent years, and severe floods in the summers of 2023 and 2025 caused substantial damage.

The study area comprises Beijing's Ecological Conservation Area. According to relevant municipal policies and the 2023 administrative-division dataset of the Beijing Municipal Civil Affairs Bureau, it includes all of Mentougou, Pinggu, Huairou, Miyun, and Yanqing districts and the mountainous parts of Changping and Fangshan districts. The area contains 14 subdistricts, 79 towns, and 15 townships, including seven towns in Changping District and one subdistrict, nine towns, and six townships in Fangshan District. Mountainous and hilly terrain, pronounced relief, and dense valley and river networks predominate. During extreme precipitation, these conditions favor flash floods, hillslope runoff, and localized inundation, while drainage and related infrastructure remain comparatively limited.

The heritage inventory comprises 1969 registered, georeferenced immovable cultural heritage assessment points across the seven study districts. Of these, 252 are associated with Major Historical and Cultural Sites Protected at the National Level, including 192 related to the Great Wall and its associated structures and 24 belonging to the Ming Tombs complex; 40 are protected at the provincial level; 351 are protected at the city or county level; and 1,326 are undesignated. Figure 1 shows the study area and the spatial distribution of the heritage assessment points.

3. Methods

3.1. Analytical Framework

This study adopted the Vulnerability Scoping Diagram (VSD) as its conceptual framework. Originally proposed by Polsky et al. [36], the VSD conceptualizes vulnerability through three interrelated dimensions: exposure, sensitivity, and adaptive capacity [37, 38]. Its defining feature is the explicit incorporation of human intervention and management capacity into vulnerability assessment [31, 39]. In the cultural heritage field, Ravan et al. [31] applied a VSD-based framework to assess flood vulnerability at the Roman Ruins of Tróia in Portugal, supporting its relevance to cultural heritage assessment.

The analytical framework (Fig. 2) comprises scenario characterization, identification of potentially affected areas, integrated assessment, vulnerability classification, and retrospective consistency checking. First, potential flood-prone-area datasets for the baseline and the CMIP6 SSP1-1.9, SSP2-4.5, and SSP5-8.5 scenarios were obtained from Jia et al. These datasets were generated previously by estimating direct runoff with the SCS-CN method under 20-, 50-, and 100-year return-period storms and delineating potential flood-prone areas through GIS-based hydrological analysis using DEM and river-network data. Second, exposure (E) was characterized by flood-prone areas for different return periods, elevation, slope, and distance to streams; sensitivity (S) by protection level, construction date, and heritage type; and adaptive capacity (A) by distance to roads, distance to township or district governments, and ownership type. Continuous indicators were then normalized using min–max normalization, equal weights were assigned within each dimension, and the relative flood vulnerability index (R) was calculated and classified.

3.2. Flood Vulnerability Assessment Methodology

3.2.1. Flood-Prone-Area Data and Exposure Calculation

Exposure (E) represents the relative spatial degree to which a heritage assessment point is exposed to flooding under a specified precipitation scenario. The SCS-CN model was not rerun in this study. Instead, spatial datasets of potential flood-prone areas in Beijing, generated by Jia et al. using a GIS-based SCS-CN method, were adopted [28]. In their original modeling procedure, rainfall runoff was estimated at the sub-watershed scale, and potential flood-prone areas under different water levels were delineated using a digital elevation model and GIS-based surface-volume analysis. This approach supports rapid flood screening at the regional scale. The model principles, curve number (CN) determination, runoff calculation, and delineation procedure are described in Refs. [16, 28, 40]. The datasets were provided by the research team of Jia et al. and used with authorization.

3.2.2. Indicator Framework and Weighting

Flood vulnerability assessment requires the exposure, sensitivity, and post-disaster adaptive capacity of the elements at risk to be defined and quantified [20, 21]. Based on the literature review and data availability, 12 indicators were selected to characterize these three dimensions [25, 41]. Equal weighting was applied. Each dimension—exposure, sensitivity, and adaptive capacity—was assigned an overall weight of 1, which was then distributed approximately equally among the indicators within that dimension. Table 1 presents the resulting framework, which balances regional-scale applicability with data availability and supports quantitative comparison among heritage assessment points.

Table 1
Indicators and weights used for flood vulnerability assessment of cultural heritage.

Dimension	Indicator	Abbreviation	Data source	Direction	Weight
Exposure	20-year flood/storm	E1	Simulated flood-prone area using GIS-based SCS-CN method	+	0.16
	50-year flood/storm	E2		+	0.16
	100-year flood/storm	E3		+	0.17
	Elevation	E4	Calculated from DEM data in ArcGIS	-	0.17
	Slope	E5		+	0.17
	Distance to stream	E6		-	0.17
Sensitivity	Protection level	S1	Third Cultural Heritage Survey Data of Beijing	+	0.33
	Construction date	S2		+	0.34
	Heritage type	S3		+	0.33
Adaptive Capacity	Distance to roads	A1	Calculated via ArcGIS	-	0.34
	Distance to township or district government	A2		-	0.33
	Ownership type	A3	Third National Cultural Relics Census data for Beijing	+	0.33
Note: “+” indicates that a higher indicator value produces a higher score for the corresponding dimension, whereas “-” indicates that a higher value produces a lower score.					

3.2.3. Exposure Indicators

Exposure represents the relative spatial likelihood that cultural heritage will be affected by flooding. In the VSD operationalization used here, this dimension incorporates hazard-related spatial characteristics and is broadly aligned with the hazard component of the IPCC risk framework. Previous studies identify proximity to rivers, topography, and the frequency of extreme floods as important parameters for characterizing the flood exposure of cultural heritage [42–44]. Accordingly, exposure was represented by flood-prone areas for different return periods, elevation, slope, and distance to streams.

Potential flood-prone-area layers for the 20-, 50-, and 100-year return periods under the baseline, SSP1-1.9, SSP2-4.5, and SSP5-8.5 scenarios were standardized to a common coordinate system and spatial extent and overlaid with the 1969 georeferenced heritage assessment points. For each return period, a point within a potential flood-prone area was assigned 1, and a point outside the area was assigned 0. These binary variables formed indicators E1, E2, and E3.

Elevation and slope represented topographic controls on flooding and related secondary hazards. Lower elevations and steeper slopes were assumed to correspond to greater potential for inundation and secondary hazards, respectively. Distance to streams provided an additional measure of hydrological exposure, with points closer to streams considered more highly exposed.

3.2.4. Sensitivity Indicators

Sensitivity represents the intrinsic susceptibility of cultural heritage to damage when exposed to flooding [10, 21] and is determined primarily by the characteristics of the heritage asset. Construction age, material type, structural form, and

conservation condition can influence flood-induced damage to historic buildings [45, 46]. Protection level (S1), construction date (S2), and heritage type (S3) were therefore included in the sensitivity dimension.

Protection level represents the social, historical, and cultural value assigned to a heritage property, with higher protection levels corresponding to higher heritage value. Based on the Third National Cultural Relics Census data for Beijing, records were grouped into four categories: Major Historical and Cultural Sites Protected at the National Level, provincial-level protected heritage, city- and county-level protected heritage, and undesignated immovable cultural heritage.

Construction dates were grouped into five periods based on the census data: before the Zhou dynasty; the Qin through Southern and Northern dynasties; the Sui through Song dynasties; the Yuan, Ming, and Qing dynasties; and the modern and contemporary period. These categories represent differences associated with structural aging and long-term weathering.

Heritage types were classified according to structural materials and spatial characteristics because sensitivity to flood damage varies among types. Bridges, docks, and above-ground historic buildings, for example, are generally more susceptible to flooding than underground or stone-built heritage. Table 2 presents the classification and scoring criteria.

Table 2
Scoring criteria for sensitivity indicators.

Indicator	Type	Score
Heritage protection level (S1)	National level	1.000
	Provincial level	0.750
	City- and county-level	0.500
	Undesignated	0.250
Construction date (S2)	From 1912 to 2020	0.200
	During the Yuan, Ming, and Qing dynasties	0.400
	From the Sui to Song dynasties	0.600
	From the Qin to the Southern and Northern dynasties	0.800
	Before the Zhou dynasty and heritage sites of unknown construction dates	1.000
Heritage type (S3)	Grotto or stone carving	0.200
	Ancient tomb	0.400
	Other unclassified cultural heritage	0.500
	Important modern or contemporary historical site or representative building	0.600
	Ancient architecture	0.800
	Archaeological site, bridge, or dock	1.000

3.2.5. Adaptive Capacity Indicators

Adaptive capacity represents the ability of cultural heritage to resist, respond to, and recover from flooding [24, 25, 47] and reflects the combined effects of human management and social-support systems [48, 49]. It was characterized

using distance to roads (A1), distance to township or district governments (A2), and ownership type (A3).

Greater transport accessibility was assumed to facilitate emergency response, while shorter distances to administrative centers were assumed to improve post-disaster coordination and resource mobilization. Ownership type represented institutional protection conditions because management responsibilities and financial support differ among ownership arrangements. Heritage managed by government departments or collective organizations was assumed to have greater maintenance and emergency-response capacity, whereas heritage under individual ownership or without an identifiable owner was considered to receive comparatively less support.

All spatial-distance indicators were calculated in ArcGIS. Table 3 presents the scoring criteria for ownership type. Incorporating management conditions, preparedness, and response resources helps overcome the limitations of heritage assessments based only on physical exposure and intrinsic susceptibility [12, 26, 50].

Table 3
Scoring criteria for the ownership-type indicator.

Ownership type (A3)	No identifiable owner	0.250
	Individual	0.500
	Village committees or social organizations	0.750
	Government department	1.000

3.2.6. Indicator Normalization

The continuous indicators were elevation, slope, distance to streams, distance to roads, and distance to township or district governments; their units were meters or degrees. To remove scale effects, min–max normalization was used to transform the raw values linearly to [0,1]. Categorical indicators were scored according to Table 2 and Table 3.

Indicators were classified as positive or negative according to their relationship with the corresponding assessment dimension. Slope was treated as positive because steeper terrain can increase surface-runoff velocity and scour and therefore the potential for hydraulic impacts on heritage. Elevation, distance to streams, distance to roads, and distance to township or district governments were treated as negative. Larger values correspond to a lower probability of inundation, poorer emergency-response accessibility, and longer post-disaster coordination times, respectively, and therefore yield lower standardized scores for the corresponding dimensions.

Positive indicators were normalized as:

$$X'_{ij} = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)} \#(1)$$

Negative indicators were normalized as:

$$X'_{ij} = \frac{\max(X_j) - X_{ij}}{\max(X_j) - \min(X_j)} \#(2)$$

where X'_{ij} is the normalized value of indicator j for heritage assessment unit i ; X_{ij} is the corresponding raw value; and $\max(X_j)$ and $\min(X_j)$ are the maximum and minimum values of indicator j within the study area, respectively. Following transformation, all indicator values ranged from 0 to 1. Higher normalized values indicate a greater contribution to the respective assessment dimension. For exposure indicators, higher values therefore represent greater exposure, whereas for adaptive-capacity indicators, higher values represent stronger adaptive capacity, including greater proximity to roads or administrative centers.

3.2.7. Vulnerability Calculation and Classification

After normalization to [0,1] as described in Section 3.2.6, the exposure score (E), sensitivity score (S), and adaptive-capacity score (A) were calculated for each heritage assessment point using the weights in Table 1:

$$E = \sum_{i=1}^n E_i \times W_{Ei} \#(3)$$

$$S = \sum_{i=1}^n S_i \times W_{Si} \#(4)$$

$$A = \sum_{i=1}^n A_i \times W_{Ai} \#(5)$$

where E_i , S_i , and A_i are the standardized values of the i th exposure, sensitivity, and adaptive-capacity indicators, respectively; W_{Ei} , W_{Si} , and W_{Ai} are their corresponding weights; and n is the number of indicators within the respective dimension.

Following the VSD framework, exposure and sensitivity increase vulnerability, whereas adaptive capacity moderates it. The relative flood vulnerability index (R) for each heritage assessment point was therefore calculated as follows:

$$R = \frac{E \times S}{A} \#(6)$$

As A approaches zero, R theoretically approaches infinity. In this dataset, however, the adaptive-capacity score was greater than zero for every heritage assessment point; division by zero therefore did not occur. Higher R values indicate greater relative flood vulnerability.

Five-class schemes have been used previously to map cultural heritage flood assessment results [16]. Here, fixed thresholds were defined from the distribution of R values across the 1969 heritage assessment points. Thresholds of 0.07, 0.15, 0.30, and 0.50 differentiated the right-skewed distribution: under the baseline, 71.2% of points had $R < 0.07$, whereas only 1.1% had $R \geq 0.50$. Table 4 presents the resulting five vulnerability classes. Stream proximity and modeled flood-prone areas were retained as interpretive references rather than used to derive the thresholds mathematically. Comparable regional cultural heritage studies have also categorized assessment outputs to support spatial comparison and prioritization [13, 16, 17].

Table 4
Classification of the relative flood vulnerability index.

Vulnerability class	R range	Interpretive description	Associated exposure-related characteristic
V. Very high	$R \geq 0.50$	Potential direct-scour exposure	Distance to stream < 100 m or within 100-year flood edge
IV. High	$0.30 \leq R < 0.50$	High exposure	Distance to stream 100–300 m or within 50-year flood edge
III. Moderate	$0.15 \leq R < 0.30$	Moderate exposure	Distance to stream 300–500 m or low-lying terrain
II. Low	$0.07 \leq R < 0.15$	Low exposure	Distance to stream 500 m–1 km or moderate adaptive capacity
I. Very low	$R < 0.07$	Minimal exposure or strong adaptive capacity	Distance to stream > 1 km

3.3. Data Sources

Historical observations and future climate projections were integrated in the flood vulnerability assessment. Monthly temperature and precipitation data for 1901–2021 were obtained from the National Tibetan Plateau Data Center (<https://data.tpdac.ac.cn/home>) at a spatial resolution of 1 km. Future climate data for 2021–2100 were obtained from the same repository and comprised CMIP6 multi-model ensembles under SSP1-1.9, SSP2-4.5, and SSP5-8.5 [35].

The Beijing Municipal Cultural Heritage Bureau provided heritage locations, types, protection levels, and construction dates. A 30-m digital elevation model, 1:250,000 river-network data, and land-use data were obtained from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences (<https://www.resdc.cn/>). The Beijing Population Census Yearbook, Beijing Water Resources Bulletin, and 2023 administrative-division dataset of the Beijing Municipal Civil Affairs Bureau provided supplementary information.

4. Results

4.1. Flood Vulnerability under Different Climate Scenarios

Assessment of the 1969 georeferenced heritage points under the baseline and three IPCC Shared Socioeconomic Pathway scenarios (SSP1-1.9, SSP2-4.5, and SSP5-8.5) indicated an overall increase in flood vulnerability under future climate conditions (Table 5; Fig. 3).

Under the baseline, R values were generally low, with a mean of 0.101 and a maximum of 0.625. Of the heritage assessment points, 1,401 (71.2%) were classified as having very low vulnerability ($R < 0.07$), whereas only 21 (1.1%) were classified as having very high vulnerability ($R \geq 0.50$), producing a strongly bottom-heavy class distribution. Mean R increased to 0.123, 0.126, and 0.120 under SSP1-1.9, SSP2-4.5, and SSP5-8.5, respectively. The proportion of very-low-vulnerability points decreased from 71.2% to 62.8%–64.5%, while the number of high- or very-high-vulnerability points ($R \geq 0.30$) increased from 192 under the baseline to 271–294 under the future scenarios. SSP2-4.5 contained the largest number of high- and very-high-vulnerability points (294). The maximum R increased by 19.2%, from 0.625 under the baseline to 0.745 at the Shangying Castle Site in Gubeikou Town, Miyun District.

Table 5
Distribution and summary statistics of R values under the baseline and three future climate scenarios.

Vulnerability class	Baseline	SSP1-1.9	SSP2-4.5	SSP5-8.5
I. Very low	1401 (71.2%)	1256 (63.8%)	1236 (62.8%)	1269 (64.4%)
II. Low	211 (10.7%)	207 (10.5%)	205 (10.4%)	215 (10.9%)
III. Moderate	165 (8.4%)	226 (11.5%)	234 (11.9%)	214 (10.9%)
IV. High	171 (8.7%)	248 (12.6%)	260 (13.2%)	240 (12.2%)
V. Very high	21 (1.1%)	32 (1.6%)	34 (1.7%)	31 (1.6%)
Maximum R	0.625	0.745	0.745	0.745
Mean R	0.101	0.123	0.126	0.120

4.2. Spatial Distribution of Flood Vulnerability under Different Climate Scenarios

R exhibited pronounced point-level spatial heterogeneity under all four scenarios (Fig. 4). Using fixed classification thresholds, 192 points were classified as having high or very high vulnerability under the baseline, increasing to 280

under SSP1-1.9, 294 under SSP2-4.5, and 271 under SSP5-8.5. Higher R values were concentrated mainly in Pinggu, Yanqing, Huairou, and Miyun. Under SSP2-4.5, these four districts contained 237 points with $R \geq 0.30$, representing 80.6% of all high- and very-high-vulnerability points in that scenario. Very low or low R values predominated in Mentougou, Fangshan, and Changping, although localized higher values occurred. District-level means therefore did not fully represent within-district variation among individual points.

Relative to the baseline, R increased at 324 points (16.5%) under SSP1-1.9, 344 (17.5%) under SSP2-4.5, and 308 (15.6%) under SSP5-8.5. R remained unchanged at all other points, and no decreases occurred. The numbers of points moving upward by at least one vulnerability class were 266, 291, and 249, respectively. The broad spatial pattern was therefore similar across scenarios, but future increases were concentrated at a subset of heritage points while most remained stable.

Both mean R and the number of points with $R \geq 0.30$ were highest under SSP2-4.5; vulnerability therefore did not increase monotonically from SSP1-1.9 to SSP5-8.5. Heritage points with higher future R values occurred mainly in mountainous terrain, river valleys, and low-lying areas near rivers, with clusters along major river systems. Increases were particularly evident near the Chaobai, Juma, and Wenyu rivers.

4.3. Increases in Vulnerability under Future Scenarios

At the point level, all three future scenarios produced net increases in R relative to the baseline. R increased at 324 heritage assessment points (16.5%) under SSP1-1.9, 344 (17.5%) under SSP2-4.5, and 308 (15.6%) under SSP5-8.5. Rather than affecting the full inventory simultaneously, the changes comprised pronounced increases at a relatively small and spatially concentrated subset of points. Figure 5 maps the points with increased R. They occurred mainly in southern Yanqing, central and southern Huairou, northeastern Miyun, and southeastern Pinggu. Across the future scenarios, 345 points increased under at least one scenario, and 308 increased under all three.

The same five heritage assessment points had the largest increases in R under all three future scenarios (Table 6). The Gubeikou Town Wall Site in Miyun District showed the largest increase, from 0.093 under the baseline to 0.531 under the future scenarios ($\Delta R = 0.438$). The Shangying Castle Site ranked second, increasing from 0.334 to 0.745 ($\Delta R = 0.411$). The Caimugou Site in Yanqing, Ganying Paleolithic Findspot in Pinggu, and Changshaoying Site in Huairou had ΔR values of 0.348, 0.333, and 0.324, respectively. All five were archaeological sites in mountainous river valleys or near major river systems.

Except for the Shangying Castle Site, the other four points had baseline R values below 0.10 but exceeded 0.30 under the future scenarios, indicating substantial upward class shifts among some points with initially low R. The R values and ranking of all five points were identical across the three future scenarios. Their changes therefore reflected the contrast between the baseline and future climate conditions, while differentiation among the future pathways was limited.

The five points with the largest increases were distributed across Miyun, Yanqing, Pinggu, and Huairou, consistent with the four higher-vulnerability areas identified by the spatial analysis. The Gubeikou Town Wall Site and Shangying Castle Site, which had the two largest increases in R, are both in Gubeikou Town, Miyun District, and both were damaged during the 2025 “25-7” flood. Gubeikou Town thus contained the two largest modeled increases and recorded damage to multiple nationally protected heritage properties during the same 2025 event. This spatial correspondence provides an external reference for prioritizing heritage points with elevated vulnerability.

Table 6
Five heritage assessment points with the largest increases in R under the future climate scenarios.

Rank	Name	District	Protection level	Type	Baseline R	R (SSP)	Increase in R	Flood damage in 2025
1	Gubeikou Town Wall Site	Miyun District	Nationally Protected Major Historical and Cultural Site	Archaeological site	0.0933	0.531	+ 0.438	Damaged
2	Shangying Castle Site	Miyun	Nationally Protected Major Historical and Cultural Site	Archaeological site	0.334	0.745	+ 0.411	Damaged
3	Caimugou Site	Yanqing	Municipal- or County-Level Protected Cultural Heritage Site	Archaeological site	0.089	0.437	+ 0.348	-
4	Ganying Paleolithic Findspot	Pinggu	Unclassified Cultural Heritage Site	Archaeological site	0.083	0.415	+ 0.333	-
5	Changshaoying Site	Huairou	Unclassified Cultural Heritage Site	Archaeological site	0.083	0.407	+ 0.324	-

4.4. Differences among Heritage Protection Levels

Flood vulnerability responses differed among heritage protection levels (Fig. 6). Under the baseline, mean R values for national-level (n = 252), provincial-level (n = 40), city- and county-level (n = 351), and undesignated heritage (n = 1326) were 0.095, 0.095, 0.108, and 0.100, respectively, indicating relatively small differences among the four groups.

Differences became more pronounced under the future scenarios. City- and county-level protected heritage had the highest mean R, reaching 0.137 under SSP2-4.5, followed by undesignated heritage at 0.127. National-level heritage showed the smallest relative increase, rising by only 8.4% under SSP5-8.5, and remained comparatively stable. Provincial-level heritage increased by approximately 22.1%.

Figure 6b further distinguishes protection levels by both the proportion of points with increased R and the magnitude of those increases. Undesignated heritage had the highest proportion of increasing points (17.6%), followed by city- and county-level protected heritage (16.8%). Among points with increased R, however, mean ΔR was highest for city- and county-level protected heritage (0.023), slightly exceeding the values for undesignated heritage (0.021) and provincial-level heritage (0.020). Only 3.6% of national-level points increased, and their mean ΔR was lowest at 0.008, indicating comparatively limited future change in this group.

These differences were associated with variation in management conditions and adaptive capacity among protection levels. City- and county-level protected heritage generally had intermediate management support and emergency-response capacity, producing comparatively limited adaptive-capacity scores and higher mean R under the future

scenarios. National-level heritage generally benefits from more established conservation-management systems and stronger resource support, which correspond to higher adaptive-capacity scores in the present framework and moderate the increase in R. Although undesignated heritage did not have the highest mean R, it represented 67.4% of the sample and therefore constitutes a major component of regional flood vulnerability management.

4.5. District-Level Differences in Flood Vulnerability

Flood vulnerability varied markedly among districts in Beijing's Ecological Conservation Area (Fig. 7). Under the baseline, Pinggu had the highest district-level mean R (0.203), followed by Yanqing (0.115), Huairou (0.111), and Miyun (0.109). Mean values were lower in Mentougou (0.070), Fangshan (0.068), and Changping (0.067), producing an overall pattern of higher vulnerability in the northeast and lower vulnerability in the southwest.

Mean R increased to different extents in every district under the future scenarios. Pinggu remained the most vulnerable, reaching 0.239 under SSP2-4.5, while Yanqing reached 0.157 under the same scenario. Most districts reached their highest mean R under SSP2-4.5 and then declined slightly under SSP5-8.5. In this assessment, the intermediate pathway therefore produced a stronger flood-related response than the other future scenarios, rather than vulnerability increasing monotonically with scenario forcing.

5. Discussion

The coupled VSD–SCS–CN–SSP framework provides a practical basis for quantifying flood vulnerability and identifying spatial patterns across large cultural heritage inventories.

5.1. Balancing Parsimony and Representativeness in the Indicator Framework

Cultural heritage flood vulnerability assessment requires a balance between indicator completeness and representativeness [21, 35, 51]. This study therefore adopted a parsimonious indicator-selection strategy: candidate indicators with strong intercorrelations or limited spatial discriminatory power were excluded, while the information required to characterize exposure, sensitivity, and adaptive capacity was retained.

Population density and regional GDP were not included in adaptive capacity. The districts in Beijing's Ecological Conservation Area are predominantly suburban and mountainous, and the coefficients of variation in their mean population density and GDP were very low, providing insufficient spatial differentiation for vulnerability screening. Forest cover, impervious-surface proportion, and soil type are frequently used as exposure-related variables in urban flood studies [15, 52]. In the present study, however, all areas lie within the broader ecological conservation context, forest cover exceeds 50%, and land-use patterns are relatively homogeneous. These variables therefore provided limited discriminatory power at the heritage-point scale.

The final framework comprised 12 indicators. This selection retained the principal information relevant to flood vulnerability while limiting redundancy and repeated weighting, thereby improving the operational feasibility of regional comparisons across large numbers of heritage assessment points.

5.2. Retrospective Consistency Check against the 2025 Flood Damage

The July 2025 “25·7” flood was used to examine retrospective consistency between the assessment results and observed damage patterns at district, individual-point, and local-group scales (Fig. 8).

At the district scale, a major regional flood affected the Haihe River Basin in late July 2025 [53]. Post-flood statistics from the Beijing Municipal Cultural Heritage Bureau recorded damage at 57 immovable cultural heritage points across the seven study districts: 16 in Miyun, 2 in Pinggu, 1 in Huairou, and 38 in Yanqing. These were the same four districts with higher vulnerability in Fig. 8, while no damaged points were recorded in the lower-vulnerability districts of Mentougou, Fangshan, and Changping. The division between affected and unaffected districts was therefore spatially consistent with the district-level differentiation in R.

At the individual-point scale, the Gubeikou Town Wall Site, which ranked first in the increase in R ($0.093 \rightarrow 0.531$, $\Delta R = +0.438$), and the Shangying Castle Site, which ranked second ($0.334 \rightarrow 0.745$, $\Delta R = +0.411$), are both in Gubeikou Town, Miyun District. Both were damaged during the 2025 flood. The northwestern wall of the former collapsed locally, while approximately 45 m² of the northern wall of the latter collapsed. The R value of Yanglinggong Temple also increased from 0.076 under the baseline to 0.394 under the future scenarios, and part of its courtyard wall collapsed during the event. Thus, several points identified as having large increases in R or relatively high vulnerability coincided spatially with observed damage.

At the local-group scale, Gubeikou Town contained several heritage points with relatively high future R values and experienced damage to multiple nationally protected heritage properties during the 2025 flood. The model identified eight points in this area with relatively elevated R585 values ($R585 > 0.18$). This indicates spatial consistency between the modeled and observed concentrations. The shift of Yanglinggong Temple from a relatively low baseline R to a higher vulnerability class further illustrates that some points with comparatively low present-day vulnerability may undergo marked upward class shifts under future climate conditions.

Overall, the assessment and the observed 2025 damage corresponded at the district, concentration, and representative-point scales, providing an external reference for the spatial plausibility of the results. This retrospective comparison demonstrates spatial consistency, however, and should not be interpreted as a rigorous validation of predictive accuracy. In particular, Yanqing accounted for 38 damaged heritage points, substantially more than the other districts, suggesting that the framework may not fully represent short-duration mountain floods, hillslope runoff, and localized scour. Future studies should calibrate the model against observed extreme-rainfall events and more complete damage datasets, explicitly address uncertainty in regional CMIP6 precipitation projections [54], and improve the representation of runoff-concentration processes in mountainous terrain within the exposure dimension.

5.3. Conservation Strategies and Management Implications

The spatial patterns identified here indicate that cultural heritage flood management can be strengthened through priority-area screening, differentiated conservation, monitoring and early warning, adaptation measures, and coordinated governance [55].

(1) Prioritize vulnerability screening in key areas.

Pinggu, Yanqing, Miyun, and Huairou contain relatively large numbers of heritage points with high R or substantial future increases and warrant priority in regional screening. Flood vulnerability of the Great Wall requires particular attention. All 17 nationally protected heritage points with $R585 \geq 0.30$ were associated with the Great Wall (100%); thus, these 17 points formed an entirely Great Wall-related high-vulnerability group. The 2025 “25·7” flood provided event-based comparative evidence: all 10 nationally protected heritage properties damaged in Miyun District belonged to the Great Wall defensive system. The agreement between the composition of the damaged group and the modeled high-vulnerability group suggests that the framework can identify concentrations of flood vulnerability within this defensive system.

(2) Differentiate conservation by protection level and vulnerability.

For Major Historical and Cultural Sites Protected at the National Level, pre-flood inspections and emergency plans should focus on points with high R or large projected increases. City- and county-level protected heritage and undesignated heritage require stronger routine inspection and basic protective measures. Undesignated heritage accounts for 67.4% of the sample. Although its mean R is not the highest, its numerical dominance means that it should not be overlooked when conservation resources are allocated.

(3) Link vulnerability screening with monitoring and early warning.

The mapped distribution of R provides a long-term vulnerability baseline that can be integrated with real-time rainfall, water-level observations, flash-flood warnings, and field inspections. Inspection and emergency-response priorities for key heritage points can then be adjusted dynamically to observed meteorological and hydrological conditions.

(4) Apply context-specific adaptive conservation measures.

For heritage in mountain gullies, on river terraces, or near watercourses, low-intervention measures—including improved drainage, interception of hillslope runoff, vegetated buffers, wetland retention, and reversible temporary flood defenses—may be considered according to local topography and hydrology. Nature-based solutions can complement flood adaptation for cultural heritage, but specific interventions require site-level assessment of heritage value, conservation condition, and environmental context [50, 56].

(5) Strengthen coordinated management.

Cultural heritage, meteorological, water-management, and emergency-management authorities should improve information sharing. Heritage flood vulnerability should be integrated into existing flood-control and heritage-safety systems, while local administrations and community-based inspections can support routine risk identification across large, spatially dispersed heritage inventories.

6. Conclusions

This study developed a VSD-based framework that integrates multiple SSP climate scenarios, GIS-based spatial analysis, and SCS-CN-derived flood-prone-area information to assess the relative flood vulnerability of 1969 georeferenced heritage assessment points in Beijing's Ecological Conservation Area. The main conclusions are as follows.

(1) Flood vulnerability increased overall under the future climate scenarios. Mean R was 0.101 under the baseline, when 71.2% of heritage points had very low vulnerability. Mean R increased to 0.123, 0.126, and 0.120 under SSP1-1.9, SSP2-4.5, and SSP5-8.5, respectively, and the number of high- and very-high-vulnerability points ($R \geq 0.30$) increased from 192 to 271–294. The maximum R increased from 0.625 to 0.745, indicating persistently elevated vulnerability at some points across the future scenarios.

(2) Flood vulnerability was spatially differentiated and concentrated in mountainous river valleys. District-level mean R was comparatively high in Pinggu, Yanqing, Huairou, and Miyun and generally remained elevated under the future scenarios. The five points with the largest increases were all in these four districts, mainly in mountainous river valleys or near major river systems. Most districts had comparatively high mean R under SSP2-4.5, showing that vulnerability did not increase monotonically across the SSP pathways.

(3) Vulnerability responses varied among protection levels. City- and county-level protected heritage had comparatively high mean R under the future scenarios ($R_{585} = 0.131$), while national-level heritage had the smallest relative increase

(+ 8.4%). Undesignated heritage did not have the highest mean vulnerability but represented 67.4% of the sample, making it the largest group relevant to regional flood vulnerability management.

(4) Flood damage observed in 2025 was spatially consistent with the assessed vulnerability pattern. All 57 points damaged during the “25·7” flood were in Yanqing, Miyun, Pinggu, or Huairou, while none were recorded in Mentougou, Fangshan, or Changping. Points with high R or large modeled increases, including the Gubeikou Town Wall Site, Shangying Castle Site, and Yanglinggong Temple, were also damaged. This correspondence at district and representative-point scales provides an external reference for the spatial plausibility of the assessment.

(5) The coupled VSD–SCS–CN–SSP framework provides a methodological reference for regional-scale flood vulnerability screening of cultural heritage. It integrates flood exposure, heritage sensitivity, and adaptive capacity and allows hydrologically derived flood information to be assessed alongside future climate scenarios. Important limitations nevertheless remain, including indicator parsimony, the specific formulation used to calculate R, and the limited representation of mountain floods and hillslope runoff. Future work should calibrate the model using historical extreme events and more complete damage datasets and incorporate mountainous hydrological processes together with the structural and material characteristics of heritage to improve multiscale vulnerability assessment.

Declarations

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CRediT authorship contribution statement

X.X.H.: Conceptualization, Methodology, Data curation, Formal analysis, Software, Visualization, Writing – original draft, Writing – review and editing. **X.H.:** Writing – original draft, Writing – review and editing. **M.J.:** Resources, Data curation. **K.C.:** Funding acquisition, Project administration, Supervision, Writing – review and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Cultural heritage data are not publicly available because of institutional restrictions imposed by the Beijing Municipal Cultural Heritage Bureau. Climate-scenario data are available from <https://data.tpd.cn/home>. DEM, river-network, and land-use data are available from <https://www.resdc.cn/>.

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Figures

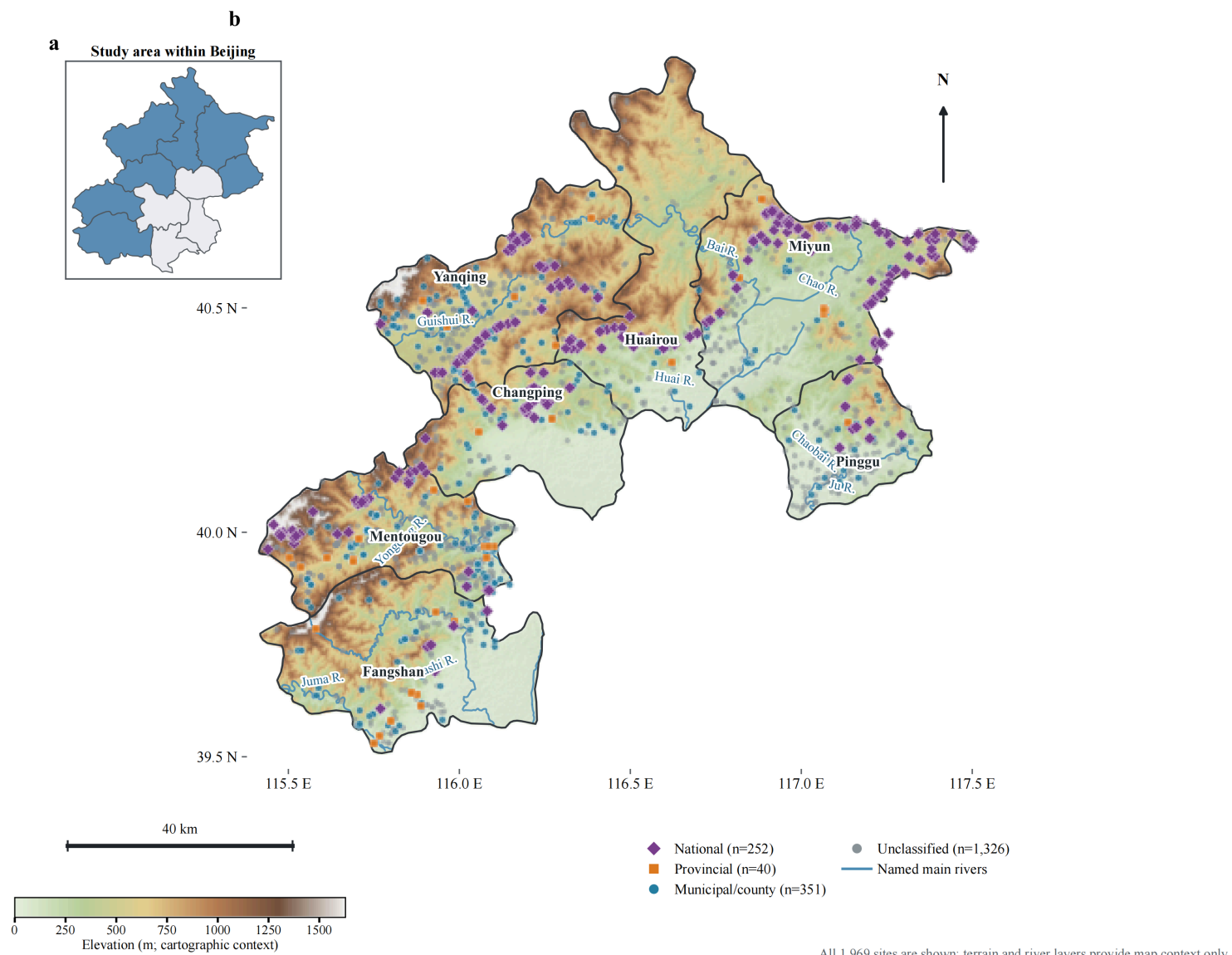


Figure 1

Study area and distribution of heritage assessment points. (a) Location of the seven study districts within Beijing. (b) Elevation, major rivers, district boundaries, and the 1969 georeferenced heritage assessment points.

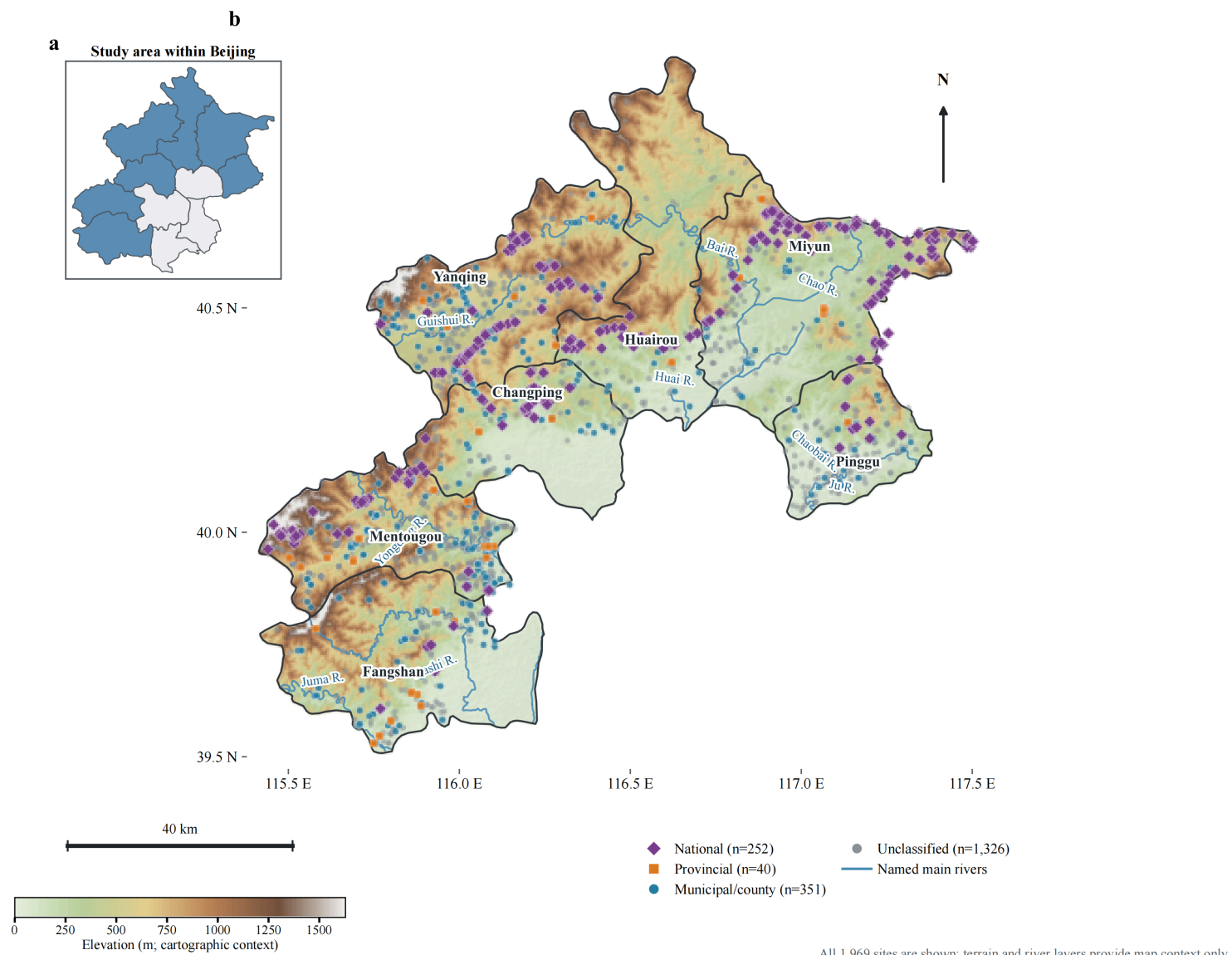


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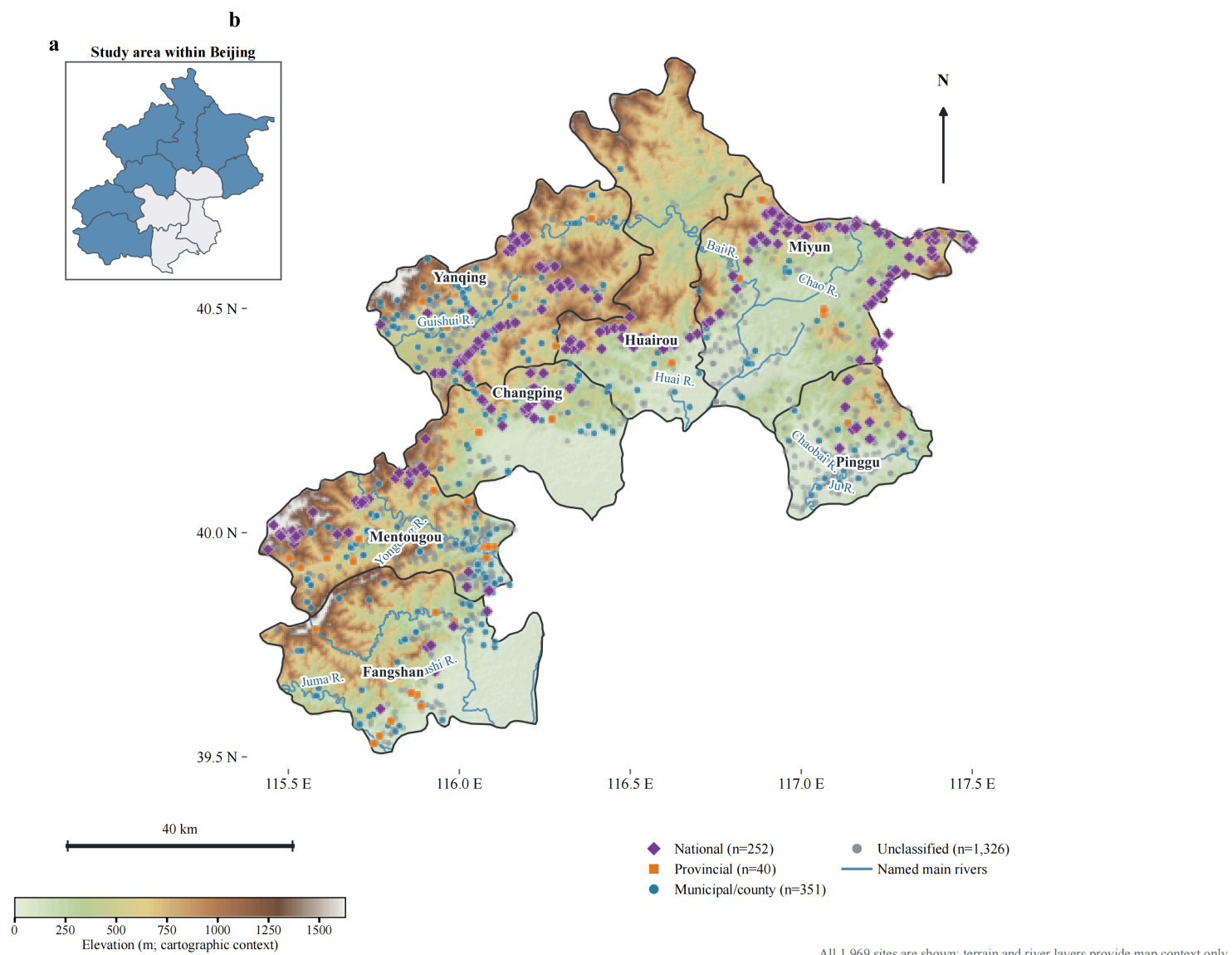


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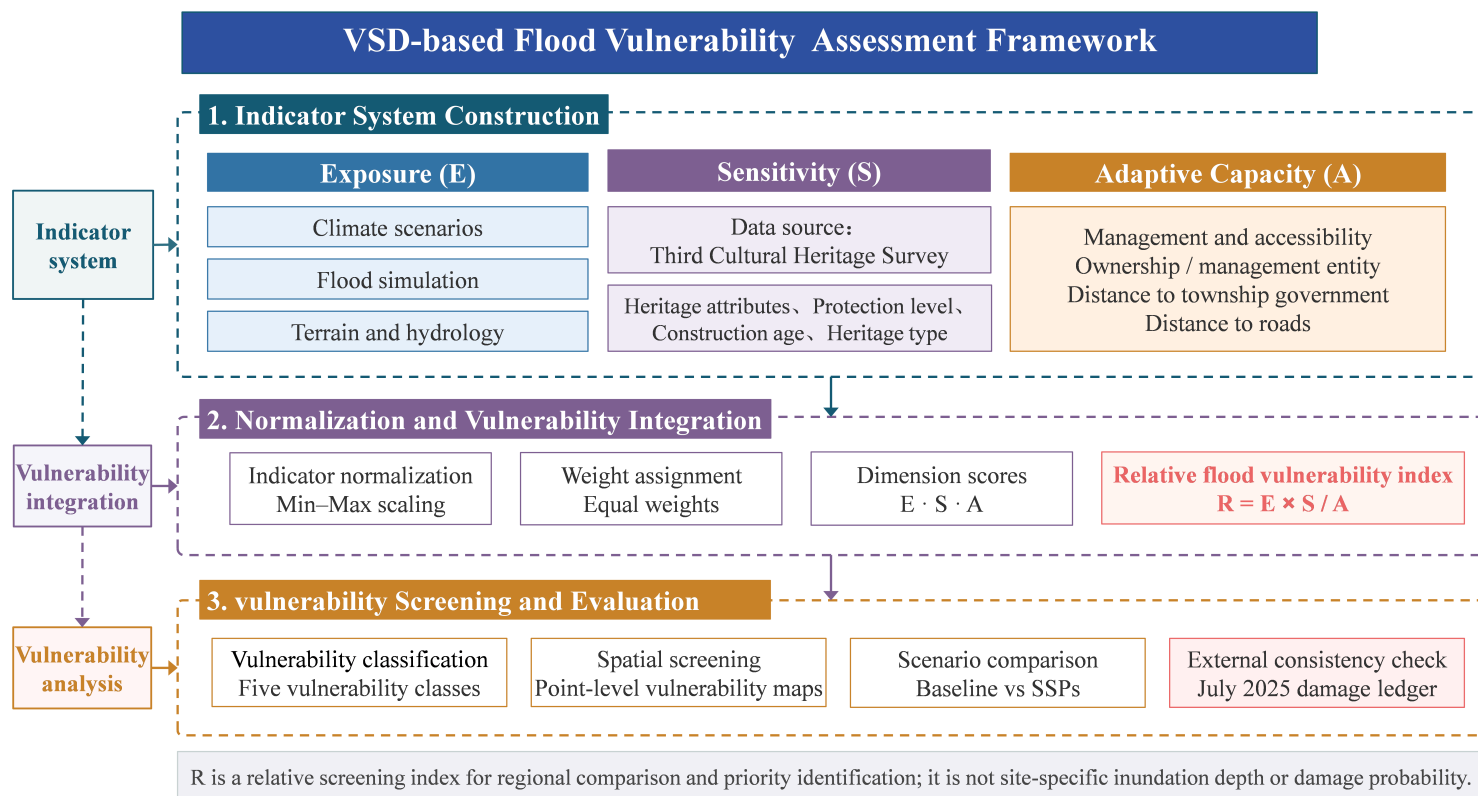


Figure 2

Regional workflow for screening the flood vulnerability of immovable cultural heritage.

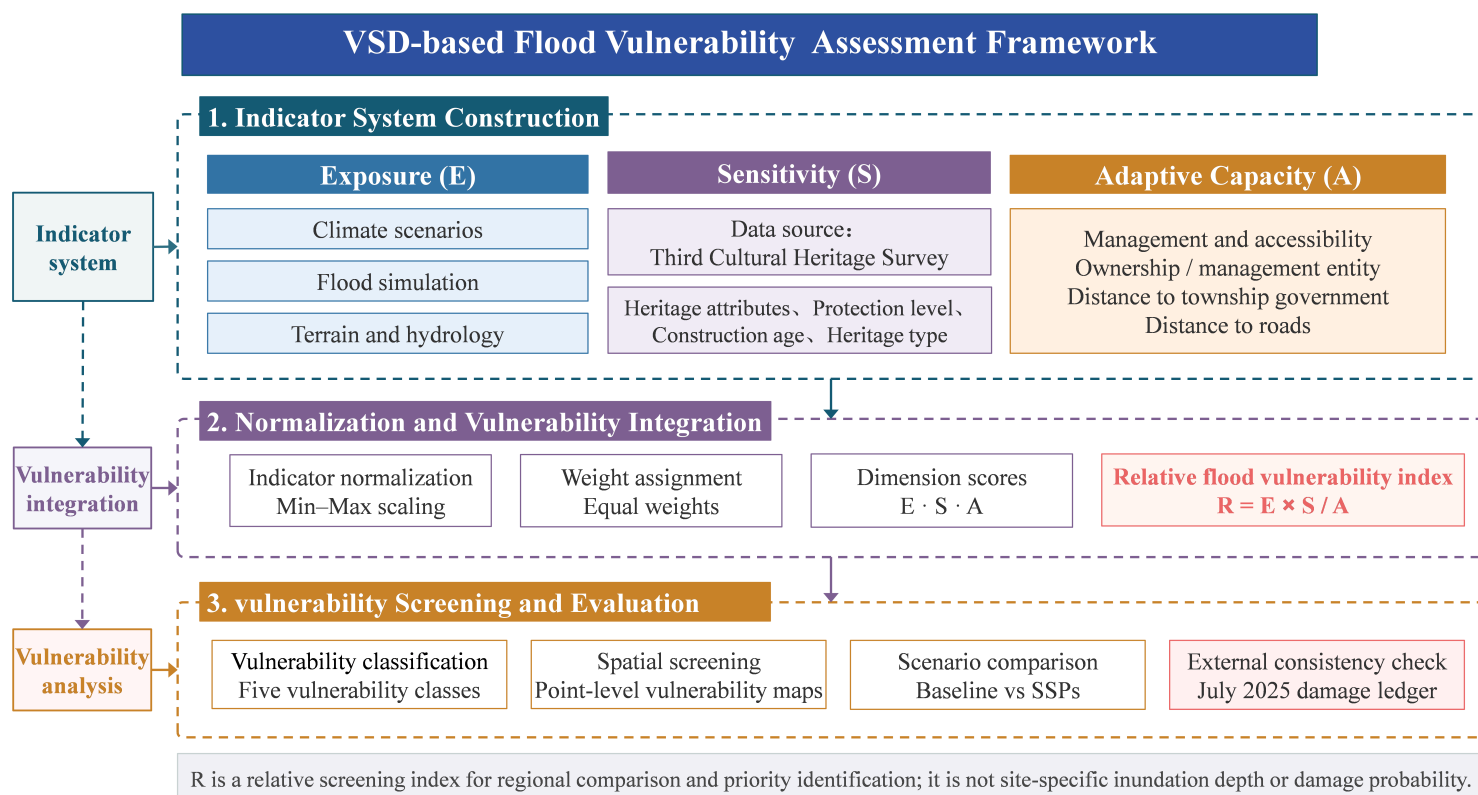


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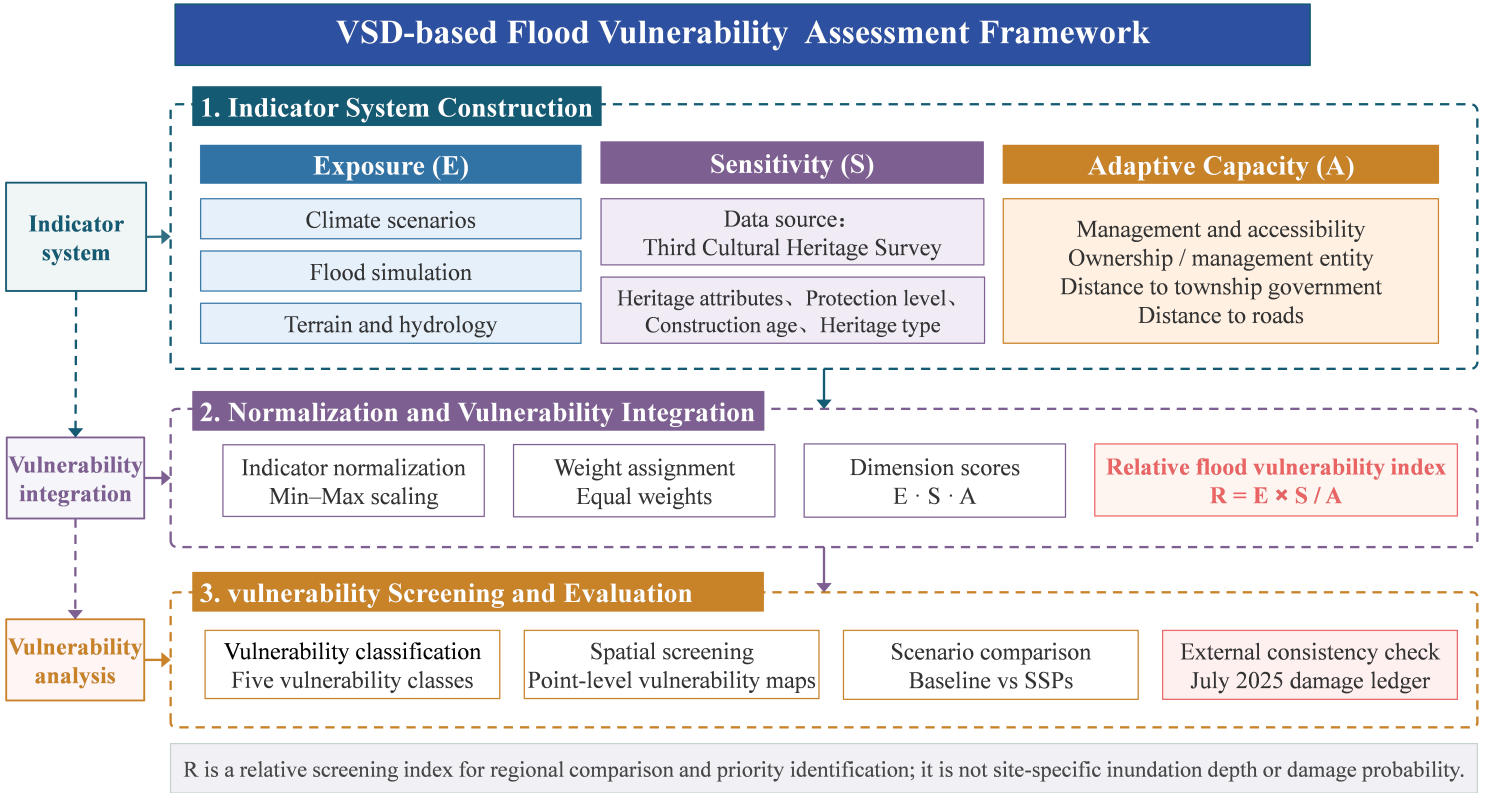


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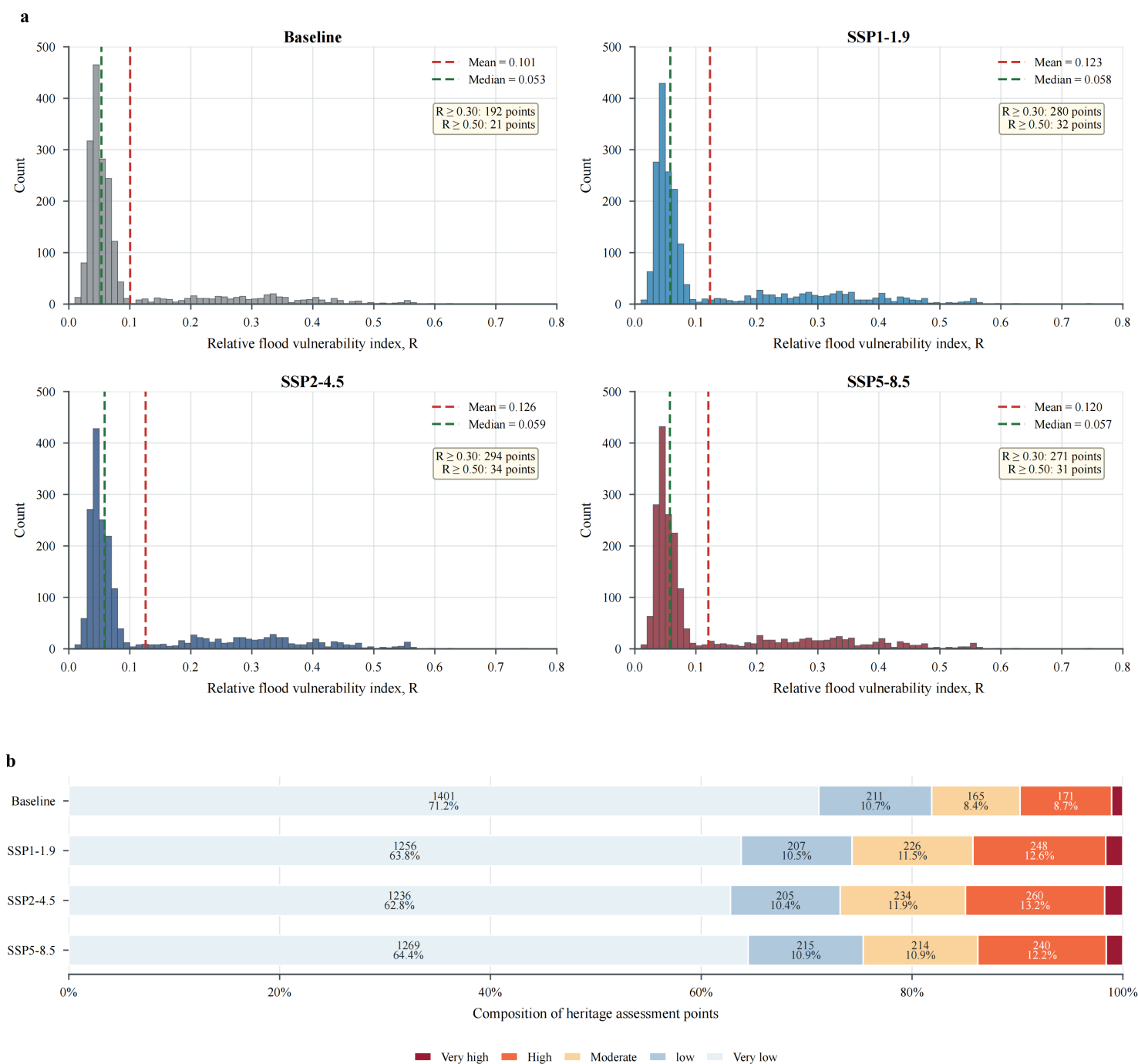


Figure 3

Distribution and class composition of the relative flood vulnerability index. (a) Distribution of R under the baseline, SSP1-1.9, SSP2-4.5, and SSP5-8.5 scenarios; red and green dashed lines denote the mean and median, respectively. (b) Number and percentage of heritage assessment points in each of the five fixed vulnerability classes.

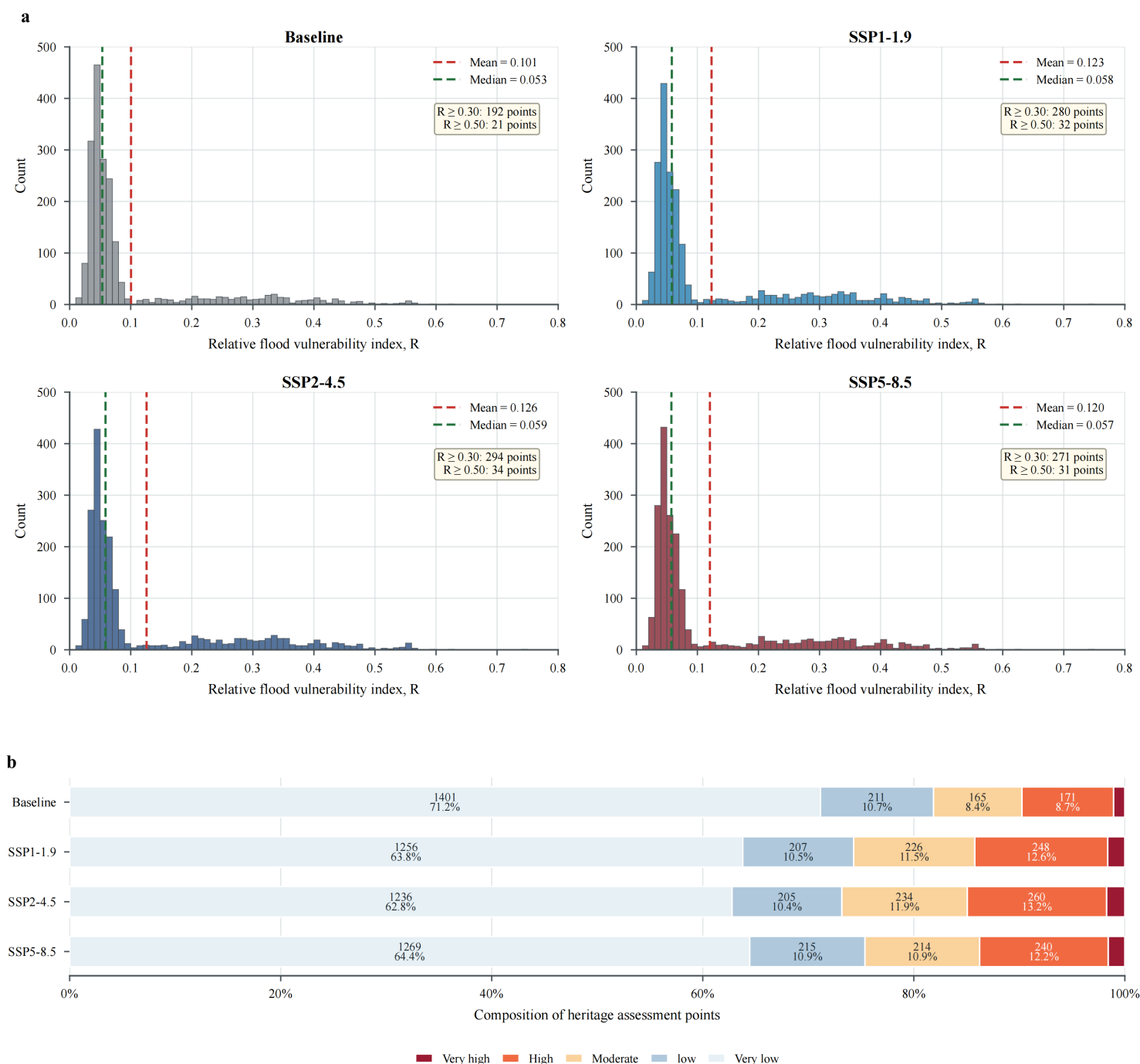


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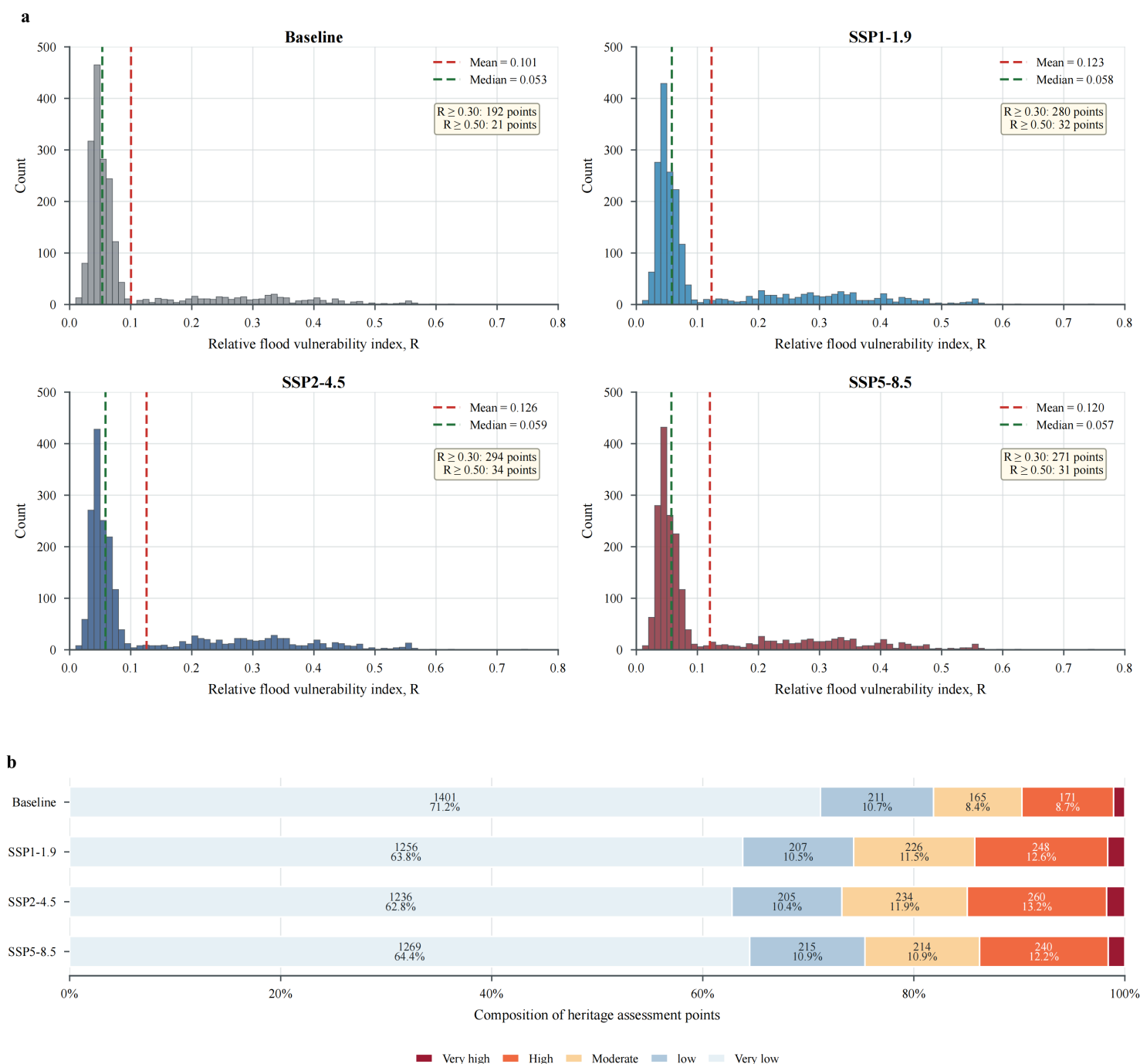
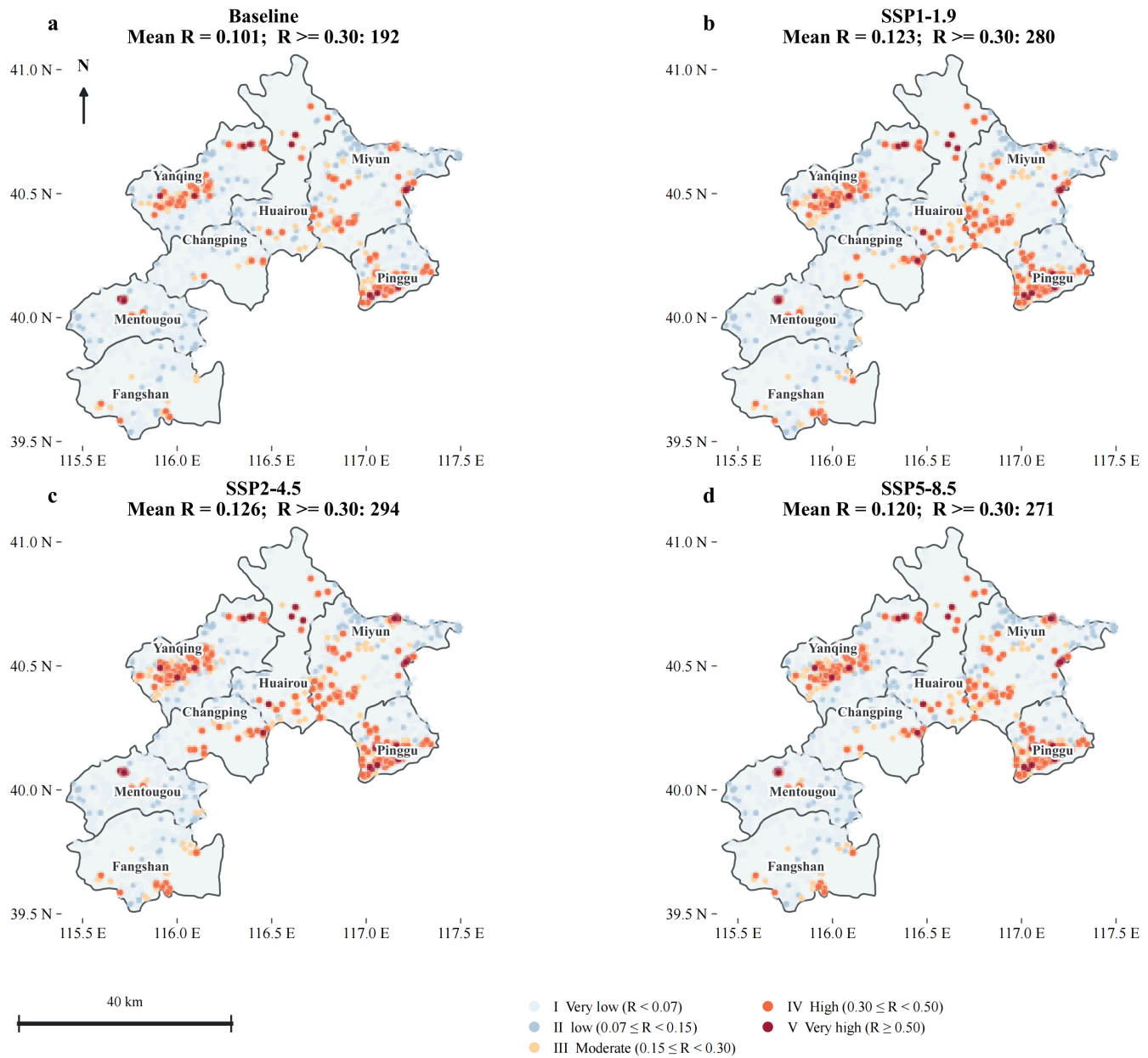


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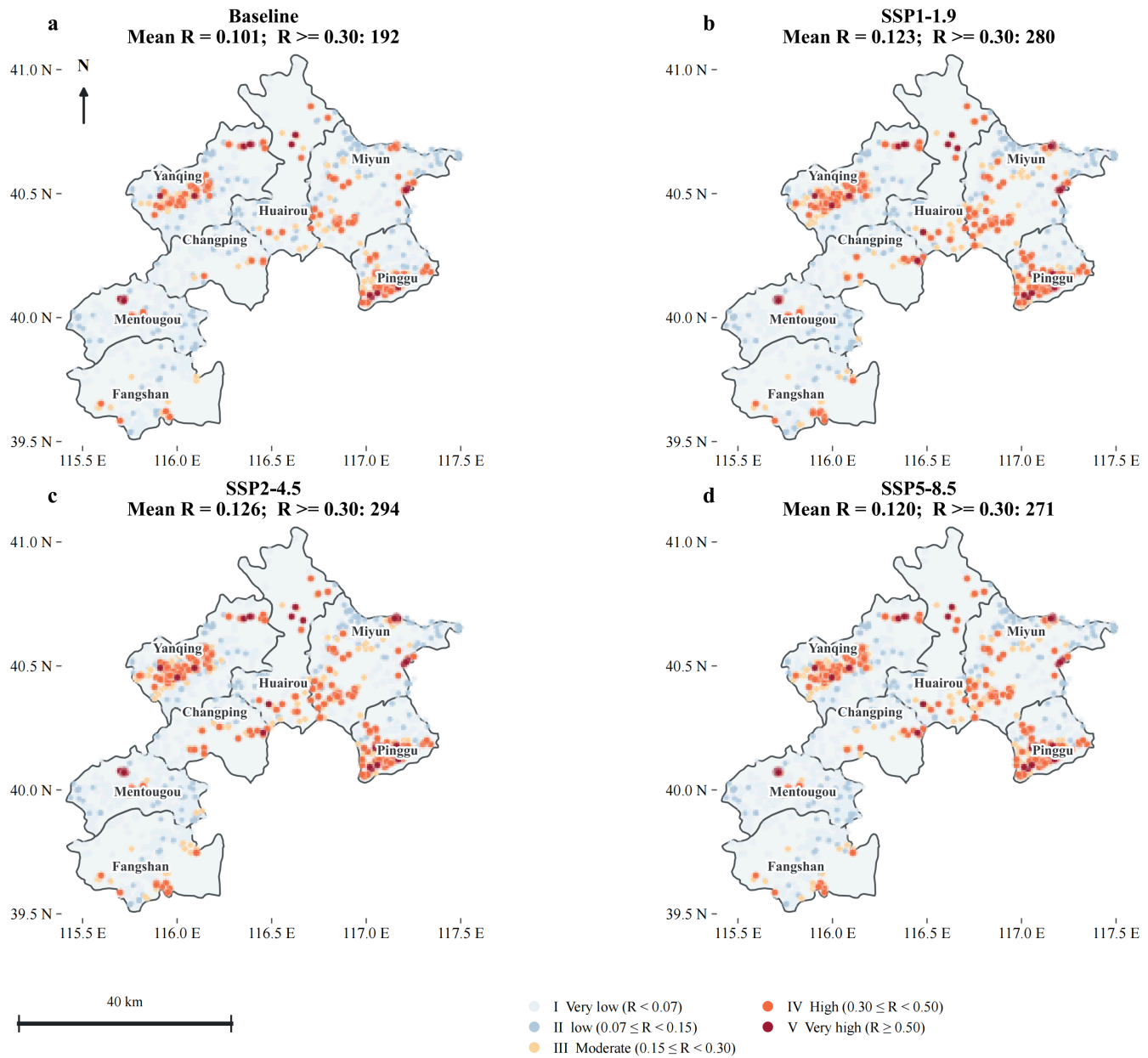
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All panels: 1,969 sites, identical extent and thresholds; only the seven study districts are mapped.

Figure 4

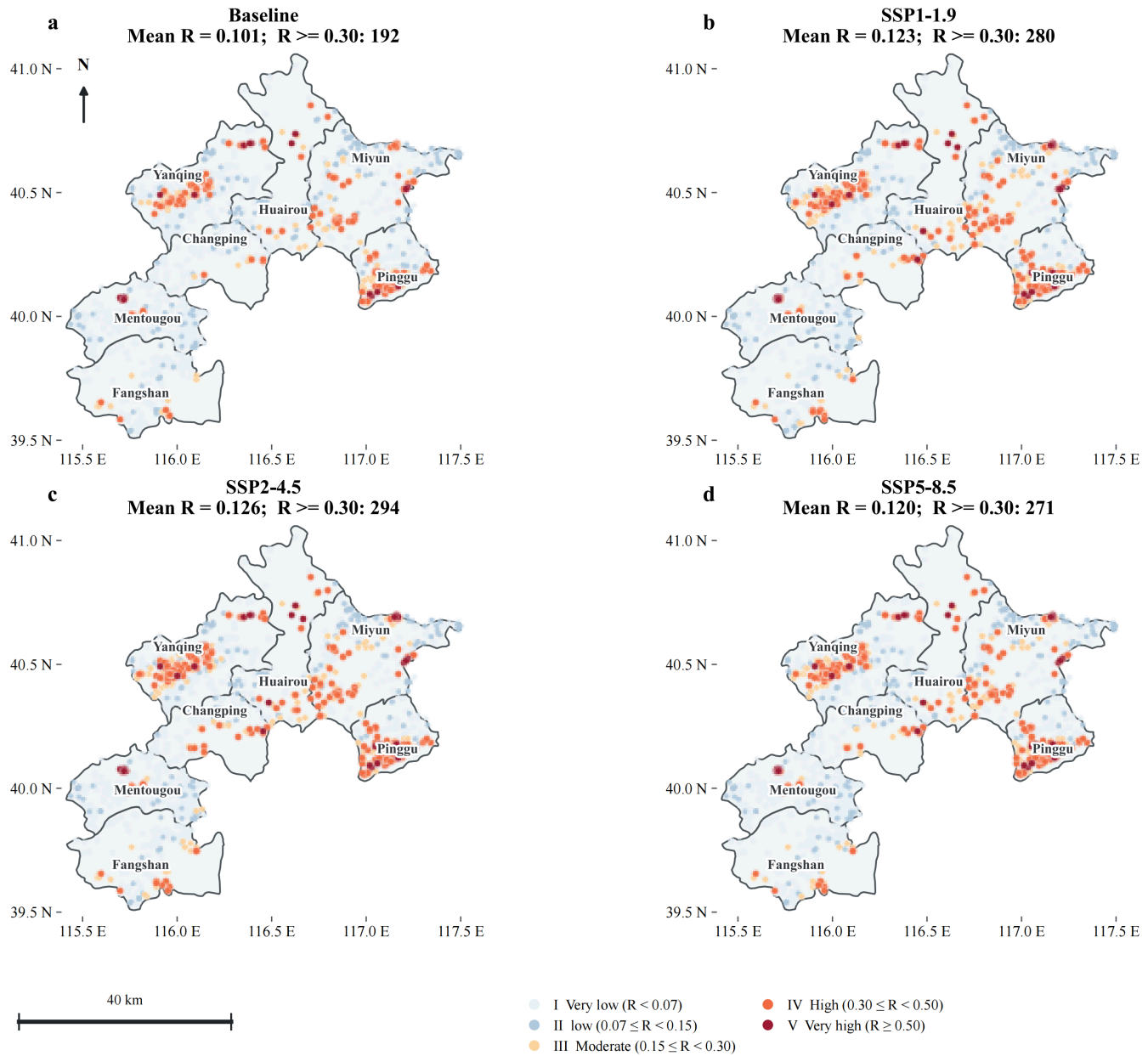
Spatial distribution of the relative flood vulnerability index across the seven study districts under the baseline and future climate scenarios. (a) Baseline. (b) SSP1-1.9. (c) SSP2-4.5. (d) SSP5-8.5. Classes are fixed across panels: I, very low; II, low; III, moderate; IV, high; and V, very high.



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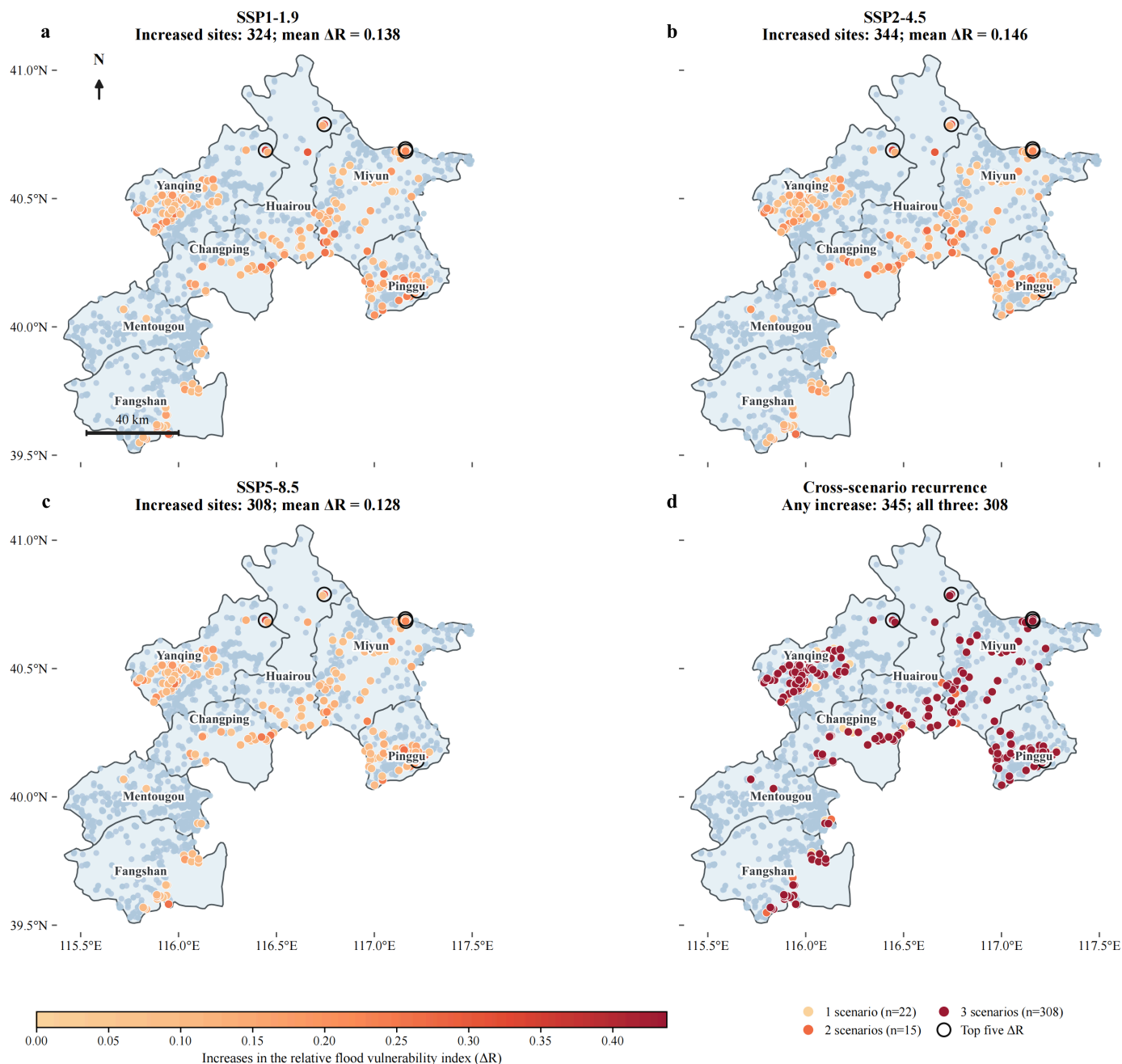


Figure 5

Spatial distribution of increases in the relative flood vulnerability index under future climate scenarios. (a–c) Point-level increases in R relative to the baseline under SSP1-1.9 (a), SSP2-4.5 (b), and SSP5-8.5 (c). Gray points were unchanged; colored points show the magnitude of ΔR on a common linear scale. (d) Cross-scenario recurrence, expressed as the number of future scenarios in which each point had $\Delta R > 0$.

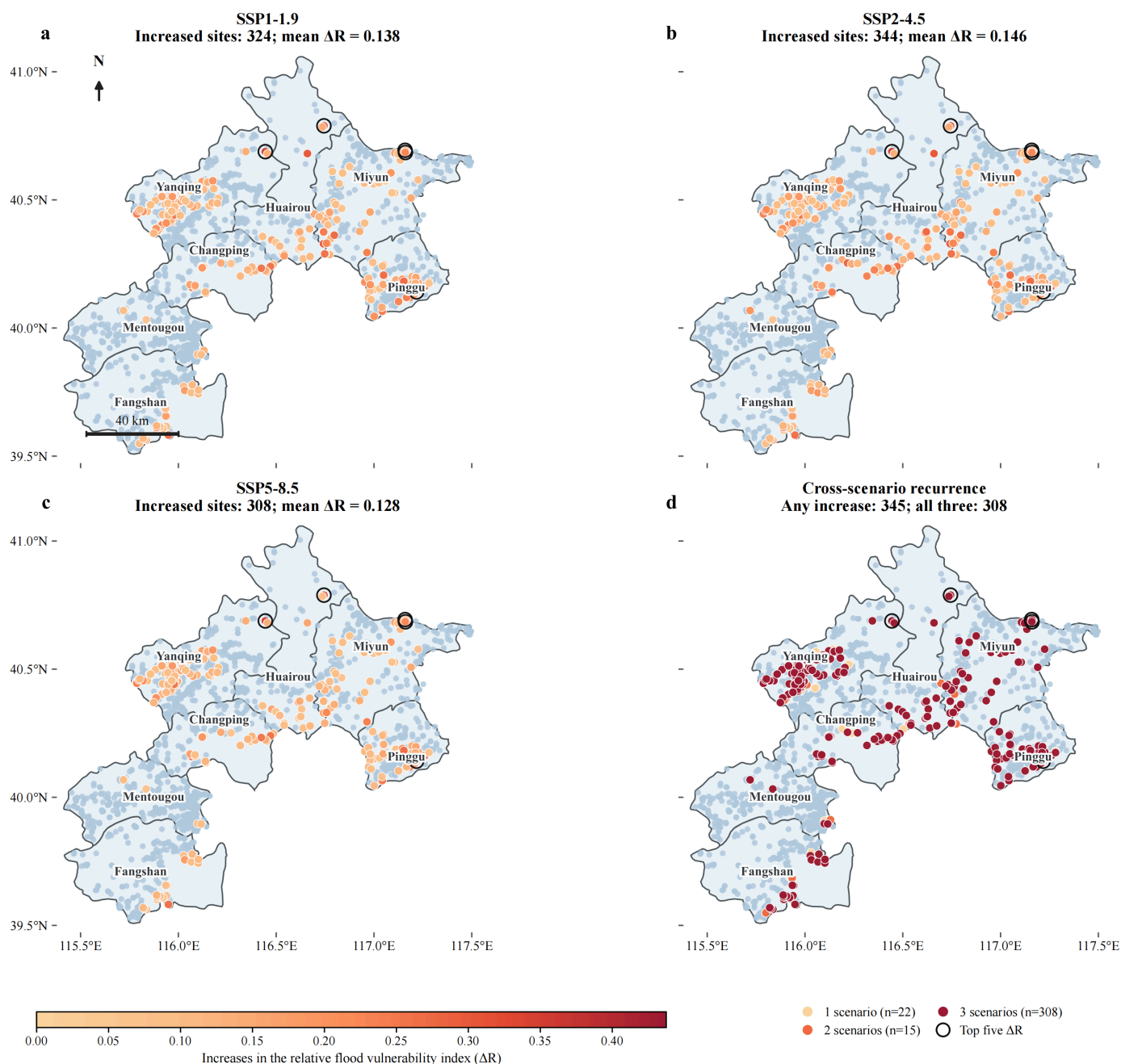


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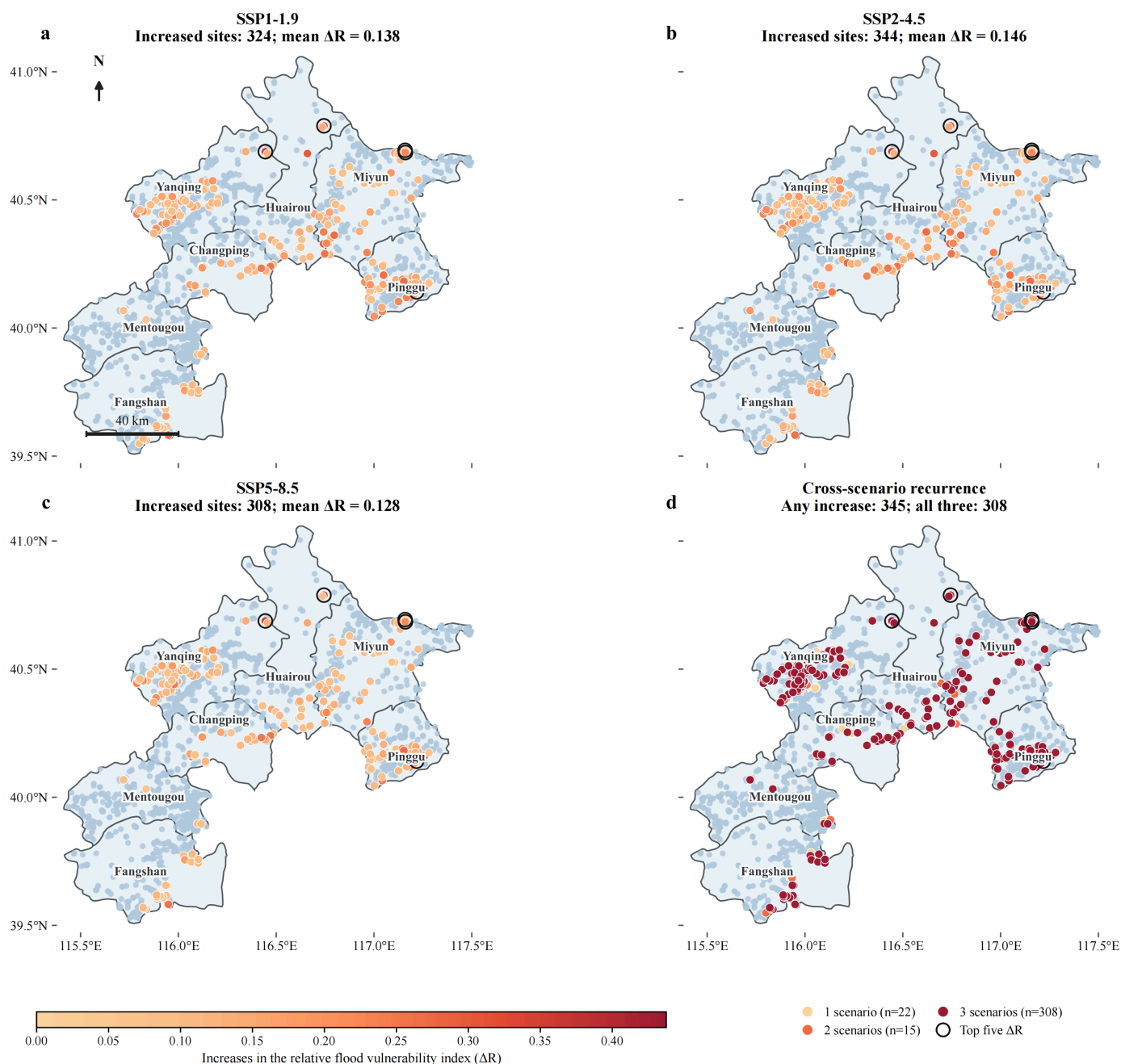


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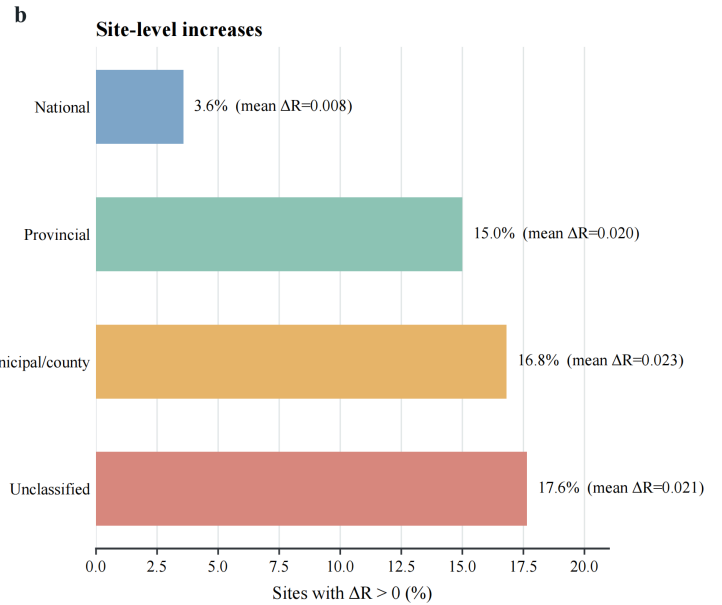
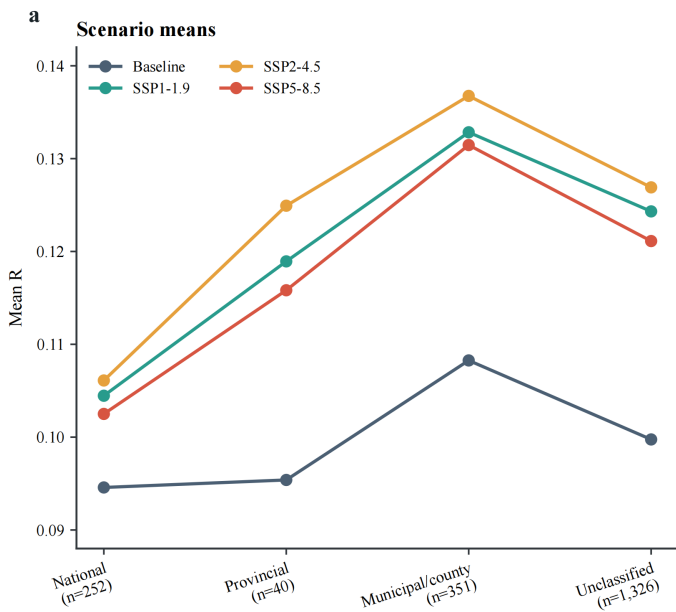


Figure 6

Scenario means and point-level changes by heritage protection level. (a) Mean R for each protection level under the four scenarios; sample sizes are shown in parentheses. (b) Percentage of heritage assessment points with increased R under SSP5-8.5 relative to the baseline.

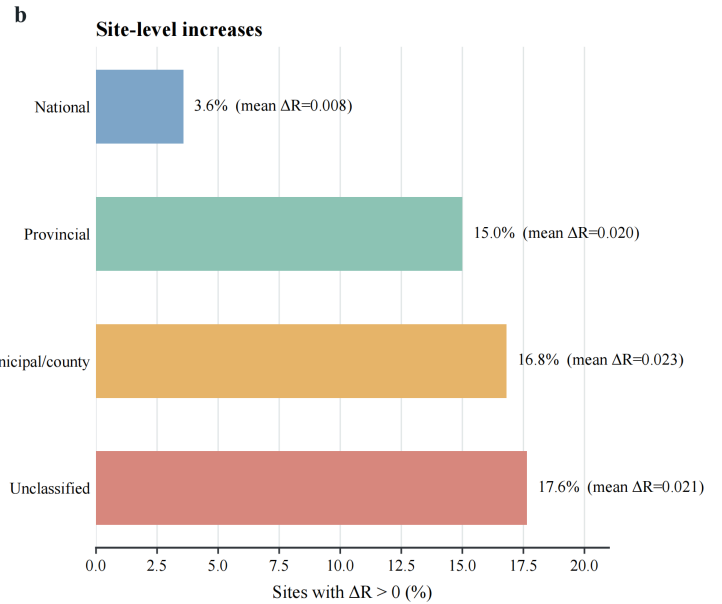
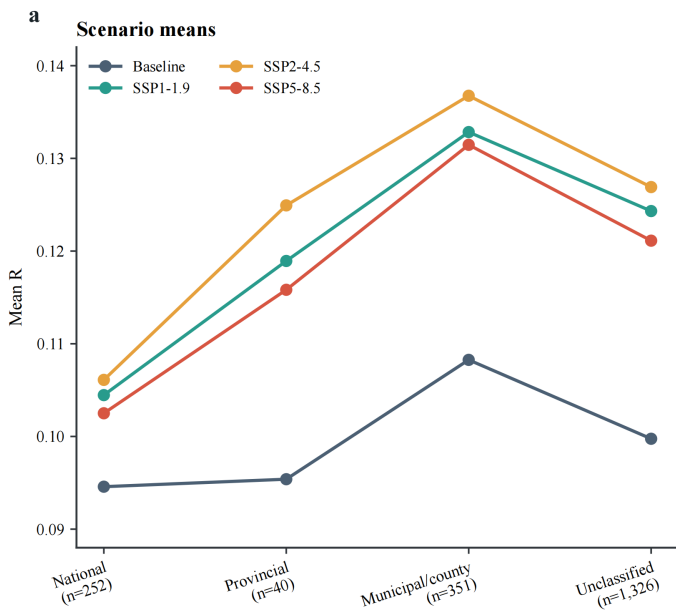


Figure 6

Scenario means and point-level changes by heritage protection level. (a) Mean R for each protection level under the four scenarios; sample sizes are shown in parentheses. (b) Percentage of heritage assessment points with increased R under SSP5-8.5 relative to the baseline.

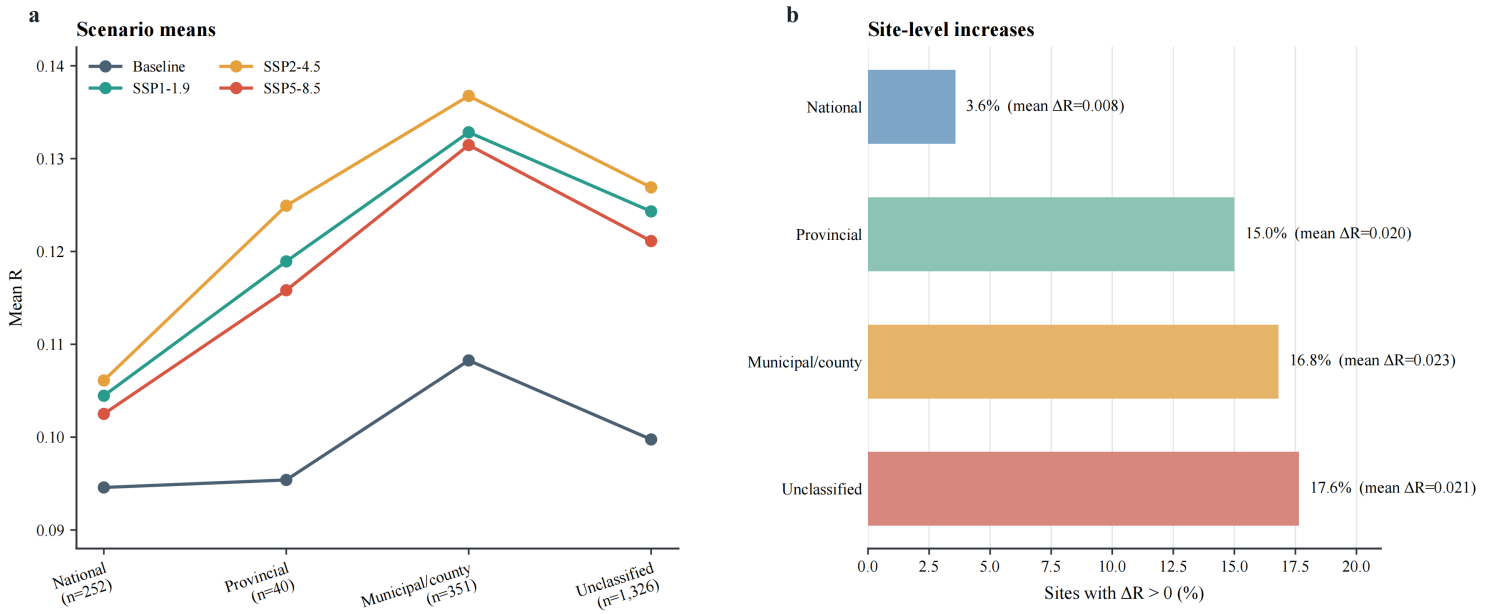


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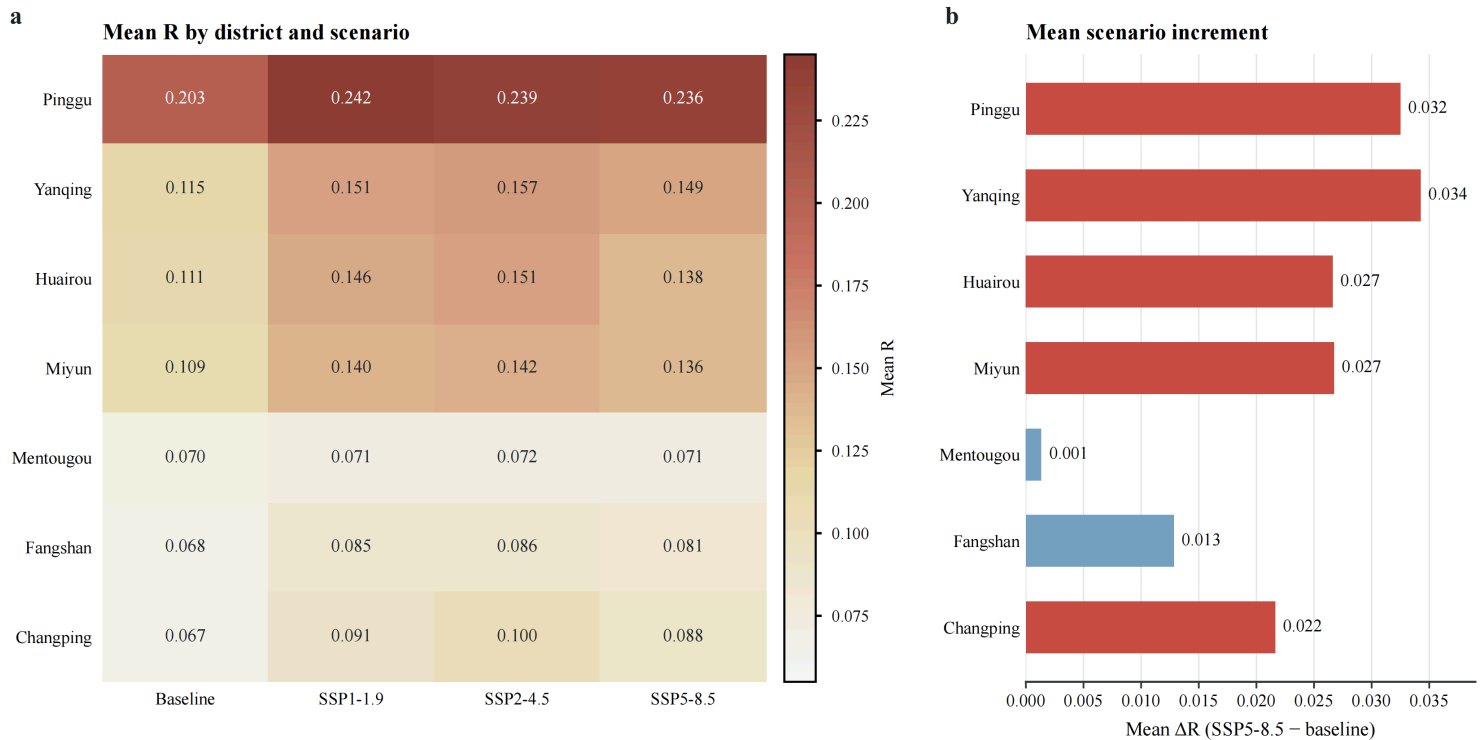


Figure 7

District-level mean relative flood vulnerability and scenario-related changes. (a) Mean R for the seven study districts under the baseline and three future climate scenarios. (b) Mean ΔR under SSP5-8.5 relative to the baseline.

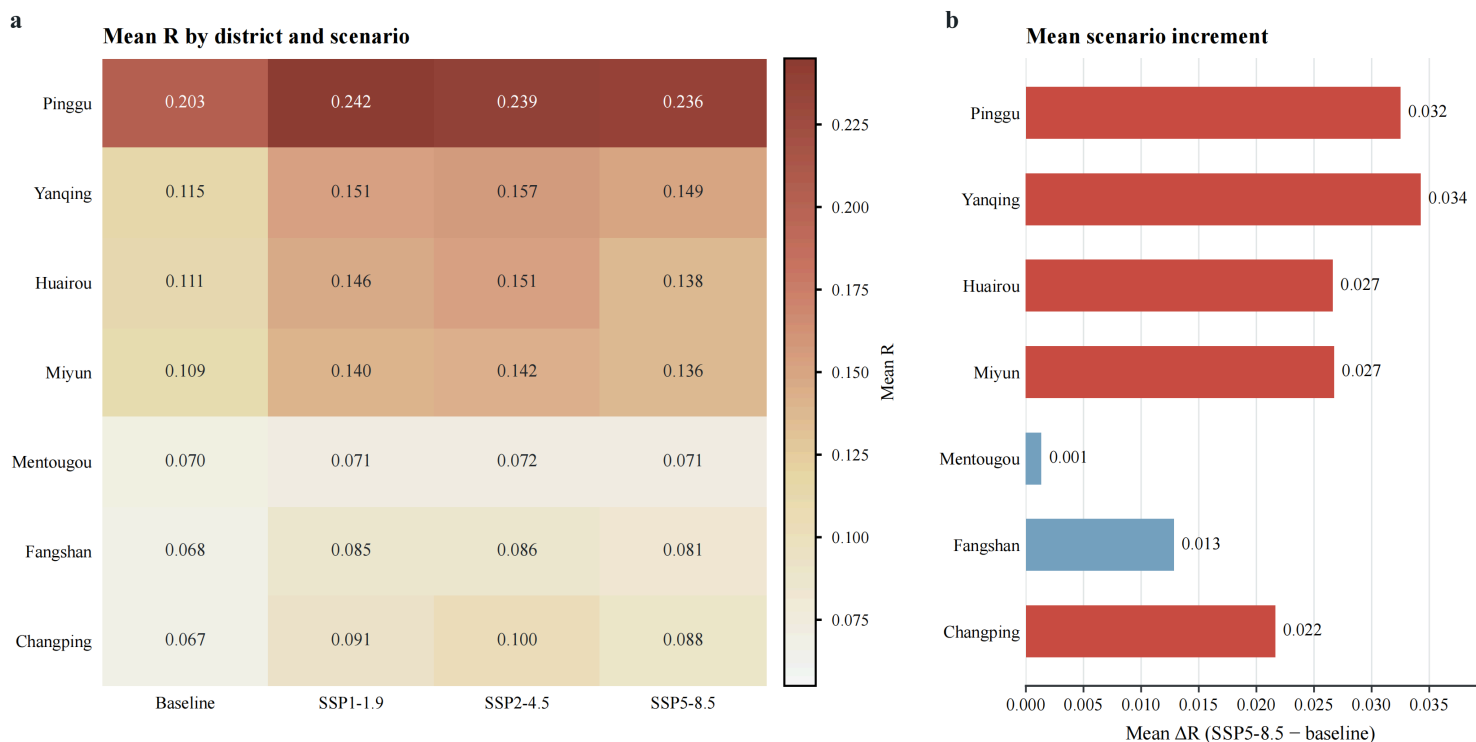


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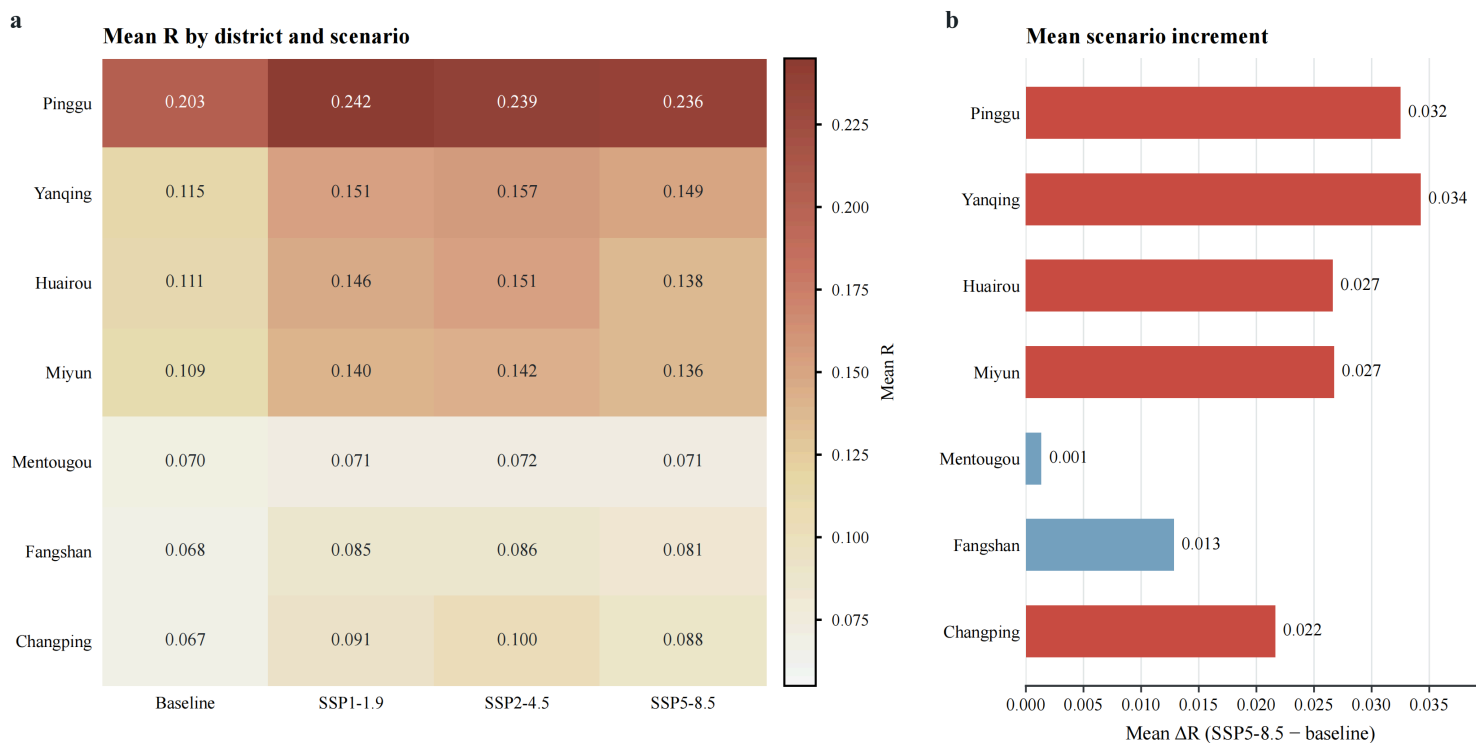
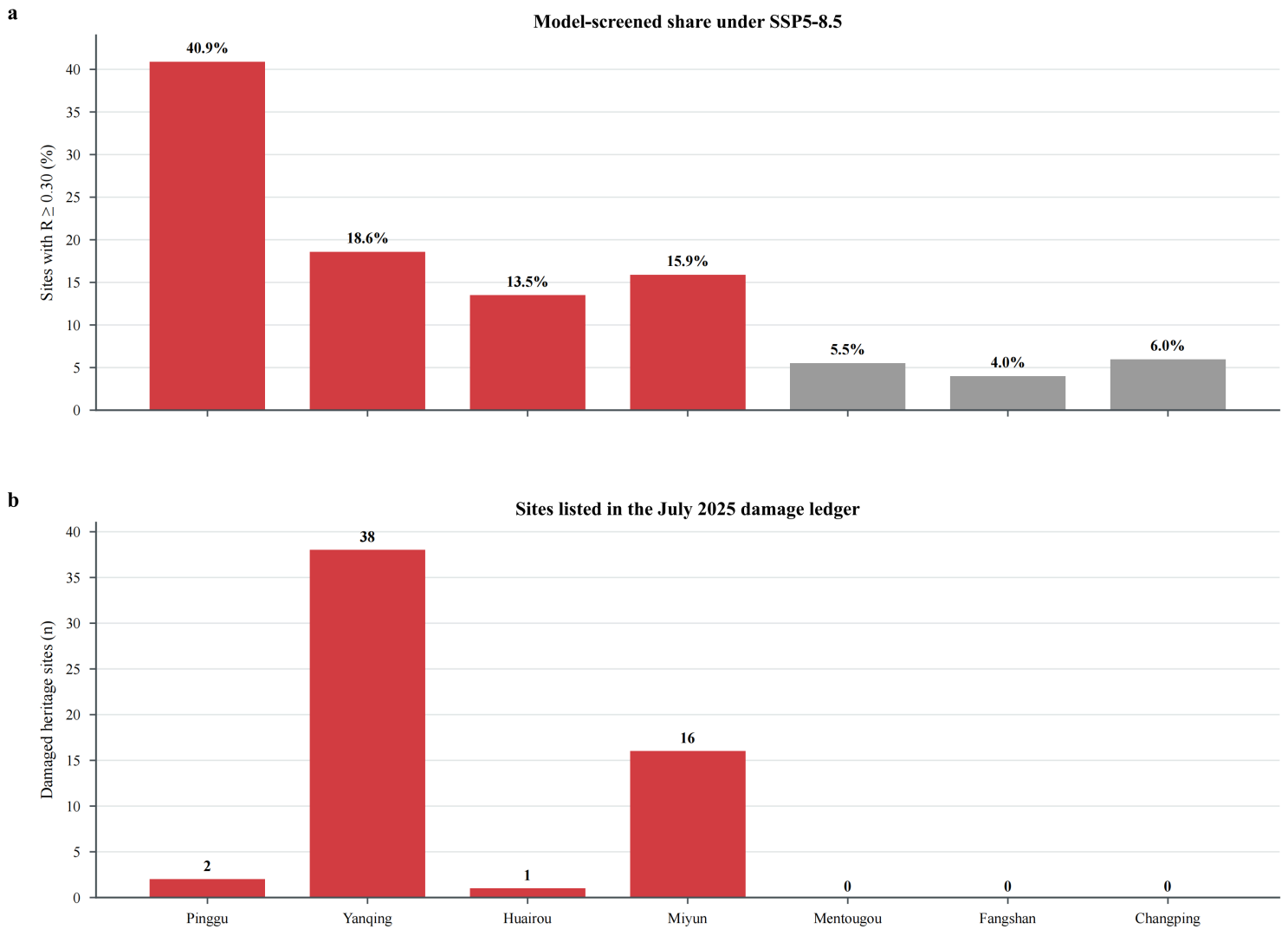


Figure 7

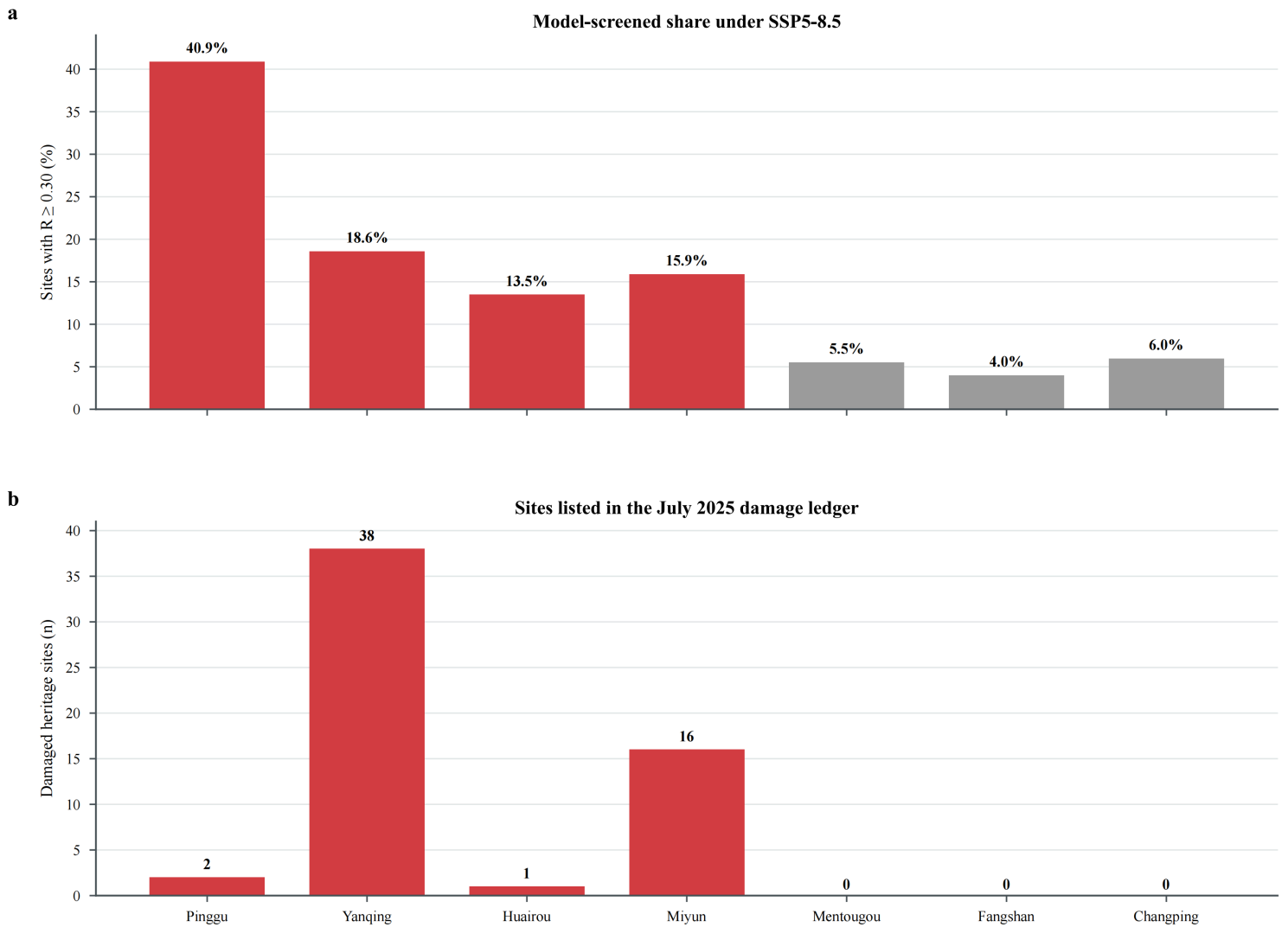
District-level mean relative flood vulnerability and scenario-related changes. (a) Mean R for the seven study districts under the baseline and three future climate scenarios. (b) Mean ΔR under SSP5-8.5 relative to the baseline.



Descriptive district-level comparison; percentages and ledger counts use different denominators.

Figure 8

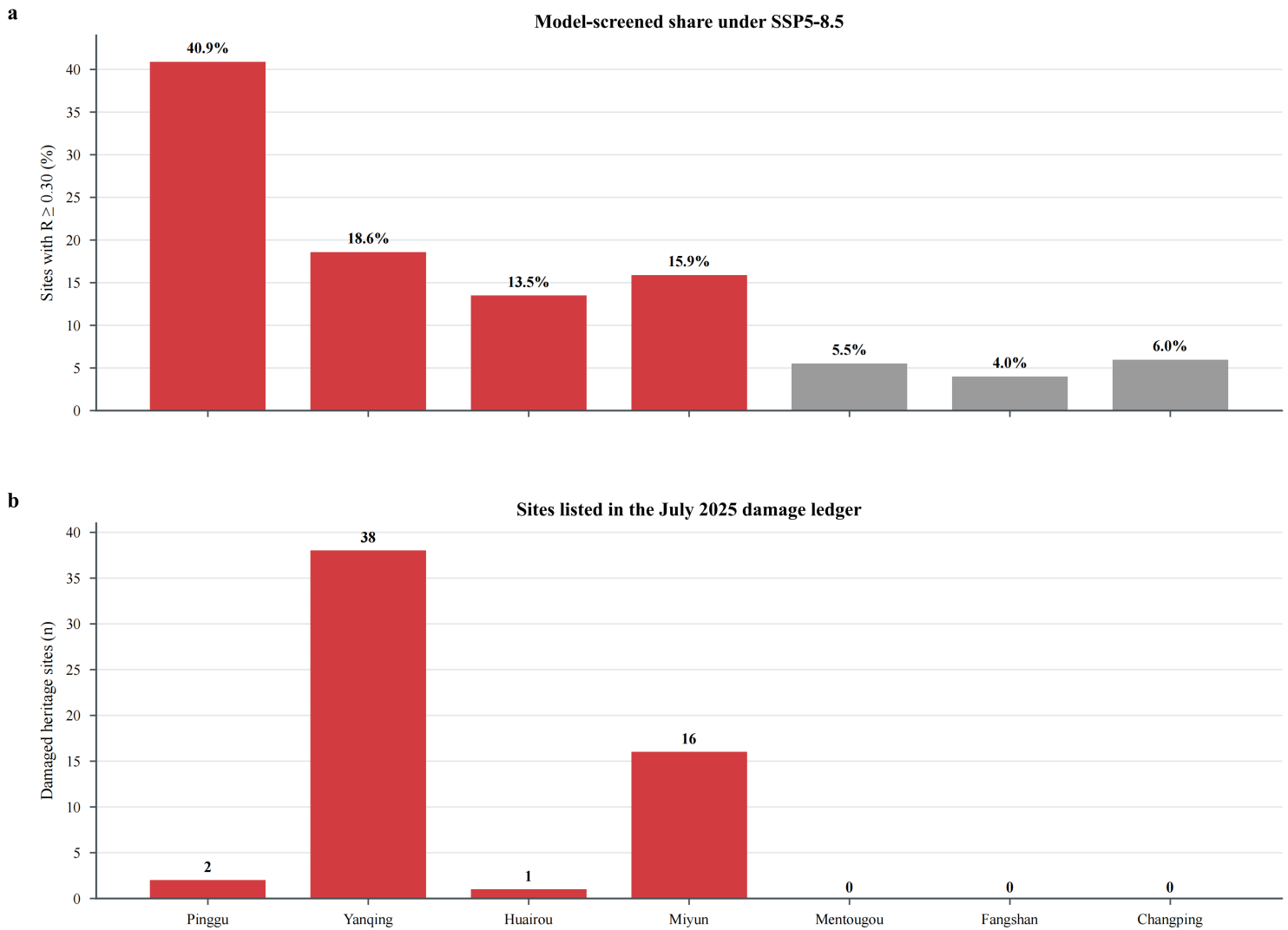
Retrospective district-level comparison of modeled flood vulnerability and observed cultural heritage flood damage in 2025. (a) Proportion of heritage assessment points with $R \geq 0.30$ (Classes IV–V: high and very high vulnerability) under SSP5-8.5. (b) Number of heritage points damaged during the July 2025 “25·7” flood, based on the post-disaster survey by the Beijing Municipal Cultural Heritage Bureau.



Descriptive district-level comparison; percentages and ledger counts use different denominators.

Figure 8

Retrospective district-level comparison of modeled flood vulnerability and observed cultural heritage flood damage in 2025. (a) Proportion of heritage assessment points with $R \geq 0.30$ (Classes IV–V: high and very high vulnerability) under SSP5-8.5. (b) Number of heritage points damaged during the July 2025 “25.7” flood, based on the post-disaster survey by the Beijing Municipal Cultural Heritage Bureau.



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