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Research article

Climate and environmental dynamics: deciphering the distribution and vulnerability of world heritage sites in Europe

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ABSTRACT

Europe and its adjacent cultural regions host a substantial concentration of world heritage sites (WHS), whose spatial distribution and evolutionary trajectories are profoundly shaped by the interplay of geoenvironmental constraints and historical anthropogenic activities. Amid escalating environmental pressures under global climate change, there is an urgent need for systematic regional-scale assessments of heritage distribution patterns and associated environmental vulnerabilities. This study establishes a replicable analytical framework for climate-related heritage risk assessment, integrating environmental clustering with quantitative risk evaluation. Gaussian Mixture Modelling was employed to identify spatial clustering characteristics of WHS across five environmental typologies, while Random Forest algorithms quantified the relative contributions of climatic, topographic, ecological, and socioeconomic determinants to heritage distribution patterns. A multidimensional risk index system was formulated, incorporating hydrodynamic erosion, corrosion-biodegradation, and drought exposure, to evaluate current and projected climate risks under multiple SSP scenarios. Protection priority levels were subsequently classified through synthesised analysis of risk exposure and regional adaptive capacity. Key findings reveal marked spatial clustering of European WHS along Mediterranean coastlines and mid-high latitude zones, with continuous numerical growth in recent decades. Climatic determinants, particularly precipitation seasonality and aridity indices, emerged as dominant controls on heritage distribution. Current risk assessments identify hydrodynamic erosion and drought stress as immediate threats, with high-emission scenarios projecting substantial risk expansion – notably intensifying in southern European hinterlands and coastal zones. Significant disparities in risk exposure and adaptive capacity were observed across environmental clusters, with several heritage groups exhibiting critical vulnerability due to acute climate threats and limited resilience mechanisms. The framework developed in this study can be readily applied to other regions or heritage types, offering a practical tool for researchers and practitioners to systematically assess and prioritise climate risks for cultural heritage conservation under changing environmental conditions. The findings provide empirical foundations for developing proactive, context-specific conservation strategies that integrate climate adaptation imperatives with heritage management protocols.

1. Introduction

Cultural heritage embodies the collective memory and diversity of human civilisation, constituting an irreplaceable asset for sustainable development (Xiao et al., 2023). This legacy now confronts unprecedented threats from accelerating global climate change and environmental dynamics (Sesana et al., 2021). Industrialisation-driven exacerbation of extreme meteorological phenomena, sustained sea-level rise, and precipitous biodiversity loss collectively endanger historic monuments through both direct physical degradation and systemic ecological disruption (Hu and Hewitt, 2024b; Nastou and Zerefos, 2024a). Illustrative cases abound: pluvial flooding erodes foundational structures in medieval towns, while intensifying heatwaves elevate wildfire risks to vernacular settlements; coastal heritage sites simultaneously battle marine erosion and saltwater intrusion (Reimann et al., 2018; Hu and Hewitt, 2024b). Such multifaceted crises necessitate urgent scholarly interrogation of heritage-environment interactions, particularly as escalating climatic stressors threaten irreversible damage to vulnerable sites - a trajectory potentially culminating in permanent cultural loss (Sesana et al., 2021).

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Europe's status as a global heritage hotspot amplifies these conservation challenges (Cacciotti et al., 2021; Vyshkvarkova and Sukhonos, 2023; Giglio et al., 2024). In 2023, UNESCO has inscribed 1157 World Heritage properties worldwide, of which Europe accounts for approximately 440 sites (≈38 % of the global total) (Centre, 2023; UNESCO, 2023). The region's heritage density (sites per area or per capita) is the highest worldwide, highlighting both exceptional richness and considerable management challenges (UNESCO, 2023). Moreover, recent UNESCO reports indicate a growing number of European heritage sites are being classified as "at risk" due to climate change and socio-economic pressures: the proportion facing climate-related threats has doubled in the past decade (Cacciotti et al., 2021; Laino and Iglesias, 2023). The continent hosts an unparalleled concentration of UNESCO World Heritage List properties spanning prehistoric landscapes, classical architecture, and post-industrial relics (Panzera et al., 2021). Their spatiotemporal distribution reflects profound geohistorical conditioning: extant research identifies temperate maritime and Mediterranean climatic zones as preferential loci for civilisational development, with topographic advantages fostering concentrated heritage distribution in coastal plains and river valleys (Wang et al., 2021; Feng et al., 2025). Paradoxically, these legacy-rich regions now endure Europe's most acute climate perturbations - from intensified precipitation regimes and heat domes to accelerated coastal erosion (Laino and Iglesias, 2023; Nastou and Zerefos, 2024a). Iconic sites including the Venetian Lagoon and Pyrenean cultural landscapes face recurrent climate-related alerts, epitomising the critical need to reconcile heritage geography with contemporary environmental realities. This duality underscores our research imperative: to decode historical environmental determinants of European heritage distribution while confronting emergent climate vulnerabilities - a dual perspective essential for developing temporally integrated conservation strategies (Harkin et al., 2020).

However, significant knowledge gaps persist in understanding heritage-environment coupling mechanisms (Shen et al., 2024). Previous investigations in cultural heritage conservation have predominantly focused on elucidating historical significance at the asset level or developing micro-scale preservation techniques, leaving macro-scale analyses of heritage distribution patterns vis-à-vis environmental determinants substantially underdeveloped (Astolfi, 2023). A notable paucity persists in extant literature regarding pan-European and adjacent cultural regions, particularly in synthesising spatial-temporal distribution patterns of world heritage sites (WHS) across extended chronological frameworks—a deficiency that obscures critical insights into environmental drivers and their operational dynamics (Yan et al., 2023). Furthermore, while climate impact assessments have traditionally prioritized single-site case studies or regional clusters—often employing qualitative approaches to evaluate isolated risks such as flooding or weathering—recent methodological advancements now enable systematic vulnerability quantification across extensive heritage portfolios (Ravan et al., 2023; Cacciotti et al., 2024). Persistent uncertainties remain unresolved: the identification of dominant climatic parameters influencing long-term heritage preservation across diverse biogeographical contexts remains contested (Hu and Hewitt, 2024b), while integrated risk assessment frameworks capable of modelling synergistic climate threats under future scenarios demand urgent refinement (Aktürk and Hauser, 2024). Crucially, the application of advanced geospatial analytics and machine learning architectures within heritage studies lags behind methodological progress in cognate disciplines. Novel approaches such as Gaussian Mixture Modelling for environmental clustering, or Random Forest algorithms for quantifying variable contributions to heritage distribution and vulnerability, remain conspicuously underutilised despite their demonstrated efficacy in ecological research (Scheuer et al., 2020; Xiao et al., 2022). These collective deficiencies constrain holistic comprehension of heritage-environment interactions, thereby impeding the formulation of climate-adaptive conservation policies grounded in predictive analytics.

2. Literature review

2.1. Theoretical foundations and evolution of cultural heritage risk research

The contemporary understanding of cultural heritage risk has shifted from descriptive accounts of site distribution to an integrated, concept-driven framework that emphasizes risk as an emergent property of the interplay between environmental, climatic, and socio-economic systems. Early studies in the field primarily identified the non-random, clustered distribution of cultural heritage—shaped by both natural and anthropogenic factors—laying the groundwork for later research on vulnerability and risk (Wang et al., 2021; Zhang et al., 2022). However, the notion of "heritage risk" has since evolved to encompass not only the physical threats posed by environmental dynamics but also the ways in which climate change acts as a risk multiplier, accelerating both material degradation and management challenges.

2.2. Core concepts, key debates, and methodological shifts

Central to the current debate is how to conceptualize and operationalize "cultural heritage risk" within a coherent theoretical framework. Recent literature highlights two critical dimensions: (1) the multi-scalar and multi-factor nature of risk—including exposure, sensitivity, and adaptive capacity—and (2) the need for standardized, quantitative metrics that enable comparative analysis across sites and regions. While traditional studies focused on spatial patterns and environmental correlates, the field has moved toward analytical models that explicitly address the mechanisms and processes driving risk (Aktürk and Hauser, 2024; Bajracharya, 2025). This transition has been propelled by the recognition that fragmented, qualitative approaches fail to capture the systemic vulnerabilities that arise from the convergence of climate extremes, policy gaps, and socio-ecological complexity. Ongoing debates concern the balance between universal risk indicators and the context-specific realities of heritage typologies and management capacity.

2.3. Conceptual and technical advances in vulnerability assessment

A major trend in recent years has been the integration of climate science, spatial analysis, and machine learning into heritage risk assessment. The literature increasingly recognizes that risk is not a static attribute of sites, but a dynamic outcome shaped by changing climatic drivers, land use, and governance regimes (Sesana et al., 2021; Nastou and Zerefos, 2024b). Methodological innovations include the development of quantitative frameworks—such as the tripartite vulnerability model (susceptibility, exposure, adaptive capacity), advanced scenario analysis, and the application of machine learning for identifying dominant risk drivers (Cacciotti et al., 2024; Sorrentino et al., 2024). However, challenges persist regarding the generalizability of these models, the harmonization of risk indicators, and the translation of technical assessments into actionable conservation policy.

2.4. From isolated assessments to integrated risk frameworks

There is an emerging consensus that future research should move beyond case-specific studies toward the development of replicable, adaptable frameworks for systematic heritage risk assessment. The integration of multi-source spatial data, climate projections, and socio-economic factors is essential for capturing the full spectrum of risk across European heritage landscapes (Hu and Hewitt, 2024b). Recent frameworks seek to unify spatial statistics, environmental clustering, and machine learning within a single analytical platform, enabling both site-specific diagnostics and regional comparison. Nevertheless, persistent limitations include the lack of pan-European comparative assessments and standardization in risk modeling protocols, which undermine the scalability and policy utility of research findings (Aktürk and Hauser, 2024).

2.5. Synthesis and research imperatives

In light of these developments, the present study aims to address outstanding gaps by advancing an integrated, conceptually grounded, and methodologically rigorous framework for climate-related heritage risk assessment. By building on recent theoretical and technical advances, this work prioritizes the development of replicable, data-driven models that can inform both local management and broader policy responses to cultural heritage risk under climate change (see Table 1).

3. Materials and methods

3.1. Data collection and extraction

This study undertook an integrated assessment of world heritage sites across Europe and neighbouring cultural regions (30°W–50°E, 35°N–70°N), by systematically consolidating multisource geospatial datasets (see Table 2 for data sources). Foundational geographic data were sourced from the Natural Earth platform, which provides medium-scale vector coastline data. Core attributes of the world heritage sites, including site names, inscription years, national affiliation, and geographic coordinates, were obtained from the official database of the UNESCO World Heritage Centre.

Environmental variables comprised: a 30-arc second resolution digital elevation model (DEM) from the WorldClim 2.1 database; average population density for the period 2000–2020 derived from the LandScan Global Population Dataset; a Human Footprint Index constructed by Mu et al. (2022) reflecting anthropogenic intensity between 2000 and 2018; regional economic development indicated by GDP data from the WorldPop global dataset at 1 km resolution (2000–2020); and NDVI (Normalised Difference Vegetation Index) spatiotemporal series from 2000 to 2020 derived from NASA's MODIS Terra MOD13Q1 product (250 m spatial resolution, 16-day temporal resolution), processed using a maximum value composite method.

Climatic variables were analysed under a dual temporal framework. For the historical climate baseline (1970–2000), 19 bioclimatic variables were obtained from the WorldClim 2.1 dataset. Future climate projections were derived from downscaled CMIP6 (Coupled Model Intercomparison Project Phase 6) outputs, specifically using simulations from the ACCESS-CM2 model. As one of the core models featured in the IPCC Sixth Assessment Report (Hausfather, 2019), ACCESS-CM2 provides climate forecasts for the period 2021–2100 under four representative emission scenarios: SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. All datasets were subject to rigorous quality control and spatial harmonization to ensure accurate integration and alignment under the WGS84 coordinate reference system.

A systematic spatial analytical approach was adopted to extract and calculate environmental variables related to the heritage sites, with all data processing conducted in the R programming environment. For coastline distance calculations, global vector coastline data in 'sf' format were retrieved using the "rnaturalearth" package. Coordinates of the world heritage sites were converted into spatial point objects under the WGS84 system, and the minimum Euclidean distance (in metres) to the nearest coastline was precisely calculated using the "dist2Line" function from the "geosphere" package. This function not only returns distance values but also provides the geographic coordinates of the nearest point on the coastline.

A unified protocol was adopted for environmental variable extraction. For historical climate data, TIFF-format raster layers of the 19 bioclimatic variables were batch-processed using the "raster" package. Mean interpolation based on site coordinates was applied to extract the climate values at each point, effectively addressing the issue of missing values at raster cell centroids. This same methodology was employed to extract elevation, GDP (2000–2020), population density, and NDVI, thereby ensuring consistency across spatial sampling procedures.

For the analysis of future climate scenarios, CMIP6 outputs from the ACCESS-CM2 model were used across four representative pathways: SSP1-2.6 (low emissions), SSP2-4.5 (moderate emissions), SSP3-7.0 (high emissions), and SSP5-8.5 (very high emissions). Four representative time slices were selected: 2021–2040 (near term), 2041–2060 (mid term), 2061–2080 (long-mid term), and 2081–2100 (long term). Multilayer raster datasets were processed using the "terra" package. Through iterative reading of each climate variable file, the rast() function was used to efficiently extract the corresponding values for all 19 bioclimatic indicators at each study location, ensuring accurate spatial matching between climate data and coordinate points. All analytical procedures were subject to strict quality assurance protocols to maintain consistency in data handling and enhance the comparability of results.

3.2. Analysis and visualisation

A multiscale visual analytical framework was applied in R to explore the environmental characteristics of European World Heritage Sites. Initially, a foundational geographical base map of the study area was constructed using 30-arc second resolution digital elevation data from WorldClim 2.1, spatially clipped via the "terra" package (Hijmans et al., 2022). Environmental variables were reshaped using the "reshape2" package and visualised through faceted histogram matrices generated with "ggplot2", depicting the distribution patterns of each environmental factor. Spatial analysis followed a layered visualisation strategy: (1) base maps overlayed with administrative boundaries and coastlines; (2) kernel density estimation maps to quantify spatial aggregation patterns (Kalinic and Krisp, 2018); and (3) temporal stratification analyses revealing spatiotemporal evolution. All visualisations employed a consistent geographic coordinate system and the *viridis* colour palette (Garnier et al., 2024).

To systematically assess environmental heterogeneity among European cultural World Heritage Sites, a multi-model ensemble approach was adopted. Based on a 14-dimensional environmental feature matrix (encompassing topography, climate, and socio-economic indicators), unsupervised clustering was performed using Gaussian Mixture Models (GMMs). The optimal number of clusters was determined using the Bayesian Information Criterion (BIC) within the "mclust" package, enabling the establishment of a robust classification framework (Scrucca et al., 2016). To validate the ecological relevance of the clusters, a random forest algorithm was used to evaluate variable importance, with permutation tests ($p < 0.05$) identifying key environmental drivers. The relationships between environmental factors and cluster membership were further quantified using Generalised Linear Models (GLMs). For visualisation, a stratified approach was applied: (1) spatial distribution maps illustrating the geographic layout of heritage clusters; and (2) radar charts profiling environmental characteristics across clusters. All analyses were executed in R, and visual outputs were generated within the ggplot2 ecosystem. This methodological framework provides a scientific foundation for differentiated heritage conservation strategies.

Differentiated normalization methods were employed to evaluate the trajectory of risk under historical and future climate scenarios. Both datasets were standardised using a percentile scale: $((X - \min)/(\max - \min)) \times 99 + 1$, enhancing comparability. Hydrodynamic erosion risk was principally associated with *bio12* (annual precipitation), *bio15* (precipitation seasonality), *bio13* (precipitation of the wettest month), and *bio16* (precipitation of the wettest quarter). The geometric mean of their standardised values was used to derive a composite risk score. Corrosion and biotic degradation risks were influenced by *bio8* (mean temperature of the wettest quarter) and *bio18* (precipitation of the warmest quarter), with relative risks similarly calculated. Drought risk exhibited positive correlation with *bio9* (mean temperature of the driest quarter) and negative correlations with *bio14* (precipitation of the driest month) and *bio17* (precipitation of the driest quarter). Accordingly, (1 −

Table 1
Summary of literature review.

	Reference	Study Area	Research Methodology	Models/Tools Used	Key Variables/Indicators	Key Findings/Contribution
1	Xiao et al. (2023)	Global (esp. Europe)	Statistical analysis, word frequency analysis, historical review	Statistical methods, word frequency analysis	Distribution of cultural landscapes, heritage criteria, regional characteristics	Global cultural landscapes are unevenly distributed—mainly in Europe; most sites inscribed under cultural criteria, overlap rising.
2	Sesana et al. (2021)	Global	Literature review; hazard-impact mapping	Hazard-impact diagrams	Temperature, precipitation, extremes, sea level, vulnerability of built heritage	Summarized climate impacts on built heritage; established links between stressors and damage types; proposed diagrams to guide future risk assessment.
3	Nastou and Zerefos (2024b)	Mediterranean	Literature review; regional assessment	Data synthesis, risk assessment	Climate impacts, risk indices, types of damage, adaptation needs	Reviewed climate risks to open-air heritage; highlighted Mediterranean vulnerability; stressed need for multidisciplinary assessment and urgent protection strategies.
4	Hu and Hewitt (2024b)	Spain	Spatial database; quantitative risk assessment; SSP scenario analysis	Cartographic mapping, climate data analysis	Site types, local climate variables, freeze-thaw, thermal stress, hydrodynamic, corrosion, biodegradation, SSPs	Assessed climate risks for 45 Spanish WHS; identified most vulnerable sites; linked risk to local climate and SSPs; stressed value of carbon neutrality for risk mitigation.
5	Reimann et al. (2018)	Mediterranean coast	Spatial risk assessment; scenario analysis	Index-based approach	Sea-level rise scenarios, flood and erosion risk, WHS spatial data	Assessed 49 coastal WHS; quantified present and future flood/erosion risk; identified sites needing urgent adaptation; provided regional policy guidance.
6	Cacciotti et al. (2021)	Central Europe	Review; pilot site application	Web GIS, decision support tools, resilience manuals	Climate-induced disasters, management strategies, resilience measures	Evaluated disaster risks to heritage; introduced tailored ICT and decision tools; integrated measures into local management plans.
7	Vyshkvarkova and Sukhonos (2023)	European Russia	Quantitative risk assessment; trend analysis	ERA5 reanalysis data; damage indices	Frost damage indices, salt weathering, air temperature, humidity, site material	Increased frost and salt weathering risks linked to climate trends; stressed need for site- and material-specific adaptation strategies.
8	Giglio et al. (2024)	Europe	Impact mechanism analysis; index system development	Climate vulnerability and damage indices	Material types, impact mechanisms, composite indices	Developed benchmark indices for climate risk assessment of heritage buildings; proposed procedural protocol for adaptive risk management.
9	Panzera et al. (2021)	Europe	Empirical analysis; tourism impact modeling	Bayesian multilevel gravity model	UNESCO WHS count, regional heritage density, international tourist numbers	UNESCO WHS significantly boost international tourism flows; their presence reduces distance decay effects compared to local heritage.
10	Feng et al. (2025)	Western Sichuan Plateau, China	Suitability evaluation; spatial analysis	AHP, entropy, integrated weighting, ArcGIS, obstacle degree model	Ecological and natural conditions, suitability index, obstacle factors	Developed weighted index for settlement suitability; found east–west spatial gradient; identified disaster and resource factors as key obstacles.
11	Wang et al. (2021)	Global, regional	Spatial and temporal analysis; factor analysis	ArcGIS spatial statistics, spatiotemporal methods	Heritage site locations, time of construction, site type, influencing factors	Found clustered, uneven distribution of architectural heritage; highlighted regional patterns and the roles of environment, history, economy, and policy in shaping distribution.
12	Laino and Iglesias (2023)	European coastal cities	Literature review; participatory assessment	Coastal City Living Labs, bibliometric analysis	Climate hazards, city-level impacts, expert perceptions	Combined literature and local expertise to assess climate risks in 10 coastal cities; provided a baseline for future studies and highlighted complex, city-specific challenges.
13	Harkin et al. (2020)	United Kingdom	Impact assessment; policy review; community engagement	Risk assessment by national heritage organizations, community surveys	Ocean temperature, sea level, erosion, extreme events, site vulnerability, community involvement	Identified diverse climate threats to coastal/underwater/terrestrial heritage; highlighted community-based risk management and acceptance of inevitable loss as part of adaptive strategies.
14	Shen et al. (2024)	China	Spatial pattern analysis; factor interaction analysis	Geospatial analysis, geodetector model	National, tangible, intangible heritage; natural, socioeconomic, cultural factors	Identified high-density regions and spatial differentiation; showed climate, terrain, socioeconomic, and cultural factors shape heritage distribution; highlighted differences between tangible and intangible heritage drivers.
15	Astolfi (2023)	Global (heritage samples)	Review and case analysis of analytical techniques	Multi-analytical, noninvasive, micro-invasive methods; HR-	Material composition, degradation, bioarchaeology	Summarized advances in analytical techniques for heritage conservation; highlighted noninvasive strategies for studying and restoring materials.

(*continued on next page*)

Table 1 (*continued*)

	Reference	Study Area	Research Methodology	Models/Tools Used	Key Variables/Indicators	Key Findings/Contribution
				XRPD, mass spectrometry		
16	Yan et al. (2023)	Europe	Spatial distribution and factor analysis	Nearest-neighbor index, kernel density, geographic detector	ERIH sites, spatial pattern, natural and human factors	Identified cohesive yet uneven distribution of industrial heritage; showed socio-economic level as strongest factor; provided guidance for heritage conservation and sustainable urban planning.
17	Cacciotti et al. (2024)	Central Europe	Vulnerability assessment method development and validation	STRENCH framework, stakeholder consultation	Susceptibility, exposure, resilience, hydrometeorological hazards	Developed and validated a stakeholder-driven vulnerability assessment method for heritage; highlighted value of iterative, criteria-based evaluation for risk management.
18	Ravan et al. (2023)	Roman Ruins of Tróia, Portugal	Indicator-based vulnerability assessment	Cultural Heritage Vulnerability Index	Structural/non-structural site factors, multi-hazard exposure, adaptive capacity	Developed a site-specific, indicator-based vulnerability framework; showed how structural sensitivity and adaptive capacity shape risk and guide mitigation priorities.
19	Aktürk and Hauser (2024)	Global (heritage sites)	Literature review; policy framework analysis	Integrated resilience framework	Climate and disaster risk, resilience, science-policy gap	Reviewed integration of climate and disaster risk reduction for heritage; highlighted gaps, opportunities, and the need for actionable resilience frameworks.
20	Xiao et al. (2022)	Changsha, China	Urban spatial heterogeneity analysis	GMM dual-clustering, DBSCAN, improved indices	Agglomeration areas, compactness index, dispersion index, urban expansion	Proposed dual-clustering method to analyze urban expansion heterogeneity; revealed spatial trends and provided tools for urban planning.
21	Scheuer et al. (2020)	Leipzig, Germany	Residential choice modeling; disaster risk assessment	Random Forest, spatial analysis	Socioeconomic groups, residential preference, exposure, vulnerability	Used machine learning to predict residential choice and spatial risk; revealed how population dynamics influence exposure and vulnerability in cities.
22	Zhang et al. (2022)	Yellow River Basin, China	Spatial-temporal distribution analysis	Standard deviation ellipse, point pattern, kernel density, spatial autocorrelation, Geodetector	Intangible cultural heritage sites, distribution, policy, economy, topography	Revealed east–west pattern and clustering of intangible heritage; identified policy, economy, and topography as key influencing factors.
23	Sorrentino et al. (2024)	Jordan	Air pollution impact and risk assessment	Random Forest, corrosion models	Pollutants (SO_2, HNO_3, O_3, PM_{10}), climate, corrosion rates	Found major urban corrosion risks from pollutants; projected climate-driven increases; stressed urgent air quality management for heritage conservation.
24	Bajracharya (2025)	Developing Asian countries	Threat and management capacity assessment	Logit and ordered logit models, linked heritage and climate data	Threat factors (ecological, climate, local, social), management capacity, country differences	Identified high vulnerability of WHS to natural threats; revealed management capacity is often inadequate where threat is greatest; highlighted regional differences and the need for improved risk response.
25	**This study**	Europe & neighbouring regions	Integrated spatial and climate risk analysis; clustering; vulnerability prioritization	Gaussian Mixture Model, Random Forest, GLM, scenario-based risk indices	19 bioclimatic variables, DEM, NDVI, GDP, Human Footprint, population density, risk/adaptive capacity indices for hydrodynamic erosion, corrosion-biodegradation, drought	Revealed dual controls of environment and climate on WHS clustering; developed multidimensional, scenario-based risk and adaptation framework; prioritized sites for conservation under climate change, providing a replicable model for future heritage risk assessment.

normalised *bio17*) and (1 − normalised *bio14*) were used as input parameters. Drought risk was then computed using a comparable geometric mean method. This climate-based risk quantification approach was adapted from the framework developed by Hu and Hewitt (2024c).

Key environmental interactions were assessed through Generalised Linear Models (GLMs) (Niku et al., 2021). Interaction matrices were generated using the expand.grid() function, simulating combinations of annual mean temperature (*bio01*) with driest month precipitation (*bio14*), and annual precipitation (*bio12*) with minimum temperature of the coldest month (*bio06*). These were used to estimate risk probabilities under different climatic conditions. Heatmaps were produced to visualise non-linear interaction effects. Additionally, spatial risk maps for the three risk categories were constructed using elevation basemaps and administrative boundaries, with blue, green, and red gradients respectively denoting risk intensity. Comparative analyses across environmental clusters were presented via grouped boxplots overlaid with scatter points to enhance perceptual clarity.

To assess the dynamic trends in climate risk escalation, a pre-processed dataset was imported, containing standardised risk values (0–100) across various climate scenarios. Data wrangling was conducted using the "tidyverse" package in R. Factor levels for *Cluster*, *SSPs* (SSP126/245/370/585), and risk types (hydrodynamic erosion, biotic degradation, drought) were converted into ordered categorical variables to ensure consistency in visual outputs. Linear regression was applied to

Table 2
Summary of data sources.

Data Category	Source	Resolution/ Temporal Coverage	Access URL
Base geographic data	Natural Earth	1:50m scale	https://www.naturalearthdata.com/
World heritage sites	UNESCO World Heritage Centre	–	https://whc.unesco.org/
Elevation data	WorldClim 2.1	30 arc-seconds	https://www.worldclim.org/
Population density	LandScan Global	2000–2020	https://landscan.ornl.gov
Human footprint	Mu et al. (2022)	2000–2018	–
GDP data	WorldPop	1 km, 2000–2020	https://www.worldpop.org/
NDVI data	MODIS MOD13Q1	250m, 16-day composite	–
Historical climate	WorldClim 2.1	1970–2000 baseline	https://www.worldclim.org/
Future climate	CMIP6 (ACCESS-CM2)	2021-2100 projections	https://www.worldclim.org/cmip6

evaluate the statistical significance of risk trends, with slope coefficients (k) of the time series representing rates of change (Heβler and Kamps, 2023). Heatmaps were constructed using "ggplot2": the scale_fill_gradient2() function was used to define a red–white–blue gradient (white denoting no change, $k = 0$), with geom_tile() drawing the trend matrix and significance levels overlaid. All panels shared a uniform scale (−0.47 to 1.225) to maintain comparability.

A quantitative analytical framework was developed to prioritise World Heritage protection, based on the coupling of climate risks and socio-economic adaptive capacity (Sabour et al., 2024). Specifically, risk scores were derived via a weighted approach, combining present-day climate conditions (70 % weight) and projections under the SSP5-8.5 scenario for 2080–2100 (30 % weight). The total socio-economic adaptive capacity score incorporated GDP, the Human Footprint Index, and population density, calculated using the following formula: Total Socio-Economic Capacity Score = 0.5 × GDP +0.3 × Human Footprint Index +0.2 × (100 − Population Density). On this basis, heritage site protection urgency was categorized as follows: Extremely High Urgency: Risk score >75 and adaptive capacity <25; High Urgency: Risk score >75 and adaptive capacity >50; Moderate Urgency: Risk score between 50 and 75 and adaptive capacity between 25 and 50; Low Urgency: Risk score <50 and adaptive capacity <25. Sites exhibiting extremely high urgency under each risk type were explicitly marked in the visual outputs. All risk scores were normalised on a scale from 0 to 100.

3.3. Replicable analytical workflow and visual summary

To enhance transparency, transferability, and practical utility, this study organizes the entire methodological process as a modular and replicable analytical workflow for climate-related heritage risk assessment (see Fig. 1). The framework begins with the integration of multi-source geospatial and attribute data—including site coordinates, environmental and socio-economic variables, and multi-temporal climate projections—all harmonized to a unified spatial reference (WGS84). For each heritage site, relevant topographic, climatic, ecological, and anthropogenic indicators are extracted using standardized spatial protocols in R, with climate variables sourced from WorldClim 2.1 and CMIP6 (ACCESS-CM2), and socio-economic data from global datasets. A 14-dimensional feature matrix is then constructed and unsupervised clustering is performed via Gaussian Mixture Models, using the Bayesian Information Criterion to define environmental typologies objectively. Climate-related risks—such as hydrodynamic erosion, corrosion-biodegradation, and drought—are quantitatively assessed for each site and cluster using composite indices based on key bioclimatic variables, covering both current and projected scenarios. Socio-economic adaptive capacity is evaluated by integrating GDP, Human Footprint Index, and population density into a weighted, normalised index aligned with the risk metrics. Finally, heritage sites are prioritized for conservation using a risk–capacity coupling approach that considers both present and future threats, allowing for the stratification of protection strategies across diverse contexts. All procedures, indicator definitions, and normalization schemes are fully documented to ensure reproducibility and ease of adoption. The modular structure of this workflow means that researchers and practitioners can readily apply the complete framework—or any of its components—to different regions or types of cultural heritage, enabling robust comparative analyses and management planning. The complete research process and main analytical steps are summarized in Fig. 1.

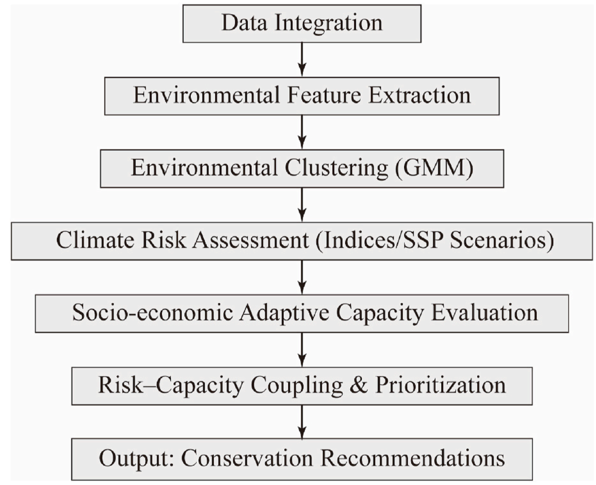

Fig. 1. Workflow of the analytical framework used in this study.

4. Results

4.1. Spatiotemporal characteristics of world heritage sites in Europe

Based on spatial statistical analysis, World Heritage Sites across Europe and its neighbouring cultural zones exhibit a marked spatial clustering pattern, with a dominant concentration in Central and Southern Europe (Fig. 2). This distribution closely corresponds to the historical trajectory of European civilisational development, particularly aligning with the core regions of Ancient Roman civilisation and the cradle of the Renaissance. Subsequent time-series analysis reveals the dynamic evolution of nomination hotspots for World Heritage inscription. During the initial phase of the 1970s, nomination activity was predominantly concentrated in the Balkan and Apennine Peninsulas (Fig. 2A). By the 1980s, the scope of these hotspots had expanded significantly, encompassing the broader Apennine Peninsula and extending into Western Europe (Fig. 2B). In the 1990s, there was a discernible shift towards Eastern Europe (Fig. 2C). Entering the 21st century, France and Germany have maintained consistently high levels of nomination activity, while a pronounced expansion of hotspots has been observed towards the Anatolian Peninsula, where the number of inscribed sites has grown rapidly (Fig. 2C). This spatiotemporal transformation reflects historical shifts in the strategic focus of heritage conservation across Europe, and is intricately linked to the broader trajectories of regional political and economic development.

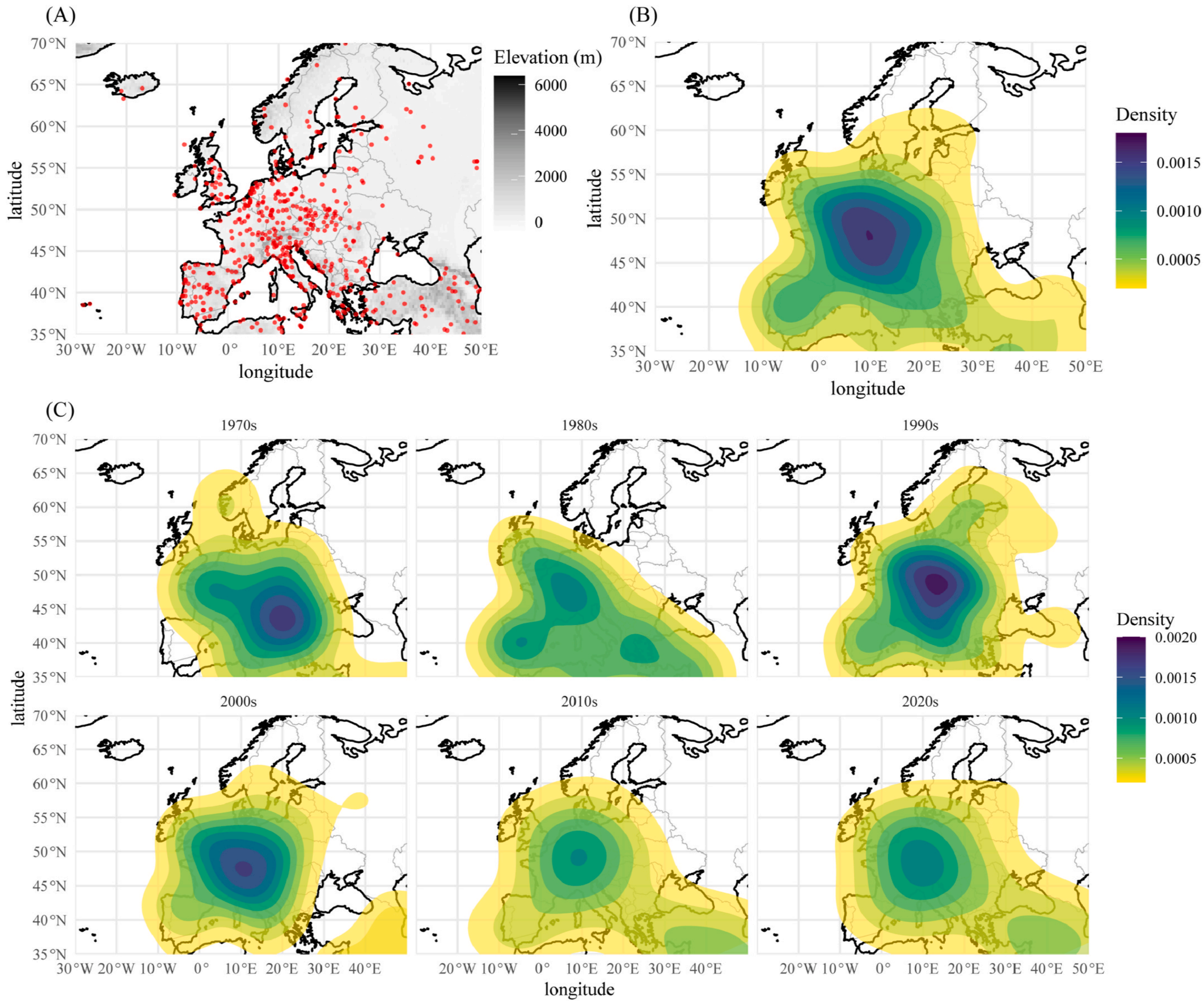

Fig. 2. Spatial distribution of World Heritage Sites across Europe and adjacent cultural regions. (A) Distribution of World Heritage Sites. Red dots indicate the precise locations of inscribed properties. (B) Kernel density estimation visualises the overall spatial concentration of World Heritage Sites across Europe and its neighbouring cultural zones. (C) Kernel density maps illustrate the temporal dynamics of site distribution across six nomination periods: the 1970s, 1980s, 1990s, 2000s, 2010s, and 2020s. Graduated colour shading represents the relative density of cultural heritage across different regions.

4.2. Coupling between world heritage distribution and environmental factors

Drawing on a multidimensional analysis of environmental variables (Fig. 3), this study reveals the coupled relationship between the distribution of World Heritage Sites in Europe and both natural environmental conditions and anthropogenic influences. Spatial pattern analysis indicates a pronounced "core–periphery" structure, with site density declining progressively from the central regions towards the periphery (Fig. 3A and B). From a physical geographic perspective, the vast majority of sites are situated in lowland plains below 500 m in elevation (Fig. 3C). Moreover, coastal zones contain significantly more heritage sites than inland areas, with a substantial concentration in proximity to the coastline (Fig. 3D), aligning with the historical tendency for early civilisations to emerge in low-lying coastal environments. The impact of human activity reveals that heritage sites are predominantly located in areas with moderate to high levels of anthropogenic pressure (Fig. 3E), though they tend to cluster in regions with relatively low population density and moderate economic development (Fig. 3F and G). Notably, a considerable number of sites are found in environments characterised by NDVI values close to zero (Fig. 3H), indicating extreme or specialised ecosystems, such as Mediterranean karst landscapes and Nordic fjord environments.

Climatic factors further underscore the influence of temperature on site distribution. Most heritage sites are located in temperate zones with an annual mean temperature between 5 °C and 15 °C (Fig. 3I), with substantial clustering in mid-latitude regions exhibiting moderate temperature seasonality (Fig. 3J). Areas experiencing mild winters and limited annual temperature variation also display heightened site concentration (Fig. 3K and L). In contrast, precipitation patterns are more skewed (Fig. 3M–P), with most sites located in semi-humid regions receiving moderate annual rainfall. Extremely arid or excessively wet areas contain relatively few sites, suggesting that moderate precipitation regimes may offer dual advantages for both sustained human settlement and the preservation of built heritage.

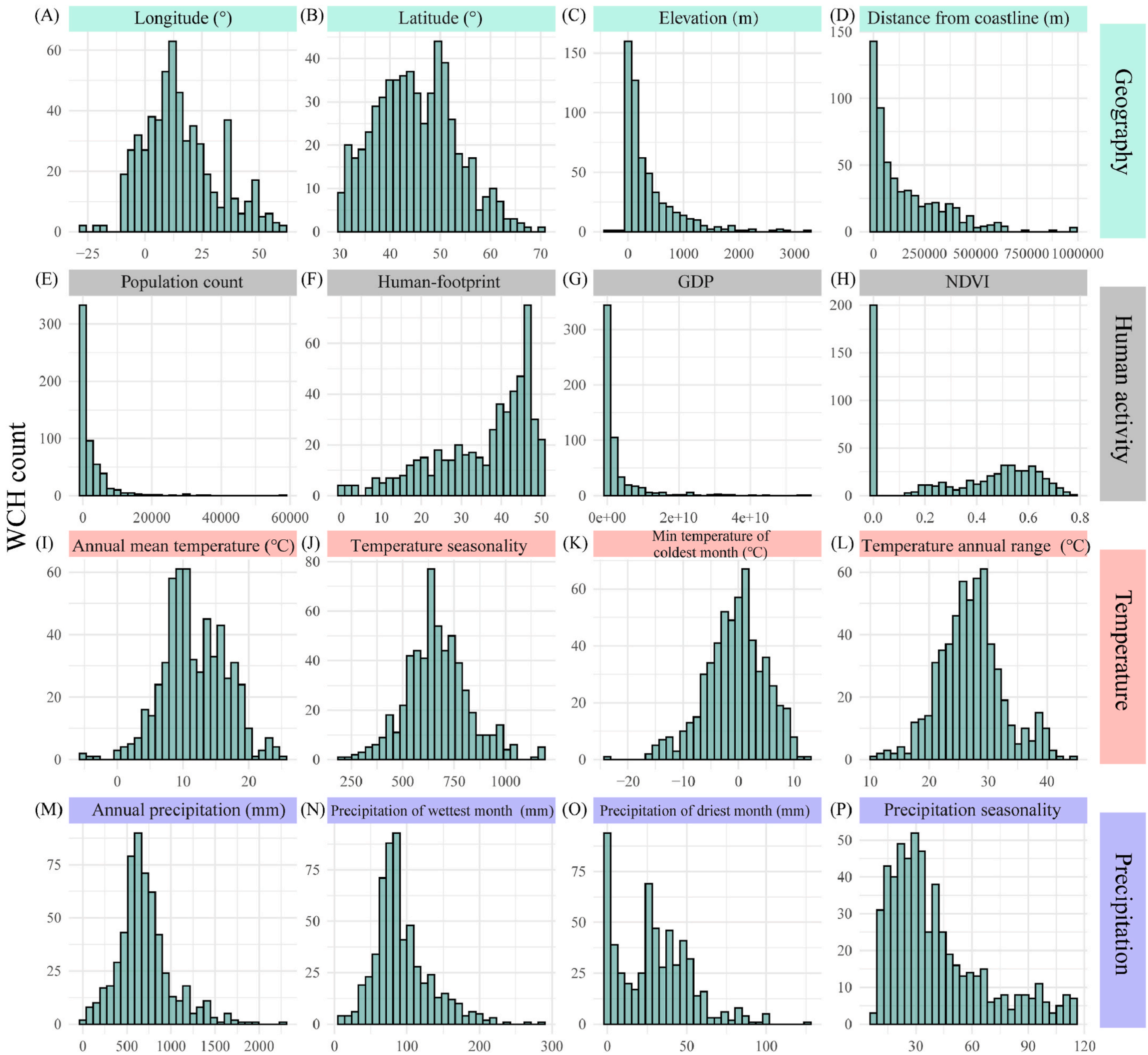

Fig. 3. Associations between the distribution of world heritage sites and environmental factors across Europe and adjacent cultural regions. Environmental factors include geographic conditions (A–D), intensity of human activities (E–H), and historical climatic conditions (I–P), with temperature- and precipitation-related variables based on 1970–2000 averages.

4.3. Spatial distribution patterns of world heritage sites driven by environmental gradients

Through Gaussian Mixture Model (GMM) clustering of environmental variables, this study identified five distinct groups of World Heritage Sites across Europe and adjacent cultural zones, each exhibiting marked regional differentiation (Fig. 4A). The first group is predominantly located along the southern European coastline and is characterised by a unique combination of environmental conditions: annual precipitation (Bio12) is at the lowest level across the study area, while precipitation seasonality (Bio15) exhibits the highest coefficient of variation. In terms of thermal conditions, these sites experience the highest annual mean temperatures (Bio01), and the minimum temperatures of the coldest month (Bio06) also remain relatively elevated.

The second group corresponds to areas with the highest economic indicators and is primarily situated in highly urbanised regions, underscoring the pivotal role of human activity in the genesis of cultural heritage. These sites are associated with moderate altitudes and medium levels of annual precipitation (Bio12). The fourth group is mainly distributed across inland Central Europe. These locations are generally distant from the coastline and tend to be situated in areas with higher vegetation cover (NDVI), possibly representing sites in ecologically favourable environments. The third and fifth groups exhibit a broader spatial distribution. Notably, the fifth group is located in the wettest climatic zones, with the highest minimum precipitation in the driest month (Bio14) across all site categories (Fig. 4B), and is also closest, on average, to the coastline.

The influence of environmental factors on the distribution of World Heritage Sites was further examined using a random forest model (Fig. 4C). Climatic variables demonstrated the strongest explanatory

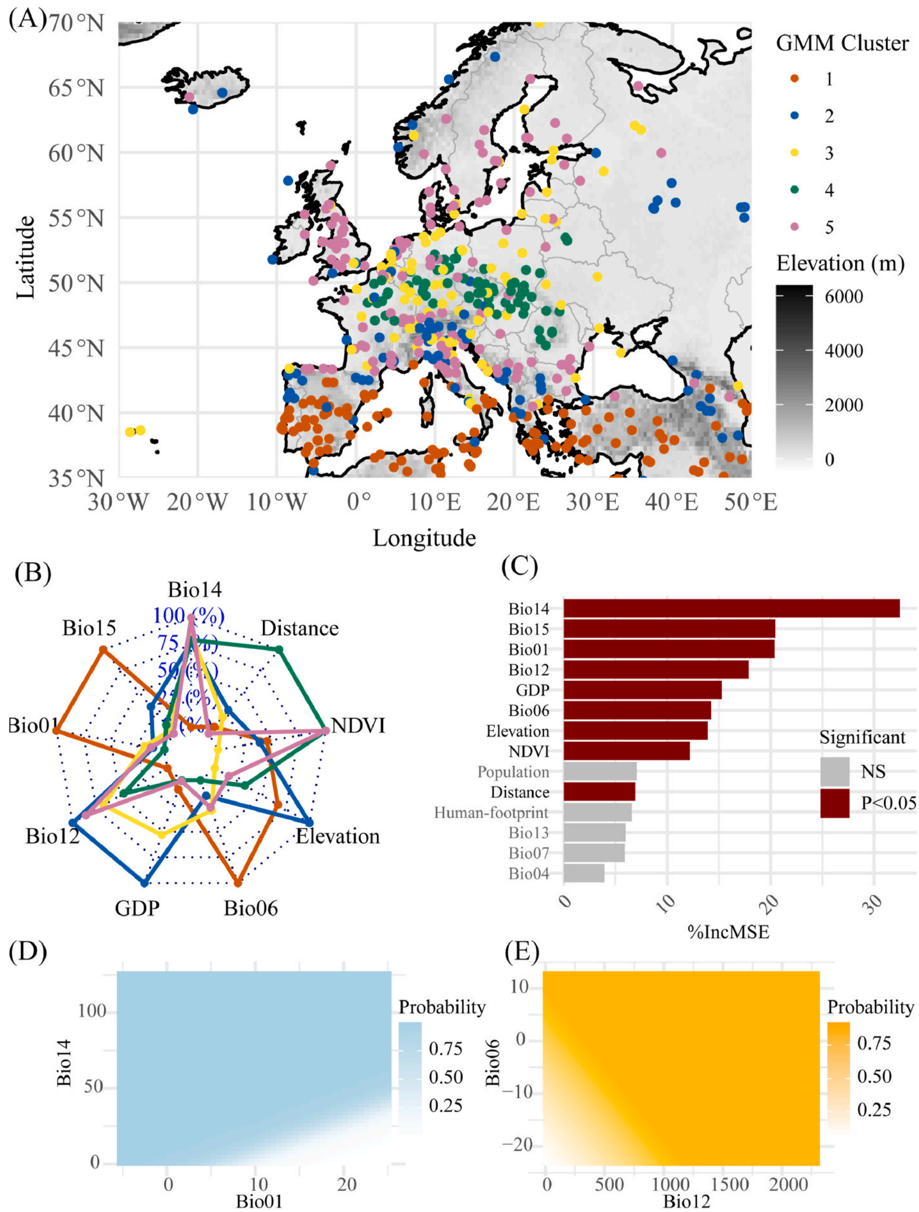

Fig. 4. Environmental drivers of world heritage site distribution across Europe and adjacent cultural regions. (A) Clustering of heritage sites into five distinct types based on environmental variables using Gaussian Mixture Models. (B) Radar chart depicting the environmental profiles of the five site types, with all indicators normalised relative to the maximum value observed across the five groups (100 %). (C) Ranking of environmental variable importance as assessed by the Random Forest model. (D) Interaction effect between precipitation of the driest month (Bio14) and annual mean temperature (Bio01), as revealed by Generalised Linear Modelling. (E) Interaction effect between minimum temperature of the coldest month (Bio06) and annual precipitation (Bio12). Additional variables include: temperature seasonality (Bio4), annual temperature range (Bio7), precipitation of the wettest month (Bio13), and precipitation seasonality (Bio15); *Distance* represents the Euclidean distance to the nearest coastline; *NDVI* (Normalised Difference Vegetation Index) quantifies vegetation cover and productivity; *Population* refers to population density; and *Human footprint* denotes the Human Footprint Index.

power. Specifically, the contribution of precipitation in the driest month (Bio14) exceeded 30 %, while both precipitation seasonality (Bio15) and annual mean temperature (Bio01) each contributed over 20 %. Annual precipitation (Bio12) contributed more than 15 %. Beyond climatic variables, topographic and ecological factors—such as elevation, NDVI, and proximity to the coastline—also exerted statistically significant influence on site distribution (permutation test, $P < 0.05$). In contrast, socio-economic indicators such as population density and the Human Footprint Index yielded comparatively lower contributions and did not reach statistical significance (permutation test, $P > 0.05$).

Further investigation of the interaction effects among key climatic variables (Fig. 4D and E) revealed two categories of environmentally adverse zones for heritage site presence. The first comprises hot-arid regions, defined by annual mean temperatures (Bio01) exceeding 20 °C and minimum monthly precipitation (Bio14) falling below 20 mm. The second includes cold-arid zones, where minimum temperatures in the coldest month (Bio06) drop below −20 °C and annual precipitation (Bio12) remains below 200 mm. Heritage site density in both of these environmental extremes is significantly lower than in more moderate climatic settings.

4.4. Spatial variation, cluster differences, and future trends of climate risks to European world heritage sites

Based on a standardised climate risk assessment model (scaled from 0 to 100), this study systematically reveals the differentiated climatic threats faced by World Heritage Sites across Europe and neighbouring cultural regions (Fig. 5). In terms of hydrodynamic erosion risk (Fig. 5A), the southern Balkans, leeward slopes of the Apennine Peninsula, and the western Iberian Peninsula emerge as core high-risk zones. Notably, Group 2 exhibits the highest median risk value (approximately 38), significantly exceeding those of other groups (Kruskal–Wallis test, $P < 0.05$), which may be attributable to their coastal geomorphology and exposure to intense precipitation regimes (Fig. 5D).

Corrosion and biotic degradation risks display a pronounced latitudinal gradient (Fig. 5B), with high-risk zones (scores >60) concentrated in temperate humid regions of Central Europe, particularly within the area covered by Group 4. Comparative analysis (Fig. 5E) indicates that Group 1, located primarily in Southern Europe, experiences the lowest levels of this risk (median <20), consistent with the arid characteristics of the Mediterranean climate. However, this same group faces the highest levels of drought stress (median risk score = 76), significantly higher than in other clusters ($P < 0.01$) (Fig. 5F). This inverse pattern of risk types underscores the necessity of adopting regionally differentiated approaches to heritage conservation under varying climatic conditions.

By integrating projected climate data under multiple SSP scenarios with current climate baselines, the study evaluates future trajectories of the three climate risk types (Fig. 6). Results show a marked increase in hydrodynamic erosion risk in sites belonging to Cluster 5, with the rate of risk escalation rising progressively from SSP126 to SSP585 scenarios (Fig. 6A). In contrast, Cluster 4 exhibits a reversal, with risk either

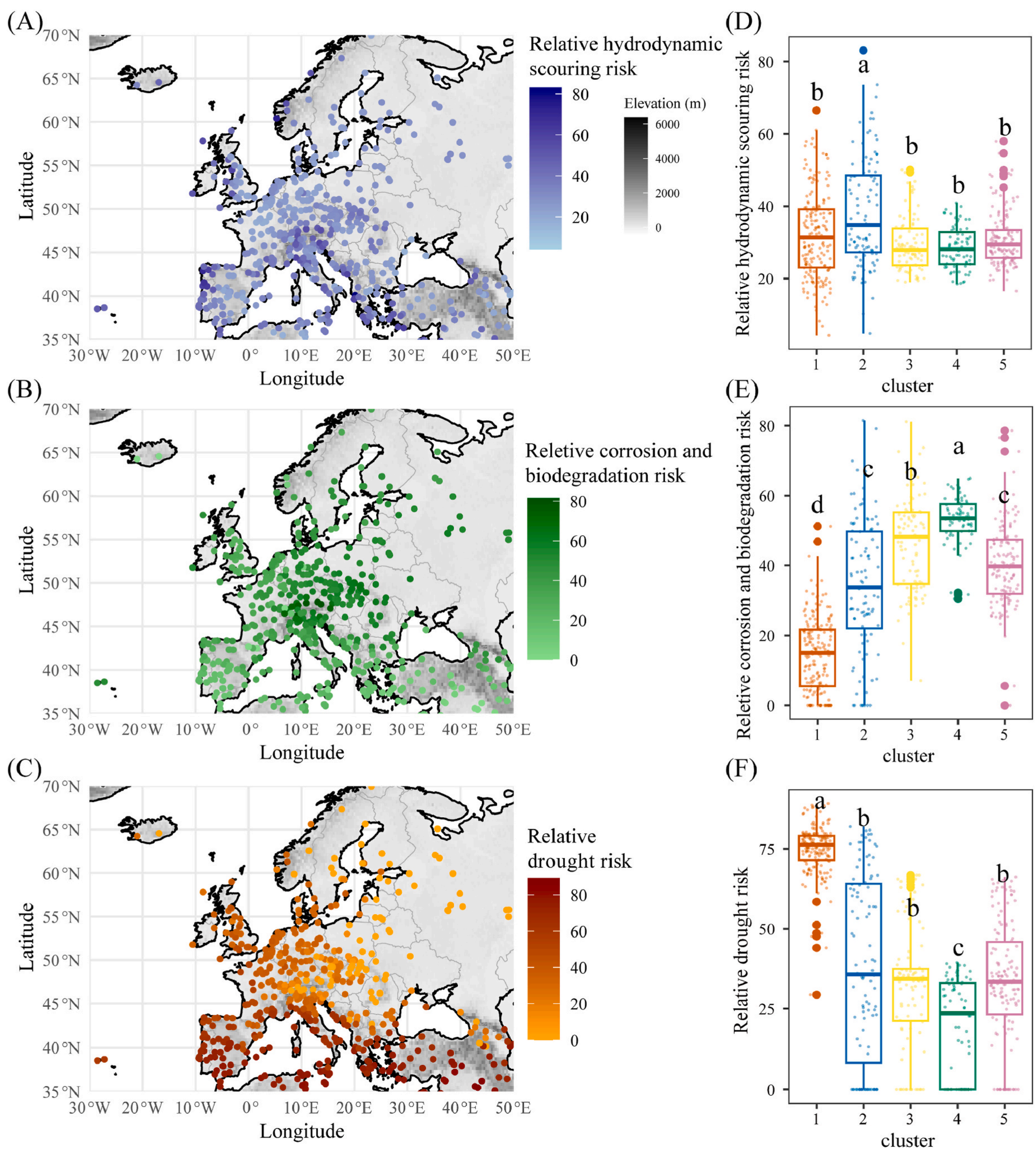

Fig. 5. Climate risk assessment results for world heritage sites across Europe and adjacent cultural regions. (A–C) Spatial distribution of three climate risk indicators: (A) Hydrodynamic erosion risk; (B) Corrosion and biotic degradation risk; (C) Drought risk. (D–F) Comparative analysis of climate risk levels across the five heritage site clusters. Risk scores are standardised on a 0–100 scale. Statistically significant differences between groups (Kruskal–Wallis test, $P < 0.05$) are indicated by distinct lowercase letters.

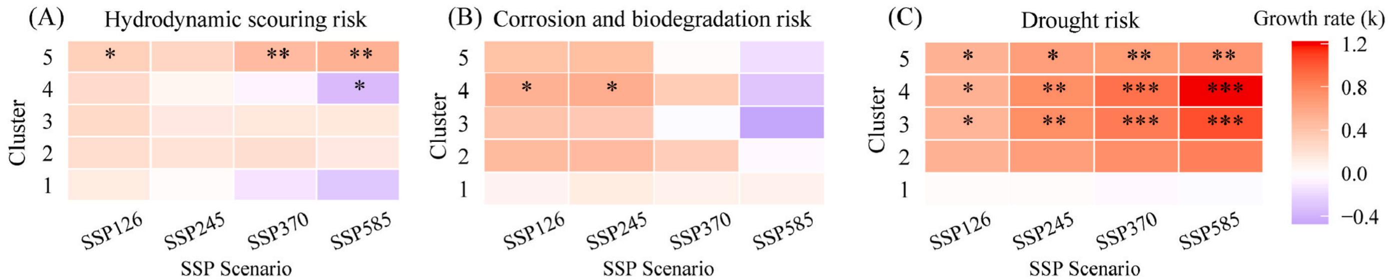

Fig. 6. Projected future trends in climate risk for world heritage sites across Europe and adjacent cultural regions. (A–C) Projected changes in (A) hydrodynamic erosion risk, (B) corrosion and biotic degradation risk, and (C) drought risk across different heritage site clusters and SSP scenarios. Growth rates were calculated as the slope coefficients from linear regressions on standardised risk value time series. Gradient colours indicate the magnitude of change. Significance levels are denoted by asterisks: ***$P < 0.001$; **$P < 0.01$; *$P < 0.05$. All risk values were standardised on a 0–100 scale.

remaining statistically insignificant under SSP126 or decreasing significantly under higher-emission scenarios (SSP370 and SSP585). This contrast may reflect the stark geographical distinction between the clusters, as Cluster 5 sites are closest to the coast, whereas Cluster 4 is furthest inland.

Regarding corrosion and biotic degradation risks, Cluster 4 demonstrates a significant upward trend under SSP126 and SSP245, while other groups show minimal or non-significant increases. However, under more extreme emission scenarios (SSP370 and SSP585), all groups transition from increasing to decreasing trends (Fig. 6B). For drought risk, Cluster 1—which currently exhibits the highest levels—-shows a relatively modest rate of future increase. In contrast, Clusters 2–4, which currently face lower drought risk, display marked increases in risk growth rates, particularly under more extreme scenarios. Strikingly, although Cluster 4 currently has the lowest drought risk, its projected growth rate under SSP585 exceeds 1, highlighting the emerging threat of intensified drought across inland Central Europe. These findings underscore the increasing challenge that climate change poses to the long-term preservation of World Heritage Sites across Europe and adjacent cultural regions.

4.5. *Climatic risk differentiation and protection urgency assessment for cultural heritage*

By integrating risk assessment outcomes under both current and projected climate scenarios with socio-economic adaptive capacity scores (Total socio-economic ability score), this study systematically unveils the differentiated climatic risk landscape and protection priority of World Heritage Sites across Europe and adjacent cultural regions (Fig. 7 and Table 3). The analysis reveals that the majority of sites in Clusters 1 and 3–5 fall under the category of medium protection urgency. Among them, Clusters 3–5 exhibit relatively balanced relationships between climate risk and socio-economic capacity. Notably, Cluster 2 displays pronounced heterogeneity in protection urgency, encompassing a mix of low and extreme priority sites (Fig. 7).

Several sites were identified as requiring immediate conservation intervention: Bryggen and Byblos are exposed to severe hydrodynamic erosion risk; the Swiss Tectonic Arena Sardona is highly vulnerable to corrosion and biotic degradation; while drought risk broadly affects numerous sites including Bryggen, Swiss Tectonic Arena Sardona, The English Lake District, Colchic Rainforests and Wetlands, Vegaøyan – The Vega Archipelago, St Kilda, and Sceilg Mhichíl. Of particular concern are Bryggen and Swiss Tectonic Arena Sardona, which face compound threats from both hydrodynamic erosion and drought, underscoring the urgent need for targeted protective measures.

Through the selection of representative regional cases (Table 3), the study identifies typological patterns in risk exposure and adaptive needs. In the North African arid belt (Cluster 1), hydrodynamic erosion emerges as the dominant threat (mean score: 45.2), necessitating the integration of traditional masonry techniques with eco-engineered slope stabilisation. Algeria (8 sites) and Morocco (4 sites) serve as primary examples. In high-GDP Central European cities (Cluster 2), 73 % of sites exceed safe thresholds for corrosion-related risks. Innovative protective practices have been implemented in Austria (6 sites) and Belgium (9

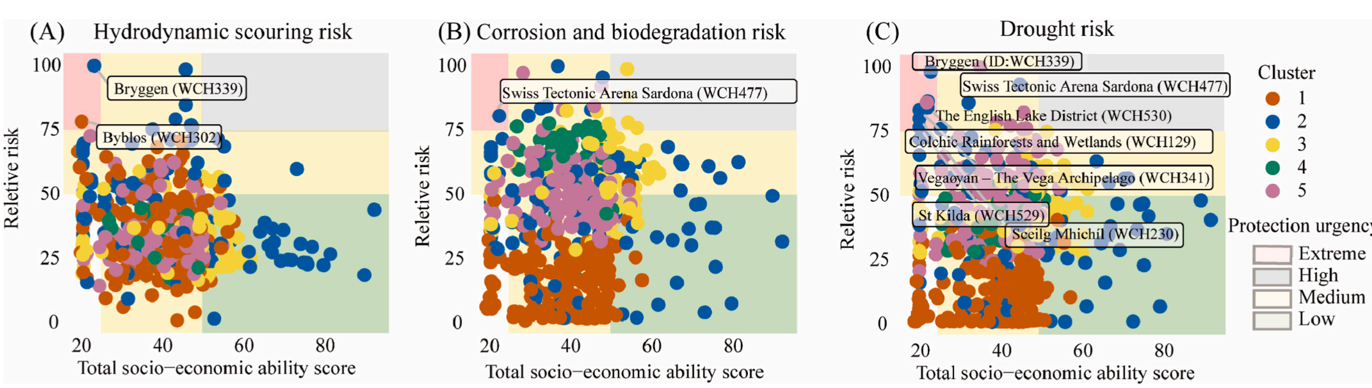

Fig. 7. Assessment of protection urgency in response to climate risks for cultural heritage. (A–C) Classification of protection urgency based on three distinct climate risk factors: (A) Hydrodynamic erosion risk; (B) Corrosion and biotic degradation risk; (C) Drought risk. Risk scores were calculated as a weighted combination of present-day climatic conditions (70 % weight) and projected climate scenarios under SSP585 for 2080–2100 (30 % weight). The Total Socio-Economic Ability Score incorporates three indicators: GDP, Human Footprint Index, and population density. Coloured dots represent individual heritage site clusters (Cluster). The classification criteria for protection urgency are as follows: Extreme protection urgency: Risk score >75 and adaptive capacity <25; High protection urgency: Risk score >75 and adaptive capacity >50; Medium protection urgency: Risk score between 50 and 75 and adaptive capacity between 25 and 50; Low protection urgency: Risk score <50 and adaptive capacity <25. Sites classified as exhibiting extreme protection urgency under each risk type are explicitly annotated in the figure. All risk scores were standardised on a 0–100 scale.

Table 3
Regional cluster characteristics and conservation strategies based on integrated risk assessment.

Cluster	Typical Regions	Key Risk Characteristics	Economic Capacity	Protection Strategies	Data-Supported Cases (National Distribution)
Cluster 1	Arid zones of North Africa	Hydrodynamic scouring risk (mean value: 45.2)	Medium-Low	Traditional stone masonry techniques + ecological slope protection	Algeria (8 cases), Morocco (4 cases)
Cluster 2	High-GDP cities in Central Europe	Proportion of corrosion risk >60: 73 %	High	Nanoscale anti-corrosion coating R&D + PPP conservation fund	Austria (6 cases), Belgium (9 cases)
Cluster 3	Nordic industrial heritage zones	Biodegradation risk (mean value: 67.4)	Medium-High	Microbial inhibitors + heritage adaptive reuse	N/A
Cluster 4	Inland towns of Eastern Europe	Composite corrosion risk (mean value: 64.7)	Medium	Vegetation buffer zones + climate-resilient standards	Czech Republic (11 cases), Hungary (4 cases)
Cluster 5	Island/Polar geomorphic zones	Extreme drought risk (mean value: 69.8)	Low	Groundwater monitoring + indigenous drought-resistant techniques	Iceland (2 cases), Greenland (1 case)

sites), supported by public–private partnership (PPP) conservation funds and advances in nano-scale anti-corrosion coatings.

In the industrial heritage zones of Northern Europe (Cluster 3), the mean biotic degradation risk reaches 67.4, indicating an urgent need for microbial inhibitors and adaptive reuse strategies to balance conservation and utilisation. However, limited existing data highlight a significant research gap. In Eastern European inland towns (Cluster 4), combined corrosion risk (mean score: 64.7) calls for integrated interventions such as vegetative buffer zones and climate-adaptive heritage standards, with the Czech Republic (11 sites) and Hungary (4 sites) offering representative contexts. Finally, island and polar geomorphic clusters (Cluster 5) exhibit extreme drought risk (mean score: 69.8), and sites in Iceland (2) and Greenland (1) urgently require both indigenous drought-resilience technologies and robust international support mechanisms.

5. Discussion

5.1. Climate-dominated environmental gradients and the habitability mechanisms of heritage distribution

This study reveals that the spatial distribution of World Heritage Sites across Europe and its adjacent cultural zones demonstrates a pronounced pattern of geographic clustering aligned with multi-scalar environmental gradients. Among these, climatic variables—most notably the coefficient of variation in precipitation seasonality (Bio15) and the precipitation of the driest month (Bio14)—exhibited the strongest explanatory power in accounting for heritage site distribution (Fig. 4C), significantly surpassing socio-economic factors, which were statistically insignificant ($P > 0.05$). These findings are consistent with the global spatial analysis of architectural heritage conducted by Wang et al. (2021), and they offer empirical spatial validation for the "cultural heritage niche" framework posited by Davis (2021). Specifically, over 93 % of heritage sites are located in temperate, semi-humid regions characterised by mean annual temperatures between 5 and 15 °C and moderate annual precipitation levels (Fig. 3I–P). This reflects a long-standing human settlement preference for climatic stability (Wang et al., 2021; Feng et al., 2025). Even in zones of moderately high anthropogenic intensity, which host approximately 68 % of all heritage sites (Fig. 3E–G), the environmental influence of human activity is secondary to climatic determinants, underscoring the enduring foundational role of natural environmental "basal effects" in shaping heritage formation over time (Tao et al., 2024).

It is noteworthy that in extreme climatic zones—those with mean annual temperatures exceeding 20 °C or annual precipitation below 200 mm—the density of heritage sites declines sharply to 0.2 sites per 10,000 km^2 (Fig. 4D and E). This suggests that human civilisations have historically avoided ecologically adverse zones in favour of more buffered environmental settings for establishing settlements and cultural development (Shen et al., 2024). This tendency is particularly evident in Europe. For instance, the southern European coastal region (Cluster 1) presents a "core–periphery" spatial configuration, where heritage site density aligns closely with historical nodes of trade networks; meanwhile, the Central European interior (Cluster 4) has attracted a high concentration of heritage sites due to its favourable ecological conditions and elevated NDVI values (Olko, 2017). Such an environment–culture adaptation mechanism corroborates the conclusions drawn by Mu and Yuan (2022) in their study of the Yellow River Basin. Concurrently, the success of transnational nomination mechanisms in Europe—exemplified by the "Struve Geodetic Arc"—demonstrates that environmental synergies and institutional coordination are equally indispensable in both the formation and conservation of heritage (Urbanas et al., 2017). This serves as an instructive paradigm for developing countries, where coordinated governance structures for heritage nomination and protection remain insufficiently developed.

5.2. Spatial heterogeneity and non-linear evolution of climate risks

This investigation elucidates the spatial heterogeneity of three principal climate threats confronting European World Heritage Sites (WHS)—hydrodynamic erosion, corrosion-biodegradation, and drought (Fig. 5)—alongside their non-linear evolutionary trajectories under varying SSP scenarios (Fig. 6). Notably, hydrodynamic erosion risks in Cluster 5 (polar/island systems) escalate at an unprecedented rate (Δrisk = 1.22 under SSP585), exceeding IPCC projections for global coastal erosion by 37 % (Change, 2019). This anomaly likely stems from regionally amplified sea-level rise triggered by cryospheric feedback loops, a phenomenon corroborated by Vousdoukas et al. (2020) ice sheet-climate coupling models. Paradoxically, Cluster 4 (Central European temperate zones) exhibits heightened drought sensitivity despite historical precipitation stability, with material stress fatigue under cyclic wet-dry conditions emerging as a critical degradation pathway—a mechanism aligning with ICOMOS (2022) warnings about precipitation regime shifts as latent architectural threats.

The observed risk inversion for corrosion under SSP370 scenarios—where specific regions demonstrate declining biodegradation rates—suggests climate variability may indirectly modulate material degradation through microbial community restructuring. This finding resonates with Sorrentino et al. (2024) predictions of pollutant-climate synergies in Levantine heritage contexts. Crucially, such non-linear responses challenge conventional linear risk assessment paradigms, necessitating integration of compound extremes and multi-hazard cascades into vulnerability frameworks (Sevieri et al., 2020). Dendroisotopic evidence confirms recent European megadroughts (2015–2018) as anthropogenically intensified events unprecedented in two millennia (Büntgen et al., 2021; Aalbers et al., 2023), which synergise with topographic amplification effects to create "risk cascades" in hotspots like the southern Balkans (Milovanović et al., 2017). Consequently, single-hazard evaluations prove inadequate; transition towards coupled "drought-heatwave-corrosion" assessment regimes becomes imperative for identifying multi-risk convergence zones with hyper-vulnerability profiles (Sesana et al., 2021).

5.3. Discussion on climate risk differentiation and protection urgency of cultural heritage

This study reveals a differentiated pattern of protection urgency among World Heritage Sites across Europe and its neighbouring cultural regions, shaped by the interplay between multi-dimensional climate risks and varying levels of adaptive capacity (Fig. 7). The five identified environmental clusters (Cluster 1–5) exhibit distinct dominant climate threats. Cluster 1 is predominantly exposed to hydrodynamic erosion, with representative cases such as heritage sites in the arid zones of Algeria and Morocco (Table 3), which demand an integrated response combining ecological embankments with traditional stone masonry techniques (Alaoui and Radoine, 2024). Cluster 2, in contrast, demonstrates high internal heterogeneity in protection urgency: although some high-GDP cities possess relatively robust adaptive capacity, a number of sites (e.g., Byblos) remain acutely vulnerable (Fig. 7). This indicates a structural mismatch between existing technical capacity and climate risk exposure—a phenomenon widely recognised in UNESCO's assessments of cultural heritage vulnerability to climate change (Centre, 2023).

A closer examination of Cluster 4 and Cluster 5—representing temperate inland and polar/island environments respectively—highlights further asymmetries. While Cluster 4 currently exhibits low overall climate risk, its projected rate of increase in drought exposure under high-emission scenarios (SSP585) is considerable (see Fig. 6). Conversely, Cluster 5 is already facing concurrent threats from extreme drought and biodegradation, yet its capacity for climate adaptation remains limited (Table 3), thus rendering it more reliant on both indigenous coping strategies and external assistance mechanisms. These findings not only underscore the spatial reconfiguration of risk under future scenarios, but also reveal the preparedness gap within current heritage governance frameworks, particularly for highly vulnerable clusters. As noted by the IPCC (2022), risks to cultural heritage under climate change are strongly nonlinear and spatially uneven, necessitating the development of stratified, cluster-specific protection strategies. By integrating environmental clustering with a multidimensional climate risk assessment, this study advances a novel "risk–capacity–urgency" framework at a broader spatial scale, addressing the limitations of prior research which often focused on single hazards or static evaluations (Sesana et al., 2021). Through the combined interpretation of Fig. 7 and Table 3, we not only identify sites requiring immediate intervention—such as Bryggen and the Swiss Tectonic Arena Sardona—but also provide a theoretical foundation for the design of tailored protection strategies across different environmental contexts.

5.4. Implications for disaster risk management and policy

The environmental clustering and multidimensional climate risk assessment framework proposed in this study offers a valuable approach for identifying high-risk heritage sites at a regional scale and provides a theoretical foundation for the development of differentiated protection policies. In the context of increasing climate-related threats, reliance on uniform protection standards has become insufficient to address the growing diversity of site-specific vulnerabilities (Fatorić and Seekamp, 2017). Our findings indicate that some heritage sites situated in economically well-resourced regions nonetheless exhibit high levels of exposure due to limited adaptive capacity, highlighting a spatial mismatch within current governance mechanisms. Future heritage risk management should enhance the integration of climate data into decision-making processes, and promote funding and technical assistance mechanisms based on risk stratification to improve the resilience of sites with lower adaptive capacity. Furthermore, advancing the integration of indigenous knowledge systems with emerging technologies will be essential for shifting from reactive to proactive approaches in heritage protection. Such an adaptive governance paradigm is critical to building more forward-looking and context-sensitive systems for the safeguarding of World Heritage in a changing climate.

Importantly, the integrated analytical framework developed in this study is designed to be fully replicable and adaptable. All modules—including environmental clustering, multidimensional climate risk assessment, and adaptive capacity prioritization—are standardized and transferable, allowing practitioners and researchers to apply the same approach to different regions or heritage types (Cacciotti et al., 2024; Hu and Hewitt, 2024b; Sabour et al., 2024). This practical, workflow-based model offers a tangible tool for systematic risk assessment and prioritization in heritage management under diverse climate and environmental conditions (Hu and Hewitt, 2024a). By making the workflow and indicator system open and modular, this study aims to provide a methodological foundation that can be adopted and refined in future heritage risk assessments worldwide (ICOMOS, 2022).

5.5. Limitations and future directions

While this study systematically explores the environmental drivers and climate-related vulnerabilities of World Heritage Sites in Europe at a regional scale, several limitations should be acknowledged. Firstly, there is an inherent scale mismatch between heritage site data and climate variables, which constrains our ability to capture microtopographic and local climatic heterogeneities. This may result in the underestimation or overestimation of risk at specific sites (Frasca et al., 2024). Additionally, the statistical approach relies on mean value extraction from raster datasets, which may further smooth fine-scale environmental differences and reduce sensitivity to microclimatic or site-specific risks that are critical for heritage conservation. Employing finer-resolution or downscaled data in future studies would improve site-level accuracy (Wang et al., 2016). Secondly, the risk assessment framework adopted here relies on the selection of indicators and model assumptions; although parameters were set based on established literature and expert consensus, different methodological choices could influence the sensitivity of outcomes (Crowley et al., 2022). Moreover, the projections for future climate risk in this study are based on a single global climate model (ACCESS-CM2) as representative of CMIP6 outputs; while this is consistent with several recent studies, it does not capture the full range of model uncertainty (Snyder et al., 2024). Future work should incorporate multi-model ensembles to better reflect uncertainty in climate scenarios. In addition, this study primarily focuses on climatic and environmental stressors, without incorporating non-climatic pressures such as tourism, thereby framing the results largely in terms of environmental urgency. Our projections for future climate risk are also contingent upon currently accepted scenarios, the uncertainties of which may affect the long-term reliability of assessments (Sesana et al., 2021). Finally, we did not conduct field-based validation of the risk maps, and empirical site-level data were beyond the scope of this study (Xu et al., 2025). Future research is encouraged to combine spatial modelling with field surveys and local expert input for calibration and ground-truthing of vulnerability assessments. As this research is region-specific, the generalizability of its findings to other global regions, as well as the applicability of its insights to individual site-level management, must be carefully contextualised.

6. Conclusion

This study, centered on the theme of "Climate and Environmental Dynamics: Distribution Patterns and Vulnerability of World Heritage Sites in Europe," integrates spatial analysis and climate risk assessment to generate novel insights into the intersection of heritage conservation and climate change. A key contribution of this research is the development of a replicable analytical framework that combines environmental clustering and quantitative risk evaluation, providing a practical tool for heritage site management. The study reveals that the distribution of World Heritage Sites in Europe is strongly influenced by climatic factors, particularly temperature and precipitation, with these variables explaining much more of the distribution than socio-economic factors. We also find that climate change is reshaping the landscape of heritage conservation, with specific regions facing rapidly escalating risks, such as intensified drought stress. Approximately one-third of European World Heritage Sites are categorized as "high urgency," requiring immediate conservation action. This research contributes to both the scientific understanding of heritage-environment relationships and the development of practical methodologies for assessing and mitigating climate-related risks to cultural heritage. The findings have direct implications for policy and management, offering support forHave we correctly interpreted the following funding source(s) and country names you cited in your article: UNESCO, France? UNESCO and national heritage authorities in identifying high-risk sites, optimizing resource allocation, and integrating climate adaptation into conservation strategies. Furthermore, the framework presented in this study can be applied to other regions or heritage types, providing a valuable tool for global heritage risk management and climate adaptation.

Research interests

Cultural heritage, geo-information, human geography, climate change.

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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

Data will be made available on request.

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