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Research Article

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Posted Date: June 25th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9914801/v1

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Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at Discover Sustainability on October 7th, 2026. See the published version at https://doi.org/10.1007/s43621-026-04551-5.

Climate risk, uneven development, and threshold-dependent tourism resilience in western China

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Abstract:

Climate risk and socioeconomic development are increasingly reshaping tourism resilience, particularly in climate-sensitive and unevenly developed regions. Yet how climate risk and economic development jointly influence tourism, and how these effects vary across regions, remains insufficiently understood. Using city-level panel data for 13 cities from 2003 to 2023, this study applies panel threshold regression, interaction analysis, and contribution decomposition to investigate the nonlinear relationships among climate exposure, sensitivity, adaptive capacity, readiness, and tourism performance. Results reveal that tourism vulnerability and resilience display pronounced threshold dependence and regional differentiation. When per capita GDP exceeds 21,357 CNY, the constraining effect of exposure is partly mitigated by stronger adaptive capacity and governance, and in some cities, exposure is reconfigured into differentiated tourism resources. By contrast, when climate risk exceeds 1.49, the negative effect of exposure intensifies, while resilience and related support conditions become more important for system stability. City-level analysis further identifies three distinct transition pathways: development-driven, tourism-driven, and risk-response, characterized respectively by resilience enhancement, improved tourism reception capacity, and heightened dependence on basic adaptive capacity and readiness under high-risk conditions. Tourism revenue is also more sensitive than tourism intensity to threshold shifts, indicating that revenue-based indicators better capture latent vulnerability and dynamic change. These findings support threshold-sensitive and place-specific sustainability governance and adaptive tourism planning in climate-sensitive and unevenly developed regions.

Key words: Climate risk, uneven development, sustainability, tourism resilience, threshold effects

1.Introduction

Against the backdrop of intensifying climate risks and regional development disparities, achieving resilient tourism development has emerged as a critical focus in sustainable tourism and regional resilience research (Luo et al., 2025; Wang et al., 2024), particularly in underdeveloped regions. Western China has long been shaped by the coexistence of rich tourism resources, severe environmental constraints, and pronounced spatial inequalities (Li et al., 2023; Yang et al., 2025). Since the rise of mass tourism in the 1990s, tourism in western China has gradually shifted from scale-oriented expansion toward a resilience-oriented pathway that balances economic returns, environmental constraints, and regional sustainability.

However, this transformation process remains constrained by climate sensitivity, vulnerability, and regional development imbalances (Lei et al., 2024). On the one hand, climate change, through long-term climate changes and more frequent extreme events, continues to impact tourist seasonality and tourist demand, infrastructure reliability, accessibility, and destination safety and income stability (Yu et al., 2025; Scott, 2024; Zeng et al., 2019). On the other hand, significant differences exist between provincial capitals, established tourist destinations, and peripheral cities in terms of infrastructure, public services, governance capacity, and hospitality levels (Fang et al., 2025). This uneven spatial development inherently dictates the differential capacities of these cities to buffer, absorb, and mitigate risks. Consequently, tourism in western China faces not merely an escalation in absolute climate risk, but rather a spatially differentiated amplification of risk impacts. Accordingly, clarifying how economic development and climate risks interact to shape tourism vulnerability and resilience is essential for understanding regional tourism resilience and designing threshold-sensitive sustainability governance in western China.

Previous research offers critical insights into the evolution of tourism systems through the distinct views of economic development, climate change, and resilience. While some studies highlight that economic advancement improves infrastructure, stimulates consumption upgrades, and drives tourism growth (Gössling et al., 2023; Scott, 2024), others demonstrate that climate exposure and extreme weather events suppress visitor demand, compromise climate comfort, and exacerbate systemic vulnerability (Scott, 2024; Zeng et al., 2019). Although resilience research increasingly underscores the importance of governance, adaptive capacity, digital infrastructure, and recovery capabilities, these studies predominantly focus on macro-trend identification or indicator fluctuations (Dogru et al., 2019; Steiger et al., 2024; Zhang, 2025). Consequently, the specific conditions triggering critical systemic transitions, alongside their underlying mechanisms, remain inadequately understood. This gap is particularly evident in underdeveloped regions facing compounded pressures, where the evolutionary dynamics of tourism may fundamentally diverge from those in developed contexts (Chakraborty et al., 2019; Lazzari et al., 2021). However, these studies provide limited evidence on how climate-risk and development thresholds can be used to diagnose sustainability constraints, identify adaptation priorities, and support differentiated governance strategies in tourism.

Furthermore, although recent studies have revealed spatial inequalities and threshold effects in tourism economic resilience (Fang et al., 2025), less attention has been paid to how development-risk coupling operates in tourism-dependent cities with different infrastructure conditions, public service capacities, and governance readiness. Therefore, it is necessary to construct a city-level analytical framework capable of simultaneously capturing development-risk coupling, threshold effects, and path differentiation, thereby providing evidence for threshold-sensitive sustainability governance.

Western China provides a valuable empirical setting for addressing these questions. Across the Qinghai-Tibet Plateau and its adjacent areas, the accelerating climate change (Duan et al., 2020; Hu et al., 2023) continues to amplify the external threats to tourism systems heavily reliant on nature-based and cultural heritage assets. The confluence of environmental fragility and socio-economic underdevelopment heightens the sensitivity of these systems to climate risks. Meanwhile, spatial disparities in infrastructure, public services, and governance capacities further widen differences in tourism vulnerability and resilience among cities. Against this backdrop, this study focuses on 13 cities in western China to unveil the evolutionary patterns of vulnerability and resilience within tourism under the coupled influence of economic development and climate risks. Specifically, this research addresses the following three core questions: 1) How do economic development and climate risks jointly shape regional tourism vulnerability and resilience in western China? 2) Do these effects exhibit significant threshold dependencies? 3) Do individual cities demonstrate divergent evolutionary trajectories, and what are the underlying commonalities and variations in driving mechanisms?

2. Materials and methods

2.1 Framework and hypotheses

This study proposes a Threshold-Governed Climate Risk–Tourism Resilience Framework. Unlike conventional approaches that implicitly assume vulnerability declines monotonically with economic development and adaptive investment, this framework conceptualizes vulnerability and resilience of tourism as regime-dependent outcomes produced through threshold-driven reconfigurations among exposure, sensitivity, adaptive capacity, and readiness. In this view, economic development and climate risk do not simply magnify or reduce impacts, but reorganize how the components of vulnerability and resilience operate across development stages and risk contexts (Fig. 1).

Within this framework, vulnerability is understood as the configuration of exposure, sensitivity, and adaptive capacity (Capela Lourenço et al., 2014) that impacts tourism, whereas resilience reflects the system's capacity to absorb shocks, reorganize, and sustain tourism performance under climate stress. Given the differentiated urbanization trajectories and governance capacities, vulnerability and resilience are expected to evolve unevenly and nonlinearly rather than along a common developmental trajectory (Datola, 2023; Simmie and Martin, 2010; Simpson et al., 2021). Empirically, the framework is operationalized through three analytical dimensions and five functional components. The three dimensions provide the substantive domains through which vulnerability is observed: (1) a climate dimension captures direct climatic pressures on tourism systems, including thermal stress, wind conditions, and extreme precipitation (Rutty et al., 2020); (2) The resource-environmental dimension reflects ecological constraints and environmental governance through indicators such as water-resource dependence and environmental investment (Aprile and Fiorillo, 2017; Ricart et al., 2024); (3) The economic–social dimension represents market foundations and institutional buffers, including poverty, inequality, infrastructure accessibility, and innovation capacity (IPCC, 2023). These dimensions (five functional components: exposure, sensitivity, adaptive capacity, readiness, and hazard) are used to trace how vulnerability and resilience are reconfigured across development and climate risk regimes.

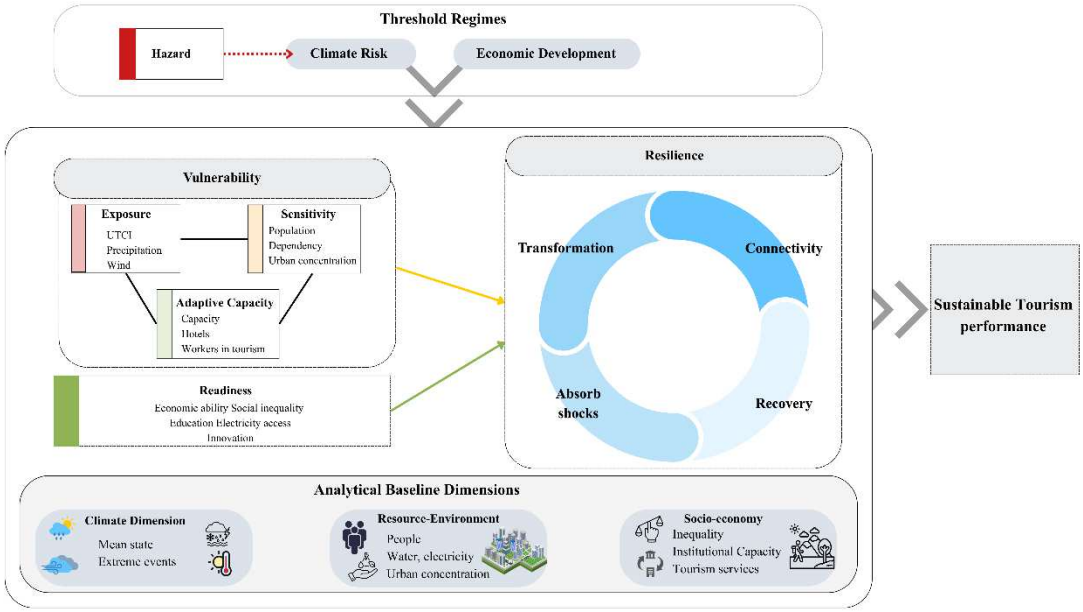


Figure 1 The Threshold-Governed Vulnerability and Resilience framework

Based on this framework, this study expects the effects of vulnerability and resilience components on tourism performance to be regime-dependent rather than uniform across development and climate risk contexts. In particular, exposure and sensitivity are expected to exert stronger constraining effects under low-development or high-risk regimes, whereas the roles of adaptive capacity and readiness are expected to become more prominent as governance conditions improve. These threshold dynamics are also expected to differ between tourism intensity and tourism revenue.

2.2 Study area

Western China contains many climate-sensitive and environmentally constrained tourism regions, where tourism development is shaped by climate exposure, infrastructure gaps, and uneven socioeconomic conditions. These systemic constraints make it increasingly difficult to meet the growing demands for sustainable tourism. For instance, the QTP shows a 1.5 times in climate anomaly higher than the whole China, differing across various altitudes (Zhou et al., 2022). Xinjiang, Tibet, Gansu, Yunnan, and Qinghai span across China's western frontier, exhibiting diverse geographical and climatic characteristics. However, these regions face severe pressures, such as Xinjiang experiences evaporation exceeding 1,500 mm, exacerbating water scarcity (Yao et al., 2022); Gansu's Hexi Corridor (including Zhangye) is significantly threatened by desertification and anomalous "warming and wetting" extremes (Wang et al., 2025; Shao et al., 2023); and glacial retreat in Qinghai's Three-River Source region threatens ecological security (Sun et al., 2019).

The above issues highlight the urgent need for resilience strategies to balance sustainable goals in the face of both environmental sensitivity and economic dependency. City-level panel data provide an appropriate scale for examining tourism resilience because tourism planning, infrastructure investment, public services, emergency response, and local adaptation policies are largely organized and implemented through city or prefecture-level governance units. The selected cities should meet the following criteria: (1) High economic dependence on tourism: Tourism must play a crucial role in the local economy, contributing ≥5% to the local GDP, with local governments officially designating it as a "pillar" or "strategic emerging" industry supported by

special policies (e.g., development funds and land support); (2) The "double disadvantage" context: The region must exhibit pronounced environmental fragility and intensifying climate extremes coupled with highly uneven economic development; and (3) Data continuity: There must be sufficient and continuous availability of both meteorological and socioeconomic panel data from reliable sources, such as local statistical yearbooks and National Economic and Social Development Statistical Bulletins.

Based on these criteria, the study selects Urumqi, Turpan, the Ili Kazakh Autonomous Prefecture, and Kashgar (Xinjiang); Lhasa and Shigatse (Tibet); Lanzhou, Zhangye, and the Gannan Tibetan Autonomous Prefecture (Gansu); Xining and the Huangnan Tibetan Autonomous Prefecture (Qinghai); and Lijiang and the Diqing Tibetan Autonomous Prefecture (Yunnan) as the research cities (Fig. 2). These locations cover a diverse spectrum of climate zones and tourism typologies, including arid basins, alpine regions, mountain lakes, glaciers, and cultural heritage sites, which provides an ideal and comprehensive spatial context for analyzing tourism vulnerability and resilience across different latitudes and risk regimes.

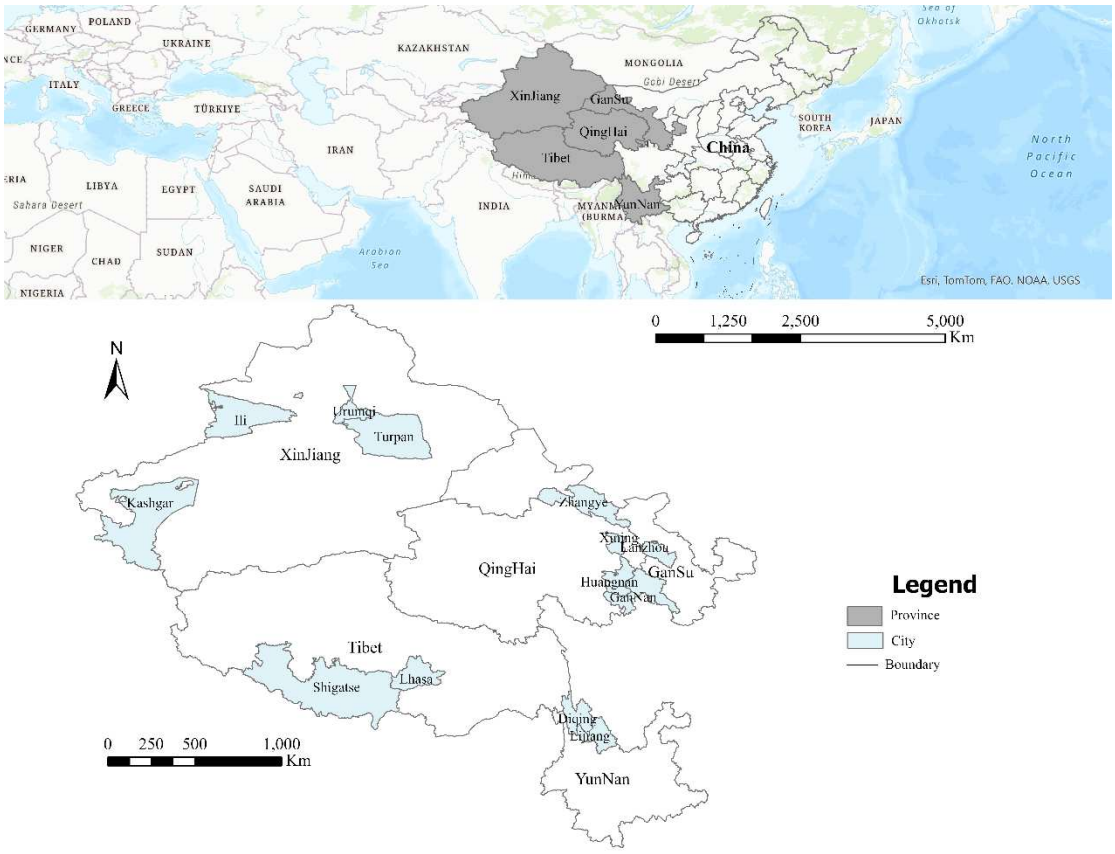


Figure 2 The study area

2.3 Datasets

The meteorological data used in this study is sourced from the fifth-generation reanalysis data of the European Center for Medium-Range Weather Forecasts, provided by the ERA5 dataset as the baseline dataset (http://cds.climate.copernicus.eu/cdsapp#!/dataset/derived-utci-historcal?tab=form). It includes temperature, precipitation, wind speed, and universal thermal climate index (UTCI), with a spatial resolution of 0.25° × 0.25°, covering the period from 1979 to 2024 were utilized to establish a robust long-term climatological baseline for accurately calculating climate anomalies and extreme event frequencies. The meteorological dataset is

selected based on the latitude and longitude range of different administrative regions, and is used to calculate climate anomaly and extreme event frequency indicators. The results are compared with existing literature to ensure the usability of the data. The economic panel data and natural disaster data are obtained from local statistical yearbooks and National Economic and Social Development Statistical Bulletins, including population, GDP, tourism intensity, tourism revenue, among others. Multi-source data is cleaned and aligned through the following steps: handling missing values (interpolation or deletion), smoothing outliers, and aggregating high-frequency climate data to annual or quarterly scales as needed to match economic data. The final panel data covers the period from 2003 to 2023.

2.4 Methodology

2.4.1 Calculation of indices

The study employs standardization procedures to eliminate dimensional effects of baseline datasets, and we calculate composite indices based on the Notre Dame Global Adaptation Initiative index framework (Dogru et al., 2019; Garschagen et al., 2021), Climate-Resilient Development (Butler et al., 2022), and urban resilience (Liu et al., 2022). The formulas for vulnerability and resilience in this study are specifically defined as follows:

$$Vulnerability = (Exposure \times Sensitivity)/Adaptive\ capacity \quad (1)$$

$$Resilience = (Readiness - Vulnerability + 1) \times 50 \quad (2)$$

Climate risk index integrates hazard and vulnerability, where vulnerability is constructed as a composite of exposure, sensitivity and adaptive capacity (equal 1). Both $Hazard$ and $Vulnerability$ are first normalized to the [0,1] range and then combined into a climate risk index:

$$Risk = \mu_1 Hazard + \mu_2 Vulnerability \quad (3)$$

Where μ_1 and μ_2 denote the relative contributions of hazard and vulnerability, respectively.

2.4.2 Baseline analysis

Tourism intensity and tourism revenue serve as dependent variables, capturing the spatial scale and economic returns of regional tourism. Pre-estimation tests verified data reliability: the Kendall Rank Correlation (Appendix Figure 1) confirmed theoretical expectations, showing negative correlations for exposure, sensitivity, and vulnerability, but positive correlations for adaptive capacity, readiness, and resilience. Diagnostics also confirmed the absence of multi-collinearity (Appendix Table 1). To prevent spurious regression, the Levin-Lin-Chu Unit Root Test (Appendix Table 2) demonstrated that most variables are stationary at levels (I(0)), while readiness and GDP are stationary at the first difference (I(1)). With vulnerability and resilience as core explanatory variables, the Pedroni Cointegration Test (Appendix Table 3) verified a long-term equilibrium relationship. Finally, Hausman test results supported a random-effects (RE) specification for the baseline linear panel model.

2.4.3 Trend analysis

To compare the dynamic evolution and phased transitions of the tourism system at different development stages, this study divides the entire period into two 11 year-time windows: Stage I (2003-2013) and Stage II (2013-2023). This study uses the Relative Change Rate method to measure the macroeconomic changes in tourism and indices between these two stages. By comparing the average levels over the two time periods, this method can effectively smooth out the interference of short-term fluctuations or extreme outliers in a single year, thus intuitively and accurately reflecting the long-term expansion or contraction trend. The formula for calculating the relative change rate is as follows:

$$Ratio = (Period_{II} - Period_I)/Period_I \; X \; 100\% \quad (4)$$

Ratio represents the relative rate of change of tourism and indices; $Period_I$ and $Period_{II}$ represent the periodic observations during Phase I (2003–2013) and Phase II (2013–2023), respectively. Through this calculation of intertemporal relative differences, this study can clearly identify the macro-evolutionary trajectory of the tourism system in various regions over the past two decades.

2.4.4 Model specification and empirical approach

This study constructs a progressive empirical analysis framework comprising threshold identification, interaction effect testing, and underlying indicator contribution decomposition. Specifically, the threshold model is utilized to identify whether the effects of core functional components exhibit significant abrupt changes across different development and risk stages; the interaction model supplements this by delineating the overall moderating trends under continuous changes in GDP and climate risk; and the underlying indicator contribution decomposition reveals the reconfiguration mechanisms and spatial differences of the internal composition within each functional component.

First, the panel threshold regression model (Hansen, 1999) is employed, utilizing economic development (GDP) and climate risk as threshold variables, to examine whether the response mechanisms of tourism vulnerability and resilience exhibit significant regime dependence. To mitigate the interference of extreme values on threshold estimation and ensure the representativeness of the divided regimes, the threshold search range is strictly restricted to the 10th–90th percentiles of the sample distribution (Chang et al., 2009; Chattopadhyay et al., 2022). To evaluate the statistical significance of the threshold effects, we implement a bootstrap likelihood-ratio (LR) test with 1,000 resamples, comparing the LR statistics with their critical values to determine whether the estimated thresholds are supported by the data. The panel threshold regression model is specified as:

$$\ln(Tourism_{i,t}) = \alpha_0 + \alpha_1 \cdot \ln(Tourism_{i,t-1}) + \beta_1^{'} \cdot \chi_{i,t} \cdot I(threshold_{i,t} \le \tau_1) + \beta_2^{'} \cdot \chi_{i,t} \cdot I(\tau_1 \le threshold_{i,t} \le \tau_2) + \beta_3^{'} \cdot \chi_{i,t} \cdot I(\tau_2 < threshold_{i,t}) + \sigma_i + \varphi_{i,t} \quad (5)$$

$$Tourism_{i,t} = [Tourism\ intensity, Tourism\ revenue] \quad (6)$$

$$X_{i,t} = [Vulnerability, Resilience, Exposure, Sensitivity, Adaptive\ Capacity, Readiness] \quad (7)$$

$$threshold_{i,t} = [GDP, Risk] \quad (8)$$

Where $\chi_{i,t}$ represent core explanatory variable vectors, $Tourism_{i,t}$represent logarithmic forms of tourism intensity and tourism revenue, respectively; τ denotes the optimal threshold value; $\beta_1^{'}$,$\beta_2^{'}$, and $\beta_3^{'}$ correspond to slope coefficients for the aforementioned variable groups across different threshold intervals; $I(\cdot)$represents an indicator function that equals 1 when the bracketed condition is satisfied and 0 otherwise; σ_i represent individual random effects; $\varphi_{i,t}$ represent error terms (disturbance terms).

Secondly, based on the threshold model, an interaction model is further constructed. Unlike the threshold model, which emphasizes stage differences, the interaction model aims to analyze whether the role of core functional components exhibits continuous moderating characteristics with changes in economic development or climate risks, providing supplementary evidence for the overall trend. The interaction model is specified as follows:

$$Tourism_{i,t} = \alpha + \beta_1 \cdot \chi_{i,t} + \beta_2 \cdot GDP_{i,t} + \beta_3 \cdot Risk_{i,t} + \beta_4(\chi_{i,t} \times GDP_{i,t}) + \beta_5(\chi_{i,t} \times Risk_{i,t}) + \gamma \cdot Z_{i,t} + \varepsilon_i + \lambda_t + \varphi_{i,t} \quad (9)$$

Where, $GDP_{i,t}$ and $Risk_{i,t}$ represent economic development and climate risk, respectively; $Z_{i,t}$ is a vector of control variables; ε_i and λ_t denote city and year fixed effects.

Finally, to explain the phased changes identified by the threshold model and the marginal change in contribution, this paper decomposes the contribution of underlying indicators. Specifically, following directional standardization across the full sample, we calculate the contribution of each underlying indicator to its corresponding functional component (e.g., exposure, sensitivity, adaptive capacity, and readiness). Within the threshold interval k, the relative contribution (CR) of index j is defined as the percentage of the absolute product of its estimated elasticity coefficient and the sample mean within that interval:

$$CR_{j,k} = \beta_{j,k} \cdot \bar{X}_{j,k} / \sum_{i=1}^{m} \beta_{j,k} \cdot \bar{X}_{j,k} \; X\,100\% \quad (10)$$

$$\Delta CR_j = CR_{j,k+1} - CR_{j,k} \quad (11)$$

Where, $CR_{j,k}$represents the relative contribution of in the interval j; $\beta_{j,k}$is the weight of each index according to the framework; $\bar{X}_{j,k}$is the sample mean of the component in the interval k; and m is the total number of core components. $\Delta CR_j$is the marginal change in contribution.

3. Results

3.1 Spatiotemporal evolution of tourism performance, vulnerability, and resilience

Against the backdrop of China's all-for-one tourism policy and infrastructure expansion (e.g., high-speed rail networks), tourism in western China exhibited a long-term upward trend from 2003 to 2023 (Fig. 3), even though the COVID-19 pandemic caused only short-lived disruptions. While tourism intensity quadrupled in most cities, regions with low early-stage development but unique endowments (e.g., Lanzhou, Zhangye, Shigatse, Ili) achieved 5-11 times growth. This significant "catch-up" feature was driven by a "low-base effect" and in-depth resource development. Tourism revenue grew even more prominently, reflecting a surge in market demand. The evolution of vulnerability and resilience in these tourism systems exhibited significant phased variation and regional asymmetry. From 2003 to 2013, highly vulnerable cities (indices >0.8) were concentrated in the QTP (e.g., Lijiang, Shigatse, Huangnan, Diqing) due to weak economic foundations and limited accessibility. However, from 2013 to 2023, vulnerability decreased significantly (>40%) across most cities. This widespread improvement was closely driven by sustained economic growth, environmental investments, and systemic infrastructure upgrades. Correspondingly, regional resilience transitioned from limited recovery capacities (scores <50 before 2013) to robust levels, with most cities exceeding 70 and several, including Lijiang, Xining, and Lhasa, surpassing 90. Crucially, cities such as Urumqi and Kashgar exhibited an anomaly where vulnerability decreased without a corresponding improvement in resilience.

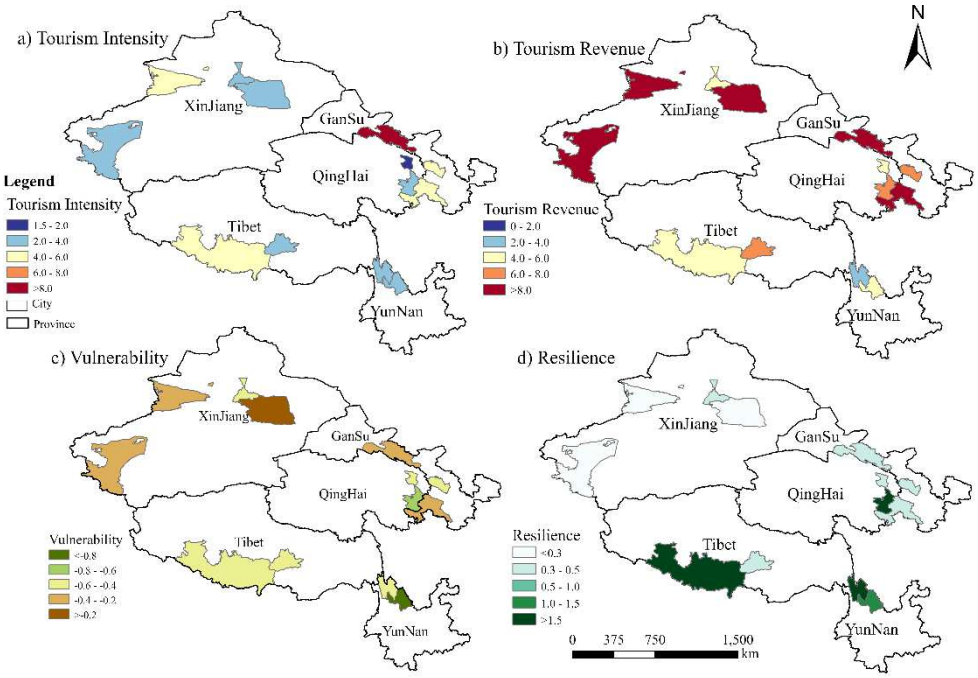


Figure 3 Dynamic Evolution during 2003 to 2023. a) Tourism intensity and b) tourism revenue, c) vulnerability and d) resilience

3.2 Temporal dynamics of core dimensions

The evolution of vulnerability and resilience was directly driven by dynamic changes across four core dimensions: exposure, sensitivity, adaptive capacity, and readiness. Adaptive capacity and readiness showed a significant long-term increase from 2003 to 2023 (Fig. 4), which essentially reflected the economic development. However, the overall trends of exposure and sensitivity showed no significant changes. Exposure was affected by regional differences in climate factors: the climate uncomfortable index and the number of strong wind days decreased, reducing the negative impacts of climate on tourism activities. In contrast, the number of heavy precipitation days increased, concentrated in the marginal cities of the QTP (e.g., Xining, Huangnan, Gannan) (Table. 1). The complex terrain and fragile environment in this region make it prone to disasters such as flash floods and landslides, resulting in persistently high local exposure levels and highlighting it as a key area for future system risk prevention and control. Sensitivity remained structurally stable due to countervailing demographic and socioeconomic shifts. Factors reducing sensitivity included declining rural populations (10%-25%), rising urbanization (5%-40%), and sharp poverty reductions across provincial capitals (>50%). However, these improvements were completely offset by factors increasing sensitivity, namely a rising total dependency ratio (by ~15%) and slight poverty increases in non-capital regions (<10%). The aggregate sensitivity of the tourism systems remained unchanged despite profound changes.

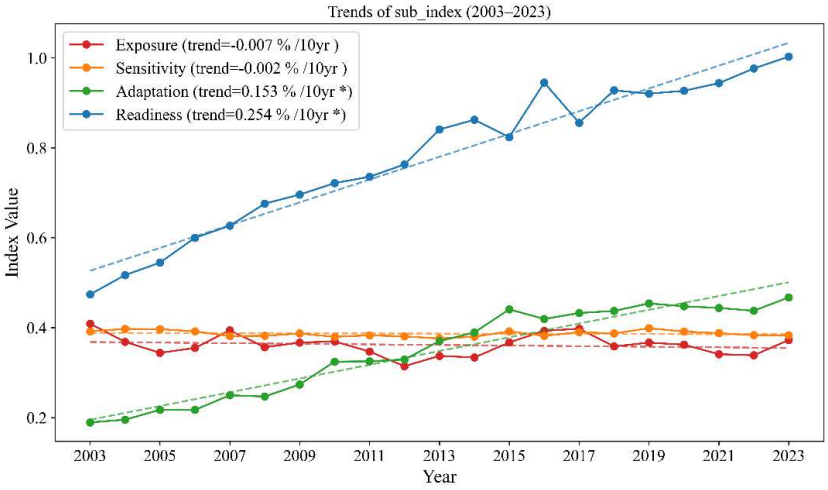


Figure 4 Trends of sub-index from 2003 to 2023 (*: when p<0.05)

Table 1 Trends of extreme weather days in cities from 2003 to 2023

City	Trends of Extreme weather % (/10yr)			
	Thermal comfort	Number of uncomfortable days	Heavy Precipitation	Strong Wind
Lijiang	0.002	-0.003	-0.02	-0.4
Lhasa	-0.28	-0.19	0.02	-0.25
Shigatse	0.03	-0.1	0.02	-0.47
Ili	-0.02	-0.05	0.01	-0.08
Turpan	0.01	-0.005	-0.04	-0.4
Xining	0.01	-0.005	0.12	-0.5
Gannan	0.02	-0.03	0.14	-0.83
Diqing	-0.004	-0.006	-0.03	0.42
Huangnan	-0.49	-0.03	0.02	-0.9
Kashgar	-0.006	-0.18	0.008	-0.38
Urumuq	0.85	-0.01	-0.1	-0.8
Zhangye	0.02	-0.2	0.07	0.05
Lanzhou	0.2	-0.004	0.06	-0.15

3.3 Impacts of climate risk and economy on tourism vulnerability and resilience

3.3.1 Threshold Effects

Threshold tests using GDP and climate risk significantly reject the null hypothesis of linearity, confirming that tourism responses exhibit clear segmented results (Appendix Tables 4, 5). Furthermore, the lower RSS and MSE values of the double-threshold models indicate that a dual-threshold specification is more effective in capturing mechanism heterogeneity across different development–risk contexts. While the aggregate effect of vulnerability is statistically insignificant, the result indicated its structurally contingent nature, and resilience remains significantly positive (Appendix Table 6). Consequently, we unpacked vulnerability into its constituent dimensions to trace their nonlinear effects (Fig. 5).

The positive and significant first-order lag terms for tourism intensity and revenue indicate strong systemic persistence. The economic threshold (GDP = 21,357 CNY) acts as a "Transformation Catalyst." Exposure shifts from a significant negative effect to a positive one in both tourism intensity and revenue, indicating a transition from a development constraint to a differentiated resource advantage. Sensitivity remains positive but weakens, and it is only significant for tourism revenue, suggesting that tourism dependence continuously promotes economic output, with a marginal weakening as the economy becomes more diversified. Adaptive capacity exhibits a strongly significant positive effect but with diminishing marginal returns, indicating that the diminishing economic returns of adaptive investments become increasingly prominent. Readiness remains positive but statistically insignificant under the GDP threshold.

Conversely, the climate risk threshold (>1.49) triggers "Impact Amplification" and "jump-like structural breaks." Under high-risk regimes, readiness shifts from insignificance to a core resilience support ($p < 0.001$). Exposure shifts from positive to a strongly significant negative effect, with revenue exhibiting greater magnitude declines than intensity. Sensitivity surges post-threshold, severely amplifying the vulnerability of low-income supply chains. Adaptive capacity shows a characteristic of "exponential growth", after crossing the threshold, the coefficient rises (tourism intensity: from 4.2 to 17.9; tourism revenue: from 6.6 to 38.2; both $p < 0.001$), becoming the core buffering factor under high-risk conditions.

Overall, the economic threshold reshapes the "transformation capacity", while the risk threshold triggers "impact amplification". Together, they determine the nonlinear responses of the tourism system in terms of both scale and output.

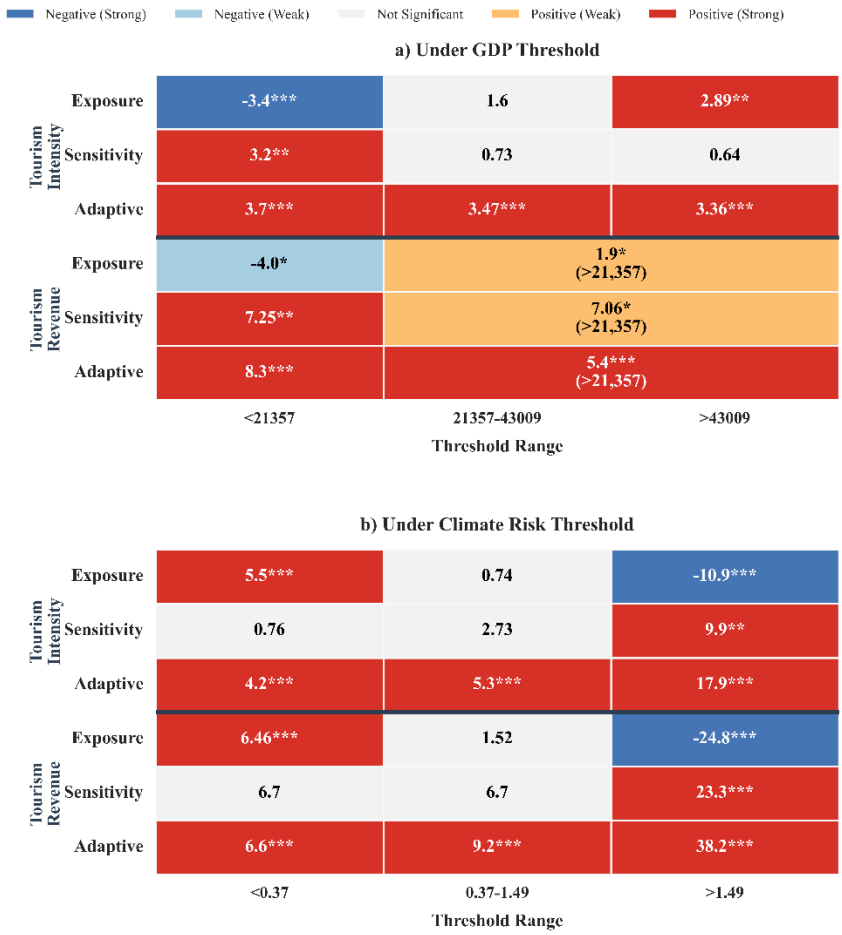


Figure 5 Threshold effects and coefficient transitions of tourism across a) GDP and b) climate risk levels

3.3.2 Interaction-based cross-mechanism analysis

The results (Fig. 6) show that the marginal effect of exposure increases significantly with GDP, suggesting that exposure tends to shift from a constraint toward a potential resource as development advances, which is consistent with the sign reversal found in the GDP threshold models. By contrast, the interaction between exposure and climate risk is insignificant, indicating that climate risk is less likely to operate through smooth linear moderation and is better captured by regime-dependent threshold effects. Similarly, although adaptive capacity and sensitivity display marked stage differences in the threshold models, their interaction terms with GDP and risk are mostly stable or low-significant. This suggests that linear interaction models capture average gradient patterns, but are less able to reflect threshold-triggered structural changes. Together, these findings imply that economic development mainly acts as a continuous moderator, whereas climate risk is more closely associated with nonlinear regime shifts.

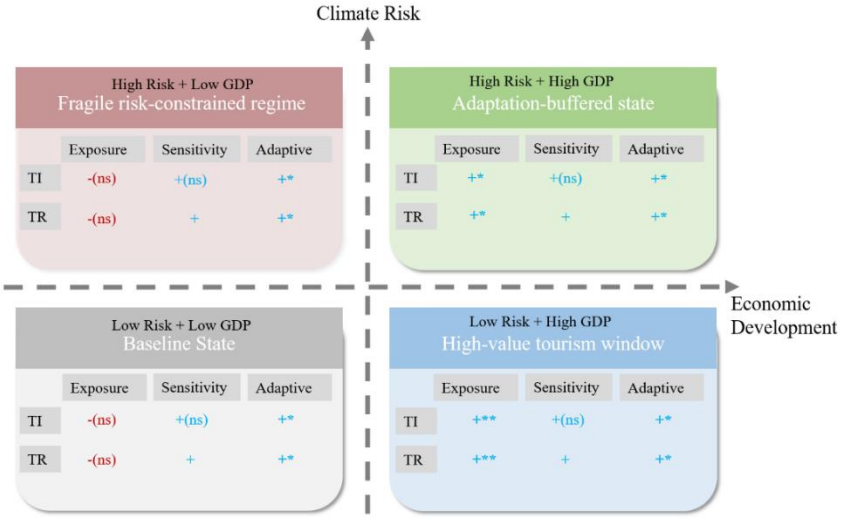


Figure 6 Interaction-based mechanisms of tourism across economic–climate risk contexts. (Note: TI: Tourism Intensity; TR: Tourism Revenue; ns: statistical insignificance)

3.4 Internal structural decomposition based on underlying indicators

Changes in the threshold range are not merely a simple increase or decrease in the overall system, but also correspond to changes in its internal composition and relative importance. Based on the changing contribution characteristics of underlying empirical indicators at different stages, cities exhibit differentiated structural adjustment trajectories (Fig. 7). Cities such as Lhasa, Zhangye, Lanzhou, Xining, Urumqi, and Turpan are closer to a "Development-driven" characteristic, mainly reflected in the increased relative importance of capacity-based elements such as urbanization, innovation, and education; such as Ili, Shigatse, Lijiang, and Diqing, they are closer to a "Tourism-driven" characteristic, with their adaptability shifting from capacity to local reception facilities and tourism labor. Conversely, in stages of escalating climate risks, there is a greater increase in the relative importance of basic defense elements such as comprehensive structural dependence, basic resource capacity, and information and communication technology. Based on this condition, cities such as Lijiang, Diqing, and Huangnan exhibit stronger "Risk-response" characteristics. Meanwhile, some cities show different emphases under different grouping frameworks. For example, Lijiang is more prominent in the GDP group in terms of carrying out reconstruction characteristics, while it shows more obvious risk response characteristics in the risk group. This indicates that the system

structure adjustment has obvious context-dependent and multi-dimensional evolutionary characteristics.

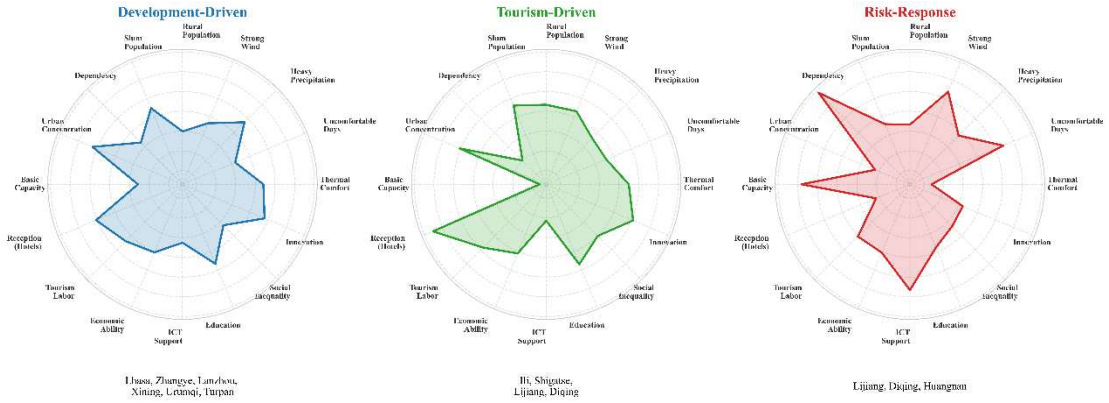


Figure 7 Three typologies of internal structural shifts among underlying tourism elements across multiple threshold regimes. (Note: the radial axes map the relative contribution changes of the 16 underlying functional indicators).

3.5 Dynamic panel robustness check

Although the baseline regressions (Appendix Table 7) provide initial estimates, tourism development exhibits the path dependence, and there may also be bidirectional interactions between vulnerability, resilience, and tourism performance, which could introduce potential endogeneity. To mitigate this, we employ the System GMM (SYS-GMM) estimator (Table 2). the Hansen tests do not reject the null hypothesis in any specification, and the AR(2) tests are insignificant throughout. The coefficients of the lagged dependent variables are positive and mostly significant, indicating evident path dependence in both tourism intensity and tourism revenue. The coefficient on resilience remains positive across all models, suggesting a relatively stable promoting effect on tourism development. Notably, vulnerability also shows positive coefficients, although its significance varies across specifications and is only significant in the tourism revenue model controlling for climate risk. Overall, the SYS-GMM results further support the main findings of the baseline regressions and confirm the dynamic persistence of the tourism system.

Table 2 Robustness Tests

Variable	Dependence Variable			
	Ln(tourism intensity)		Ln(tourism revenue)	
	Coef.	P-value	Coef.	P-value
L.Ln(tourism intensity)	0.52	0.02	--	--
L.Ln(tourism revenue)	--	--	0.34	0.003
Vulnerability	2.0	0.1	1.94	0.17
Resilience	0.04	0.1	0.05	0.08
GDP	0	0.4	0	0.03
AR(1)	-2.0	0.04	-1.97	0.05
AR(2)	1.6	0.1	1.48	0.14
Hansen test	10.47	0.1	9.74	0.13
Variable	Ln_ tourism intensity		Ln_ tourism revenue	

	Coef.	P-value	Coef.	P-value
L.Ln(tourism intensity)	0.63	0.004	--	--
L.Ln(tourism revenue)	--	--	0.3	0.05
Vulnerability	1.8	0.08	4.2	0.005
Resilence	0.04	0.06	0.09	0.001
Risk	0.3	0.4	-0.05	0.9
AR(1)	-2.12	0.03	-1.4	0.1
AR(2)	1.73	0.08	1.2	0.2
Hansen test	10.05	0.12	10.91	0.1

4. Discussion

4.1 From tourism growth to regional tourism resilience

Existing research on tourism vulnerability often relies on monotonic assumptions and national-scale aggregates, which can obscure the climate-economy nexus at the regional level (Garschagen et al., 2021; Scott, 2024). In western China, tourism development has evolved under highly uneven economic foundations and intensifying climate pressures, giving rise to marked spatial heterogeneity (Huang et al., 2023; Liu et al., 2022). This process cannot be understood as a simple process of linear growth or uniform resilience enhancement. From 2003 to 2023, tourism in western China generally expanded, and the 2023 rebound after COVID-19 disruptions suggests considerable recovery capacity. However, the share of tourist consumption in local GDP declined, reflecting structural economic change rather than market contraction. Local economies diversified more rapidly than tourism, while cross-regional online booking platforms may have increased leakage from local tourism consumption (Gössling et al., 2025). Consequently, while tourism's absolute "contribution scale" continued to expand, its relative "contribution intensity" weakened alongside regional economic diversification. This distinction is important for sustainability assessment.

These long-term changes were accompanied by uneven shifts in tourism vulnerability and resilience. Almost all cities show a decline in uncomfortable days and the frequency of strong winds, whereas increasing extreme precipitation along the margins of the QTP continues to sustain high exposure levels. Notably, although economic growth, greater environmental investment, and improved basic infrastructure contributed to sustained gains in adaptive capacity and readiness, cities such as Urumqi and Kashgar showed reduced vulnerability without a corresponding improvement in resilience. This suggests that resilience depends more strongly on optimized resource allocation, governance mechanisms, and emergency response systems (Dogru et al., 2019).

Overall, tourism development in western China has undergone a profound structural transition rather than uniform linear growth. These long-term trends provide essential contextual grounding for the regime-dependent situation, highlighting why linear assumptions may be insufficient for understanding tourism dynamics in uneven-developed regions.

4.2 Threshold effects as diagnostic signals for sustainability governance

Economic development and climate risk jointly shape the conditions under which tourism vulnerability and resilience evolve in western China, reflecting a reorganization of the system’s internal support structure. Although tourism vulnerability often acts as a constraining factor under climate disturbances (Li et al., 2020), the stronger governance response and the greater resource allocation may partially offset these negative effects and, in some cases, contribute to improvements in infrastructure and destination competitiveness (Baloch et al., 2023), as observed

in Lanzhou, Lhasa, and Xining. The GDP threshold should be interpreted not only as a statistical breakpoint, but also as a diagnostic signal for sustainability governance. Although adaptive capacity plays a key role in promoting recovery and revenue growth, its effect weakens as GDP rises, suggesting diminishing marginal returns to adaptation investment (UNEP, 2021). The general assumption is that climate exposure constrains tourism demand (Zhou et al., 2024). However, this study found that once GDP moved beyond the threshold, the negative effect of exposure is partly mitigated. As governance and adaptive capacity improved, exposure may even have begun to function as a differentiated tourism resource rather than solely as a source of constraint, particularly in Ili, Kashgar, and Shigatse.

The climate risk threshold is not merely a manifestation of increased external shocks, but rather an adjustment to the internal mechanisms in western China. This reconfiguration operates in two main ways: on the one hand, it strengthens the constraint of exposure, and on the other hand, it highlights the buffering value of adaptive capacity and readiness. Specifically, in Lijiang, Diqing, and Huangnan, the stability of the tourism system in the high-risk phase does not solely rely on general economic development, but rather on the strengthening of capabilities such as the level of local tourism service facilities, medical care, regional transportation accessibility, and information and communication technology. Further analysis of the interaction term results shows that this threshold effect is not simply a "breakpoint jump," but more likely reflects a reorganization along the climate-development phase mechanism (Fang et al., 2025). For sustainability governance, this means that policy should not assume that all cities require the same adaptation strategy. Instead, adaptation priorities should be adjusted according to whether a city is constrained mainly by insufficient development capacity, excessive climate exposure, weak readiness, or service-chain vulnerability.

4.3 Differentiated adaptive pathways for tourism resilience

The city-specific pathways identified in this study provide a basis for differentiated sustainability governance. Lhasa and Zhangye show a development-driven pattern, in which tourism resilience is supported by urban concentration, education, and innovation capacity. In these cities, tourism resilience is supported not only by tourism resources, but also by the wider development system that enables adaptation, coordination, and service upgrading. Policy attention in these cities should therefore shift from extensive expansion toward improving governance efficiency, digital coordination, and innovation-based adaptation.

Tourism-driven cities, such as Ili and Shigatse, shift from reliance on natural resource endowments toward accommodation capacity and tourism-related employment. This pathway suggests that tourism remains a central development engine, but also that resilience may be vulnerable to revenue volatility, service-chain disruptions, and changes in tourist demand. For these cities, sustainability governance should focus on improving tourism service quality, local revenue retention, employment stability, and the capacity to diversify tourism products under climate-sensitive conditions. In high-risk contexts, Lijiang remains closely tied to established tourism consumption patterns, Diqing is constrained by weak infrastructure and service-chain support, and Huangnan faces insufficient basic adaptive capacity in tourism services, healthcare, transport, and education. These differences indicate that risk-response pathways share heightened climate sensitivity but differ in the mechanisms through which vulnerability is produced. More importantly, tourism revenue also shows stronger nonlinear responses than tourism intensity, suggesting that revenue-based indicators better capture hidden vulnerability behind tourism scale.

Taken together, these findings extend climate–tourism vulnerability and resilience research by shifting the analytical focus from static assessment to the dynamic reconfiguration of tourism systems across development–risk contexts. This study shows that the formation of vulnerability and resilience depends on the changing configuration of exposure, adaptive capacity, readiness, and internal support structures. It further suggests that exposure should be understood as a context-dependent mechanism rather than a uniformly negative external shock, since its implications vary with development stage, governance capacity, and adaptive conditions. The study also highlights that vulnerability reduction and resilience enhancement are not simply symmetrical processes. By identifying multiple place-specific pathways in western China, this study challenges homogeneous interpretations of climate-sensitive regions and contributes to a more relational, threshold-dependent and context-specific understanding of tourism vulnerability and resilience.

5. Conclusion

This study shows that tourism in western China experience regime-dependent changes under the combined influence of economic development and climate risk. The GDP threshold partly modifies the effect of exposure on tourism: exposure acts mainly as a constraint in lower-development regimes, whereas its negative effect is reduced in more developed contexts with stronger adaptive and governance support. The climate risk threshold further reinforces exposure-related constraints and increases the importance of adaptive capacity, readiness, and local support systems. In addition, tourism revenue is more responsive to threshold changes than tourism intensity, indicating that tourist arrivals alone may obscure hidden economic fragilities. These findings suggest that tourism resilience should be assessed not only through scale recovery, but also through income stability, local revenue, and post-shock recovery capacity.

These findings have practical implications for sustainability and tourism resilience in relation to UN SDGs 8 (Decent Work and Economic Growth) and 13 (Climate Action) in vulnerable areas. Policy should move beyond uniform vulnerability-reduction strategies and adopt a threshold-sensitive, place-specific governance framework. For low-development or high-risk destinations, priority should be given to reducing direct climate exposure and strengthening basic adaptive capacities, including transport accessibility, medical services, communication infrastructure, tourism service facilities, early-warning systems, and emergency response. For areas that have crossed the development threshold, policy attention should shift from simply expanding adaptation investment to improving governance efficiency, cross-sectoral coordination, digital management, and resource allocation, particularly in light of the potential diminishing returns of adaptation investment. Meanwhile, climate exposure should be managed not only as a risk factor but also, within clear safety thresholds and environmental management constraints, as a basis for developing climate-adaptive tourism products. Tourism monitoring systems should also incorporate revenue-resilience indicators, such as per capita consumption, local revenue retention, income volatility, and post-shock recovery speed. Overall, tourism-dependent regions in western China should move from scale-oriented expansion toward adaptive, risk-informed, and income-resilient development.

Several limitations point to promising future research directions. While the framework captures regional regime-dependent dynamics, it does not explicitly incorporate the micro-behavioral responses of tourists, enterprises, or local communities. Additionally, ecological indicators, such as localized ecosystem fragility or water-resource security, were not integrated. Future studies should extend this framework by incorporating multi-hazard coupling, micro-behavioral data, and causal identification strategies to enhance its explanatory power and transferability to other vulnerable

destinations worldwide.

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Appendix

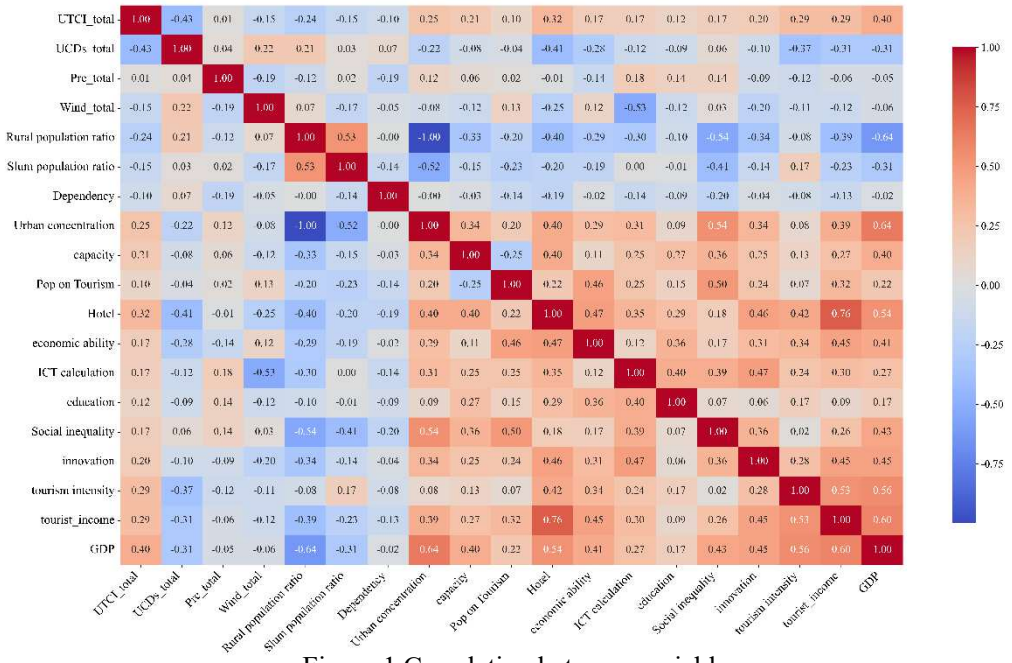


Figure 1 Correlation between variables

Table 1 Multi-collinearity

Dependent variable	Variable	VIF	Tolerance
Tourism intensity	Exposure	1.04	0.95
	Sensitivity	1.04	0.96
	Adaptation	1.01	0.98
	Readiness	1.00	0.99
Tourism revenue	Exposure	1.04	0.95
	Sensitivity	1.04	0.96
	Adaptation	1.01	0.98
	Readiness	1.00	0.99

Table 2 Levin-Lin-Chu unit root tests

Variables	Adjusted t*	Stability	Results
exposure	-5.14***	Yes	I(0)
sensitivity	-2.53***	Yes	I(0)
adaptive capacity	-3.38***	Yes	I(0)
readiness	0.00	No	I(1)
gdp	4.35	No	I(1)
vulnerability	-21.72***	Yes	I(0)
resilience	-11.12***	Yes	I(0)
risk	-15.67***	Yes	I(0)
ln_tourism intensity	-3.97***	Yes	I(0)
ln_tourism revenue	-5.01***	Yes	I(0)

Table 3 Pedroni test and Hausman test

Dependent Variable	Variables	Panel				Group			Hausman
		v	rho	t	ADF	rho	t	ADF	
Tourism intensity	exposure, sensitivity, adaptive capacity, readiness vulnerability, resilience, risk	0.74	-0.65	-2.61	5.29	0.21	-3.01	6.19	RE p>0.05
		-0.21	0.04	-0.68	3.48	0.64	-0.43	5.22	
Tourism revenue	exposure, sensitivity, adaptive capacity, readiness vulnerability, resilience, risk	0.25	0.04	-2.72	3.81	1.36	-2.73	6.5	RE p>0.05
		-0.37	-0.18	-0.16	2.94	1.24	-0.93	4.81	

Table 4 Results of Vulnerability and Resilience Threshold Effect Test

Independence	Threshold	Variables	Number	Fstat	Threshold value	RSS	MSE	R^2
Ln_tourism intensity	GDP	Vulnerability Resilience	Single	80.8***	18296/ 70292	62.9	0.2	0.7
			Double	20.8***		58.0	0.2	
Ln_tourism revenue			Single	78.7***	16860 /18296/31140	117.7	0.4	0.8
			Double	25.1***		106.9	0.4	
Ln_tourism intensity	Risk	Vulnerability Resilience	Single	32.9***	0.62 /0.72/1.27	73.6	0.3	0.7
			Double	16.3**		69.1	0.2	
Ln_tourism revenue			Single	22.8***	1.09	142.2	0.5	0.7

Table 5 Results of Exposure, Sensitivity, Adaptive and Readiness Threshold Effect Test

Independence	Threshold	Variables	Number	Fstat	Threshold value	RSS	MSE	R^2
Ln_tourism intensity	GDP	Exposure Sensitivity Adaptive Capacity Readiness	Single	132.3***	19494 / 43009	43.2	0.2	0.8
			Double	20.3***		39.9	0.1	
Ln_tourism revenue			Single	144.3***	21357	93.7	0.3	0.8
Ln_tourism intensity	Risk	Exposure Sensitivity Adaptive Capacity Readiness	Single	32.9***	0.37/1.49	58.5	0.2	0.78
			Double	25.6***		53.0	0.2	
Ln_tourism revenue			Single	86.1***	0.37/1.49	110.1	0.4	0.8
			Double	28.6***		98.6	0.4	

Table 6 Estimation Results of Vulnerability and Resilience

Independence	Control		Range	Variable	
		coef			coef
Ln(tourism intensity)	L.tourism intensity	0.02***	GDP<18296	Vulnerability	0.16
				Resilience	0.01
			18296<GDP<70292	Vulnerability	0.41
				Resilience	0.02***
			GDP>70292	Vulnerability	0.32
				Resilience	0.03***
Ln(tourism revenue)	L.tourism revenue	0***	16860<GDP<18296	Vulnerability	-0.02
				Resilience	0.01
			18296<GDP<31140	Vulnerability	0.6
				Resilience	0.03
Ln(tourism intensity)	L.tourism intensity	0.03***	0.62<Risk<0.72	Vulnerability	-1.53
				Resilience	0.03***
			0.72<Risk<1.27	Vulnerability	-0.22
				Resilience	0.02**
			Risk>1.27	Vulnerability	0.04
				Resilience	0.01
Ln(tourism revenue)	L.tourism revenue	0***	Risk<1.09	Vulnerability	0.5
				Resilience	0.06***
			Risk>1.09	Vulnerability	1.27
				Resilience	0.04**

Table 7 Basic Regression

Variable	Independent variable	
	Coefficient	
	Tourism Intensity	Tourism Revenue
Vulnerability	2.7	54.3
Resilience	0.01	0.5
GDP	*0.00003***	*0.0006***
Risk	-1.7	-29.7
_cons	-1.18	-42.2
R^2	0.03	0.02

Funding Statement

This research was supported by Chinese Scholarship Council and Ludwig-Maximilians-University Munich.

Contributions

All authors contributed significantly to the development of this manuscript. Lanyue Zhou wrote the main manuscript text, developed the methodology, performed the formal analysis, curated the data, and contributed to the conceptualization of the study. Hanqing Bao and Qian Wang contributed to the conceptualization and manuscript review and editing. Junhao Li contributed to manuscript review and editing.

Declarations

Ethics approval

Not applicable.

Consent to Participate
Not applicable.

Consent for publish
Not applicable.

Competing interests
The authors declare no competing interests.

Data availability
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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