S1 Detailed explanation and calculation steps for coefficient of variation and correlation analysis

Step 1: Normalization of indicator values.

The min-max normalization method was applied to preprocess all indicator values, aiming to map both positive and negative indicator data to a range of 0 to 1, thereby eliminating the effects of dimensions and magnitudes.

$$X_{ij} = \begin{cases} \frac{x_{ij} - x_i^{min}}{x_i^{max} - x_i^{min}} & if i \in I_1 \\ \frac{x_i^{max} - x_{ij}}{x_i^{max} - x_i^{min}} & if i \in I_2 \end{cases} \quad \text{(S1)}$$

Step 2: Calculation of the coefficient of variance.

The coefficient of variation (CV) is a statistical measure that quantifies the degree of variation in observed indicator values. A higher CV indicates greater variability in the distribution and higher information content of the indicator, thereby reflecting stronger discriminatory power of the indicator, which warrants its retention. The formula for calculating the coefficient of variation is as follows:

$$CV_j = \frac{\sqrt{\sum_{i=1}^{m} \left(x'_{ij} - \bar{x}_j\right)^2}}{\bar{x}_j} \quad \text{(S2)}$$

Step 3: Spearman correlation analysis.

Correlation analysis is an effective method for eliminating indicators that contribute redundant information. When numerous redundant indicators are present, the evaluation results may become ambiguous and inconsistent. In this study, correlation analysis was applied to identify and eliminate indicators with high correlation coefficients within the same criterion layer. Indicators with correlation coefficients exceeding 0.8 were flagged, and in combination with the CV method, those with lower coefficients of variation were subsequently excluded.

$$r_s = \frac{\sum(R_X - \overline{R_Y})(R_Y - \overline{R_Y})}{\sqrt{\sum\left(R_X - \overline{R_Y}\right)^2 \sum(R_Y - \overline{R_Y})^2}} = \frac{\sum R_X R_Y - \frac{(\sum R_X)(\sum R_Y)}{n}}{\sqrt{\left(\sum R_X^2 - \frac{(\sum R_X)^2}{n}\right)\left(\sum R_Y^2 - \frac{(\sum R_Y)^2}{n}\right)}} \quad \text{(S3)}$$

S2 Improved CRITIC-Topsis Method

(1) Weight calculation based on the improved CRITIC method

Step 1: Construct the original data matrix, where x_{ij} represents the value of the j indicator for the i object.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} = [x_{ij}]_{m\times n} \quad (4)$$

Step 2: Perform data standardization. The calculation formula is provided in Eq.(S1).

Step 3: Calculate the improved variability S_j using the standard deviation coefficient method.

$$\bar{x_j} = \frac{1}{m}\sum_{i=1}^{m} x_{ij} \quad (S5)$$

$$S_J' = \sqrt{\frac{\sum_{i=1}^{m}(x_{ij}-\bar{x_j})^2}{m-1}} \quad (S6)$$

$$S_j = S_J'/\bar{x_J} \quad (S7)$$

Step 4: Compute the conflict T_j by replacing the correlation coefficient r_{ij} with its absolute value $|r_{ij}|$.

$$T_j = \sum_{i=1}^{m}(1-|r_{ij}|) \quad (S8)$$

In the formula, r_{ij} represents the correlation coefficient between indicators.

Step 5: Calculate the information content C_j of each indicator.

$$C_j = S_j \times T_j \quad (S9)$$

Step 6: Determine the weight ω_j.

$$\omega_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \quad (S10)$$

(2) Resilience index calculation based on the TOPSIS method

Step 1: Calculate the weighted matrix.

$$V = \begin{pmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{pmatrix} \quad (S11)$$

Where $v_{ij} = x_{ij} * w_{ij}$, and w_{ij} represents the weight of the j indicator.

Step 2: Identify the positive ideal solution (PIS) and negative ideal solution (NIS).

$$\begin{cases} V^+ = (v_1^+, v_2^+, \cdots, v_n^+) \\ V^- = (v_1^-, v_2^-, \cdots, v_n^-) \end{cases} \quad (S12)$$

Step 3: Compute the distance of each evaluation object from the PIS and NIS.

$$\begin{cases} S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \\ S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \end{cases} \quad \text{(S13)}$$

Step 4: Calculate the relative closeness δ_i of the i evaluation object to the PIS.

$$\delta_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad \text{(S14)}$$

The relative closeness δ represents the resilience level (UR), where a higher value indicates a greater level of resilience.

S3 OAT method

The One-At-a-Time (OAT) method was adopted in this study, which involves altering the weight value of a single factor while maintaining the weights of other factors as constant as possible. The method aims to systematically evaluate the degree of influence and regularity of individual factor weight variations on the resultant outcomes. The specific steps are as follows:

Step 1: The allowable range of percent change (RPC) was constrained to a range of ±30% relative to their original values. And the value of increment of percent change (IPC) was set 2%.

Step 2: Calculate the values of the main change factor weights $W(X_z)$ and other indicator weights $W(X_i)$.

$$W\left(X_z, c_p\right) = W(X_z, 0) + W(X_z, 0) \times c_p \quad \text{(S15)}$$

Where, $W\left(X_z, c_p\right)$ is the changed weights of $W(X_z)$, $W(X_z, 0)$ is the initial weight value, and c_p equals 2%.

$$W\left(X_i, c_p\right) = \left[1 - W\left(X_z, c_p\right)\right] \times \frac{W(X_i, 0)}{1 - W(X_z, 0)} \quad \text{(S16)}$$

Where, $W\left(X_i, c_p\right)$ is the changed weights of $W(X_i)$, and $W(X_i, 0)$ is the initial weight value.

Step 3: The weighted matrix in Eq. 11 was computed by using the normalized weights $W\left(X_z, c_p\right)$, and the relative closeness of each observation in Eq. 14 was calculated by Topsis method.

Step 4: Calculate the comprehensive evaluation results of urban resilience after each weight alteration.

$$MACR\left(X_z, c_p\right) = \sum_{k=1}^{N} \frac{1}{N} \left| \frac{R\left(X_z, c_p\right) - R_0}{R_0} \right| \times 100\% \quad \text{(S17)}$$

Where, R_0 is the evaluation result of the initial weight, $R(X_z, c_p)$ is the evaluation result after the changed indicator weights, and N is the total number of weight adjustments.

S4 Kernel density estimation

The kernel density function for a random variable X is expressed as:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{x-X_i}{h}) \quad \text{(S18)}$$

Where Krepresents the kernel function, $X_1, \ldots, X_n$ are the comprehensive resilience levels of each city, x denotes the mean value, and n is the total number of observations.

S5 Global spatial autocorrelation

The Global Moran's I is used as an indicator to measure the degree of spatial autocorrelation across the entire study area. The calculation formula is as follows:

$$I = \frac{n}{W} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(X_i-\bar{X})(X_j-\bar{X})}{\sum_{i=1}^{n}(X_i-\bar{X})^2} \quad \text{(S19)}$$

$I > 0$ indicates that the data exhibits a clustered pattern. $I < 0$ indicates that the data exhibits a dispersed pattern. $I = 0$ indicates no spatial autocorrelation.

S6 Spatial Markov Chain model

The Markov Chain is used to predict the dynamic transition trends of resilience, resulting in a state transition matrix. The diagonal values of the matrix represent the probability that a unit remains in its current state (stability), while the off-diagonal values indicate the probability of transitioning from one state to another. In this study, the following formula was used to calculate spatial lag:

$$Lag = \sum_{i=1}^{k} p_i w_{ij} \quad \text{(S20)}$$

Where Lag represents the spatial lag, p_i denotes the resilience index of the i city, and w_{ij}refers to the spatial weight matrix.

S7 Geo-detector

Geo-detector is based on the principle of spatial heterogeneity, which assumes that if an explanatory variable X significantly affects the spatial distribution of the dependent variable Y, then X and Y should exhibit similar spatial patterns. By examining the variance of Y within spatial strata, Geo-detector quantifies the explanatory power of each factor without assuming linearity or any specific functional form. The core metric is the q-statistic, which quantifies the degree to which X accounts for the spatial variation of Y. The q-value ranges

from [0,1], where higher values indicate a stronger explanatory power of X. The q-value is calculated as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \quad \text{(S21)}$$

S8 Determination of the final evaluation index system

The correlation analysis of indicators was conducted following Equation (S3). Spearman's correlation coefficient, calculated using SPSS, was employed to perform the correlation analysis. A heatmap illustrating the correlation between indicators was generated (Figure S1).

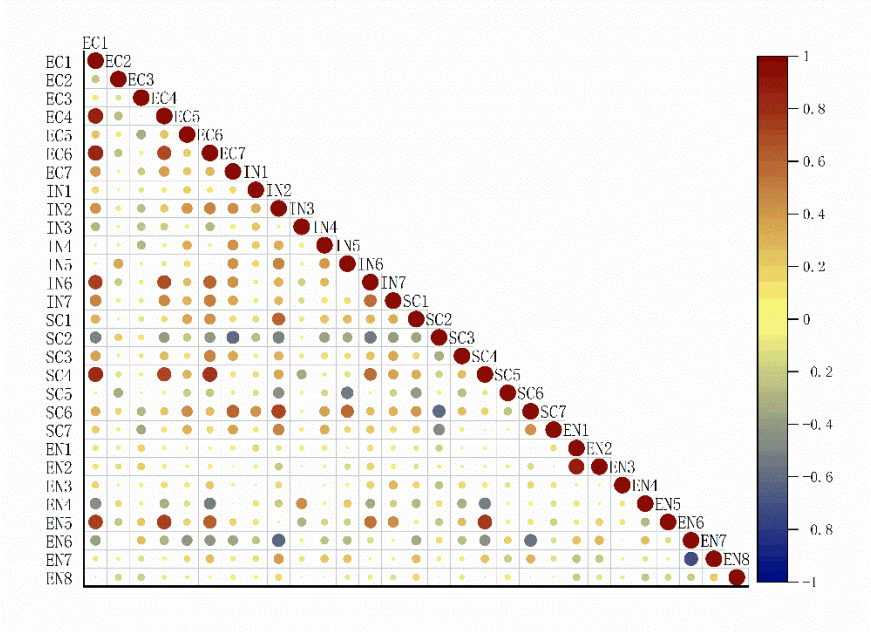


Figure S1. Heatmap of correlations for each indicator (See table 1 in the main text for details).

The results indicate that the correlation coefficients between EC1 and EC4, EC1 and EC6, EN1 and EN2, and EC1 and SC4 are 0.86, 0.85, 0.89, and 0.83, respectively, all exceeding 0.8. This high degree of correlation necessitated indicator selection. Additionally, Table S1 presents the coefficients of variation for each indicator, calculated based on Equation (S2). Consequently, EC4, EC6, SC4, and EN1 were removed, leading to the establishment of the final urban resilience evaluation index system.

Table S1. Coefficient of Variance.

ECO resilience	**EC1**	**EC2**	**EC3**	**EC4**	**EC5**	**EC6**	**EC7**	
CV	2.236	0.539	0.42	1.79	0.919	1.901	1.083	
SOC resilience	**SC1**	**SC2**	**SC3**	**SC4**	**SC5**	**SC6**	**SC7**	
CV	0.86	0.387	0.778	1.827	0.541	0.926	0.491	
INF resilience	**IN1**	**IN2**	**IN3**	**IN4**	**IN5**	**IN6**	**IN7**	
CV	0.615	0.948	0.669	0.931	0.562	1.961	2.186	
ENV resilience	**EN1**	**EN2**	**EN3**	**EN4**	**EN5**	**EN6**	**EN7**	**EN8**
CV	0.438	0.438	0.556	0.276	1.254	0.323	0.639	0.752

S9 Urban resilience levels of 16 cities in the Chengdu-Chongqing urban agglomeration, 2010-2022

Table S2. Resilience scores for the 16 cities.

Cities	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	AVE
Chengdu	0.474	0.470	0.496	0.509	0.503	0.524	0.551	0.561	0.568	0.599	0.582	0.602	0.608	0.542
Zigong	0.375	0.379	0.363	0.365	0.374	0.378	0.424	0.437	0.453	0.468	0.498	0.506	0.507	0.425
Luzhou	0.360	0.367	0.362	0.366	0.374	0.373	0.417	0.439	0.443	0.467	0.481	0.495	0.499	0.419
Deyang	0.334	0.368	0.370	0.369	0.379	0.386	0.390	0.433	0.446	0.463	0.484	0.491	0.504	0.417
Mianyang	0.340	0.365	0.380	0.410	0.411	0.416	0.437	0.465	0.520	0.524	0.523	0.537	0.537	0.451
Suining	0.345	0.350	0.354	0.350	0.365	0.377	0.413	0.410	0.422	0.437	0.440	0.438	0.454	0.397
Neijiang	0.341	0.349	0.338	0.343	0.350	0.352	0.368	0.420	0.420	0.437	0.457	0.478	0.469	0.394
Leshan	0.362	0.372	0.360	0.373	0.370	0.378	0.412	0.431	0.435	0.446	0.457	0.471	0.475	0.411
Nanchong	0.356	0.364	0.363	0.372	0.369	0.378	0.393	0.434	0.436	0.441	0.462	0.470	0.474	0.409
Meishan	0.367	0.376	0.366	0.365	0.358	0.364	0.406	0.433	0.429	0.442	0.465	0.478	0.484	0.410
Yibin	0.356	0.350	0.325	0.330	0.359	0.367	0.411	0.429	0.417	0.431	0.451	0.453	0.460	0.395
Guangan	0.365	0.368	0.362	0.353	0.354	0.363	0.368	0.398	0.425	0.452	0.466	0.456	0.463	0.399
Dazhou	0.340	0.331	0.322	0.328	0.332	0.340	0.350	0.387	0.406	0.413	0.442	0.437	0.448	0.375
Yaan	0.336	0.356	0.365	0.348	0.352	0.368	0.385	0.439	0.445	0.478	0.492	0.508	0.510	0.414
Ziyang	0.346	0.357	0.354	0.357	0.366	0.370	0.380	0.422	0.417	0.442	0.487	0.489	0.485	0.406
Chongqing	0.395	0.422	0.469	0.482	0.474	0.500	0.523	0.542	0.540	0.567	0.556	0.604	0.607	0.514