

Article

Spatiotemporal Evolution and Component Contributions to Urban Heat–Humidity Risk Changes in Sichuan Province, China, from 2000 to 2024

Minghong Wang ¹ and Yushuang Wang ^{1,2,*}

¹ School of Artificial Intelligence, China University of Geosciences, Beijing 100083, China; 1004235106@email.cugb.edu.cn

² Hebei Key Laboratory of Geospatial Digital Twin and Collaborative Optimization, Beijing 100083, China

* Correspondence: yushuangw@cugb.edu.cn

Abstract

Compound hot–humid events are placing increasing pressure on urban health and land-use governance as climate warming and urban expansion continue. This study examined urban built-up areas in 21 prefecture-level cities and prefectures of Sichuan Province for 2000, 2005, 2010, 2015, 2020, and 2024. Using the IPCC hazard–exposure–vulnerability framework, ERA5–Land, MODIS land-cover, GHSL population, and socioeconomic data were combined to construct the Humid Heat Hazard Index (HI), Population-Density Exposure Index (EI), Socioeconomic Vulnerability Index (VI), and Comprehensive Urban Heat–Humidity Risk Index (HHRI). Contribution decomposition, LISA, and standard deviation ellipse analysis were then used to examine risk changes and spatial patterns. The mean HHRI decreased from 0.42 to 0.24, but rebounds appeared in 2010 and 2024. HI varied strongly among years and drove short-term risk changes, EI declined continuously, and VI dropped from 0.87 to 0.30, making it the main factor behind long-term risk reduction. Higher-risk areas were mainly located in southern Sichuan, southeastern Sichuan, and the central-eastern Sichuan Basin. LISA results showed high-risk clusters in basin cities and low-risk clusters on the western Sichuan Plateau. The standard deviation ellipse remained mostly within the basin and followed the basin urban belt. Future adaptation should combine public-service improvement with heat warnings, cooling services, and emergency preparedness.

Keywords: heat–humidity risk; wet-bulb temperature; population exposure; socioeconomic vulnerability; principal component analysis; Sichuan Province

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1. Introduction

Climate warming is reshaping the frequency and intensity of extreme weather events. Previous research has shown that climate change can increase the likelihood of thermal conditions exceeding human thermoregulatory capacity, making heat stress one of the most direct pressures on cities [1]. These impacts are already evident in China. Cai et al. reported that “climate-related health threats in China intensified” in 2024, with heat stress causing substantial work-hour losses [2]. Hot–humid conditions deserve particular attention because humidity limits evaporative cooling through sweating; so, the human body may face stronger heat strain than air temperature alone suggests [3–5]. The IPCC

emphasizes that climate risk is not produced by climatic hazards alone, but also depends on exposure and vulnerability [6,7]. In China, summer heatwaves have become more frequent, stronger, and longer-lasting in recent decades [8], adding pressure to urban management, energy supply, and health protection. The National Action Plan for Health Adaptation to Climate Change also calls for efforts to “strengthen health adaptation actions” in response to climate-related health risks [9]. Thus, humid-heat risk should be examined at the city scale together with population distribution and socioeconomic conditions, rather than treated only as a climatic background problem [6,7,9].

Many urban heat-risk studies use air temperature, maximum temperature, or land surface temperature as thermal indicators, but these measures cannot fully capture the combined effect of heat and humidity on the human body. Wet-bulb temperature is more suitable because it combines air temperature with atmospheric moisture and reflects evaporative cooling efficiency. Earlier work treated a wet-bulb temperature of 35 °C as the “upper physiological limit” for human adaptation [3,4]. Raymond et al. similarly identified a wet-bulb temperature of 35 °C as an approximate upper physiological limit for sustained human exposure [3]. Recent empirical studies suggest that dangerous health effects can occur below this threshold. Vecellio et al. provided empirical evidence that human tolerance to moist heat may be lower than previously assumed [5]. Global evidence also shows that deadly heat-stress conditions are already occurring in some regions [1,10]. Perkins-Kirkpatrick et al. further showed that potentially non-survivable heat conditions can already emerge during present-day extreme heat events [10]. In China, the summer wet-bulb globe temperature has risen rapidly under anthropogenic climate change [11]. These findings suggest that urban heat-risk assessment should include humidity-related indicators rather than temperature alone.

Urbanization changes the local thermal environment, as well as the number and distribution of people exposed to heat. With the expansion of impervious surfaces, increasing building density, and changes in urban ventilation, local warming may be strengthened, and the spatial pattern of humid-heat hazard may also change. At the same time, cities concentrate population, industries, transport systems, and public services. As a result, the same level of climatic hazard may correspond to different levels of population exposure in different cities. Existing studies show that global urban heat exposure has increased substantially, driven by both climate warming and population growth and concentration [12]. Tuholske et al. estimated that global urban heat exposure increased by nearly 200%, affecting approximately 1.7 billion people [12]. Urbanization-induced warming may also amplify population exposure during compound heatwave events [13]. In addition, the urban heat island effect varies with background climate, city size, and urban form [14–16]. In other words, urban humid-heat risk is not only a question of “how hot it is”, but also of how many people are located in such conditions.

In addition to climatic hazard and population exposure, a city’s socioeconomic conditions also affect the consequences of humid-heat risk. Classic vulnerability studies have shown that social vulnerability is closely related to socioeconomic and demographic characteristics [17]. Cutter et al. developed a social vulnerability index using socioeconomic and demographic indicators to assess differences in vulnerability to environmental hazards [17]. In cities, income level, public services, medical resources, infrastructure, and population structure all influence the ability of residents to cope with hot and humid environments. Heat-health studies have also found that communities with weaker socioeconomic conditions, limited healthcare resources, and insufficient cooling facilities or green space often face higher heat-related morbidity and mortality [18]. In recent years, climate-health policies and related studies in China have also emphasized the need to continuously assess health risks, vulnerability, and coping capacity while identifying priority areas and vulnerable populations [2,9,19]. Therefore, including socioeconomic

conditions in humid-heat risk assessment can help explain why some cities show different risk levels even under similar climatic pressure.

Analyzing hazard, exposure, and vulnerability within the same framework helps explain where urban humid-heat risk comes from. Recent studies in China have applied this framework to heat or humid-heat risk assessment and have shown that improved sustainable development and coping capacity can reduce vulnerability, especially in urban areas [19]. Liu et al. highlighted the continuing shortage of long-term risk assessments that explicitly account for urban–rural disparities [19]. However, several limitations remain. First, many studies focus on national or regional patterns, while differences among cities within a province have received less attention. Second, assessments based on a single year or a single period cannot explain how hazard, exposure, and vulnerability change over a longer time span. Third, in areas with complex terrain and uneven urban development, single variables such as air temperature or population size are often insufficient to explain why humid-heat risk differs among cities. For a province such as Sichuan, where terrain, climate, population distribution, and development level vary greatly, this issue deserves further examination.

Sichuan Province is suitable for this study because of its strong internal contrasts. The province includes the low-elevation Sichuan Basin, where population and cities are relatively concentrated, as well as the high-elevation western Sichuan Plateau and surrounding mountainous and hilly transition zones. This geographical setting leads to clear differences in hydrothermal conditions, population distribution, and urban development within the province. Cities in the eastern and southern parts of the basin are usually located at lower elevations and are more likely to experience hot and humid summers. By contrast, the western Sichuan Plateau has higher elevation, lower population density, and weaker urbanization intensity; so, its humid-heat hazard and population exposure are relatively low. In addition, Sichuan's 21 prefecture-level cities and prefectures differ in economic development, fiscal capacity, medical resources, infrastructure, and industrial structure. This means that even under similar hot–humid conditions, different cities may vary in their risk level and ability to respond.

Following the IPCC risk framework, we examine urban humid-heat risk in the built-up areas of 21 prefecture-level cities and prefectures in Sichuan Province [6,7]. The analysis covers six representative years—2000, 2005, 2010, 2015, 2020, and 2024—to trace changes from 2000 to 2024. Google Earth Engine is used to process long-term multi-source geospatial datasets [20]. ERA5-Land, MODIS land-cover products [21], GHSL gridded population data [22], and socioeconomic statistics from the Sichuan Statistical Yearbook are then combined to build four indices: HI, EI, VI, and HHRI. These indices are used to examine the spatiotemporal pattern of urban humid-heat risk, quantify the contributions of HI, EI, and VI to HHRI changes, and discuss adaptation priorities for cities with different main sources of risk [23–25].

Accordingly, the following questions are addressed:

- How did the spatiotemporal pattern of urban humid-heat risk in Sichuan Province change from 2000 to 2024?
- How did humid-heat hazard, population exposure, and socioeconomic vulnerability contribute to changes in HHRI?
- How should different cities and prefectures develop corresponding adaptation measures according to their main sources of risk?

The findings may help support public health protection, urban renewal, climate adaptation, and territorial spatial planning in Sichuan Province.

2. Materials and Methods

2.1. Study Area and Analytical Units

The study area covers 21 prefecture-level cities and prefectures in Sichuan Province, China. The analytical units were defined as urban built-up areas within the administrative boundaries of each city or prefecture. Sichuan Province is characterized by a distinct west–east topographic gradient, with high plateaus and mountainous terrain dominating the western part and the Sichuan Basin occupying much of the eastern part [26]. The study area and its topographic characteristics are shown in Figure 1.

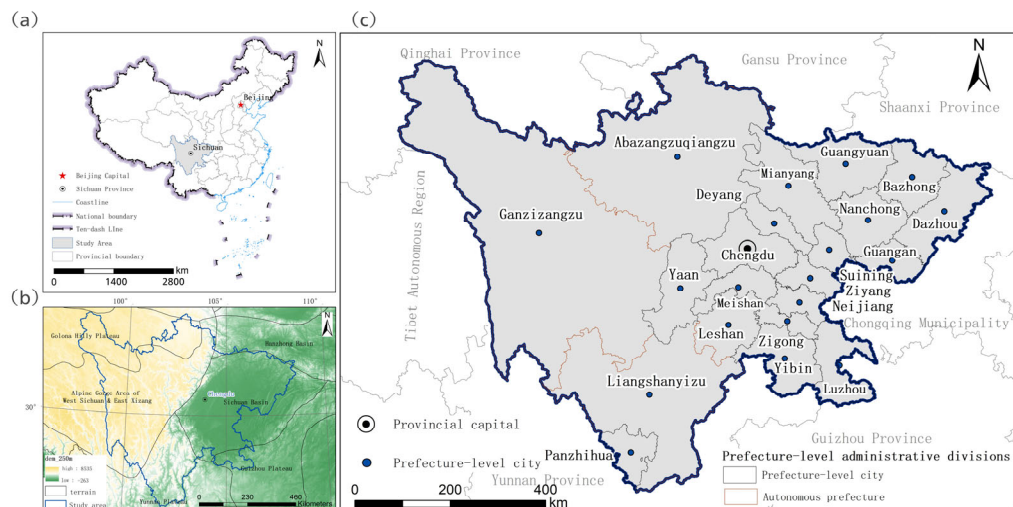


Figure 1. Location of the study area in Sichuan Province, China. (a) National-scale location of Sichuan Province, (b) regional terrain and major geomorphic units surrounding Sichuan Province, and (c) prefecture-level administrative units within Sichuan.

2.2. Data Sources and Preprocessing

This study selected six representative years: 2000, 2005, 2010, 2015, 2020, and 2024. Multi-source datasets were selected according to their temporal continuity, spatial coverage, and suitability for urban-scale humid-heat risk assessment, including reanalysis meteorological data, MODIS land-cover products, gridded population data, administrative boundaries, and socioeconomic statistics. The details of these datasets are summarized in Table 1.

Table 1. Main datasets, spatial resolutions, and applications in the urban heat–humidity risk assessment.

Category	Dataset/Source	Resolution/Scale	Purpose
Meteorological reanalysis	ERA5-Land Daily Aggregated [21]	Approximately 0.1°	To calculate daily wet-bulb temperature, summer mean wet-bulb temperature, and humid-heat hazard days
Land cover	MODIS MCD12Q1 [27]	500 m	To extract urban built-up land using class 13; the urban masks for 2000 and 2024 were approximated using

Population	GHSL GHS-POP [22]	Approximately 100 m	the 2001 and 2023 products, respectively To estimate urban population and population density; the 2024 population was obtained by linear interpolation between 2020 and 2025 [28]
Administrative boundaries [29]	Boundaries of the 21 prefecture-level cities/prefectures in Sichuan Province	City/prefecture scale	For clipping, zonal statistics, and mapping
Socioeconomic data	Sichuan Statistical Yearbook and city/prefecture statistical records	City/prefecture scale	For direction adjustment, standardization, and PCA to construct the VI [30,31]

2.3. Humid-Heat Hazard Index

To characterize the regional background humid-heat hazard associated with the combined effects of high temperature and high humidity at urban built-up locations in Sichuan Province, this study constructed a humid-heat hazard index (HI). Compared with air temperature alone, wet-bulb temperature (T_w) incorporates the combined effects of air temperature and atmospheric moisture and is therefore more suitable for characterizing humid-heat conditions [32–35]. Considering that humid-heat conditions in Sichuan Province mainly occur during summer, June–August was selected as the evaluation period.

Daily 2 m air temperature (T) and 2 m dew-point temperature (T_d) were obtained from the ERA5-Land Daily Aggregated dataset. The saturation vapor pressure (e_s) and actual vapor pressure (e) were calculated as follows [36]:

$$e_s = 6.112 \exp\left(\frac{17.67T}{T + 243.5}\right) \quad (1)$$

$$e = 6.112 \exp\left(\frac{17.67T_d}{T_d + 243.5}\right) \quad (2)$$

Relative humidity was then calculated as follows:

$$RH = \frac{e}{e_s} \times 100 \quad (3)$$

where T and T_d denote the daily 2 m air temperature and 2 m dew-point temperature ($^{\circ}\text{C}$), respectively; e_s and e represent the saturation vapor pressure and actual vapor pressure, respectively; and RH denotes relative humidity (%). To avoid anomalous values arising from numerical calculations, RH was constrained to the range of 1–100%.

Wet-bulb temperature was subsequently estimated from T and RH using the empirical approximation proposed by Stull [37]:

$$T_w = T \tan^{-1}\left[0.151977(RH + 8.313659)^{1/2}\right] + \tan^{-1}(T + RH) - \tan^{-1}(RH - 1.676331) + 0.00391838RH^{3/2} \tan^{-1}(0.023101RH) - 4.686035 \quad (4)$$

where T_w denotes the estimated daily wet-bulb temperature ($^{\circ}\text{C}$).

Before constructing HI, the ERA5-Land-derived summer mean T_w was compared with estimates based on multi-year meteorological station observations. The two datasets showed generally consistent spatial and temporal patterns, supporting the use of ERA5-Land for characterizing regional background humid-heat conditions, although a systematic cool bias was observed. Following previous studies, a daily wet-bulb temperature threshold of $T_w \geq 27^{\circ}\text{C}$ was used to identify humid-heat hazard days [19]. Liu et al. [19] adopted the same threshold in a national-scale assessment of humid-heat risk in China and used the cumulative number of threshold-exceedance days during June–August to characterize humid-heat hazard. Sensitivity analyses using thresholds of 26°C , 27°C , and 28°C showed that the principal high-value cities and the overall basin–plateau spatial

pattern remained stable under the 26 °C and 27 °C thresholds, whereas the 28 °C threshold produced a pronounced floor effect. Therefore, 27 °C was retained as an operational threshold because it is supported by previous research conducted in China and preserves sufficient spatial and temporal differentiation. For each study year, the number of days on which T_w reached or exceeded this threshold was first calculated for each ERA5-Land grid cell:

$$H_{g,y} = \sum_{d=1}^D I(T_{w,g,d,y} \geq 27^\circ\text{C}) \quad (5)$$

where $H_{g,y}$ denotes the number of humid-heat hazard days for spatial sample g derived from the ERA5-Land humid-heat surface in year y ; D denotes the total number of days during June–August; and $I(\cdot)$ is an indicator function that equals 1 when the daily wet-bulb temperature reaches or exceeds 27 °C, and 0 otherwise.

The MODIS-derived built-up-area mask was then used as a spatial sampling mask to identify urban built-up locations within each city or prefecture and to extract the corresponding ERA5-Land humid-heat hazard-day values. The mean of these sampled values was calculated to obtain the raw humid-heat hazard indicator (HI_{raw}) for each city or prefecture:

$$HI_{\text{raw},i,y} = \frac{1}{N_{i,y}} \sum_{p=1}^{N_{i,y}} H_{p,y} \quad (6)$$

where $HI_{\text{raw},i,y}$ denotes the mean number of humid-heat hazard days at urban built-up locations in city or prefecture i in year y , and $N_{i,y}$ represents the number of valid spatial samples within the corresponding built-up-area mask.

Because ERA5-Land has a coarser spatial resolution than the MODIS-derived built-up-area data, the derived wet-bulb temperature and humid-heat hazard represent regional background conditions at urban built-up locations rather than neighborhood-scale thermal conditions. The MODIS-derived built-up-area mask was used only to identify urban built-up locations for spatial sampling.

To ensure comparability across years and cities or prefectures, HI_{raw} was normalized using the minimum and maximum values of the full set of city-year samples and rescaled to the range of 0.05–0.95 [23,38]:

$$HI_{i,y} = 0.05 + \frac{HI_{\text{raw},i,y} - HI_{\text{raw},\min}}{HI_{\text{raw},\max} - HI_{\text{raw},\min}} \times 0.90 \quad (7)$$

where $HI_{\text{raw},\min}$ and $HI_{\text{raw},\max}$ represent the minimum and maximum values of HI_{raw} , respectively, across all city-year samples.

A larger normalized HI value indicates a higher frequency of summer humid-heat hazard days sampled at urban built-up locations, whereas a smaller value indicates a lower frequency. HI differs from conventional hot-day indicators based solely on air temperature because it reflects the combined influence of air temperature and atmospheric moisture [34–37]. Consequently, high air temperature alone does not necessarily correspond to severe humid-heat conditions when atmospheric moisture is relatively low [34,37].

2.4. Population-Density Exposure Index

To characterize population concentration within urban built-up areas, a population-density exposure index (EI) was constructed. Population density within urban built-up areas was selected as the indicator of density-based population exposure. In this study, EI represents the population per unit area of urban built-up-area mask rather than the absolute number of people potentially exposed to humid heat.

The EI was calculated by overlaying gridded population data with the urban built-up land mask. For each city or prefecture, the population and land area within the

corresponding built-up-area mask were extracted. Urban built-up population density was then calculated as follows [39,40]:

$$POP_{\text{density}} = \frac{POP}{AREA} \quad (8)$$

where POP represents the total population located within the urban built-up area of a given city or prefecture, AREA denotes the corresponding built-up land area, and POP_{density} represents the population density within urban built-up areas. A higher POP_{density} indicates that more people are concentrated within each unit of urban built-up land and therefore represents a higher intensity of density-based population exposure.

To ensure comparability across years and cities or prefectures, all city-year POP_{density} values were pooled and normalized using the minimum–maximum method. The normalized values were rescaled to the range of 0.05–0.95 to obtain the final EI [40,41]:

$$EI = 0.05 + \frac{POP_{\text{density}} - POP_{\text{density,min}}}{POP_{\text{density,max}} - POP_{\text{density,min}}} \times 0.90 \quad (9)$$

where $POP_{\text{density,min}}$ and $POP_{\text{density,max}}$ represent the minimum and maximum population-density values, respectively, among all city-year samples. The same normalization parameters were applied to all study years to maintain temporal comparability.

A higher normalized EI indicates greater population concentration and stronger exposure intensity per unit of urban built-up land, whereas a lower EI indicates weaker density-based exposure intensity. However, a decline in EI does not necessarily indicate a decrease in the total population potentially exposed to humid heat. When the expansion of built-up land exceeds the rate of population growth, population density and EI may decline even though the total built-up population continues to increase. Therefore, EI should be interpreted as an indicator of population exposure intensity within urban built-up areas rather than a direct person-based measure of the total exposed population.

2.5. Socioeconomic Vulnerability Index

To characterize differences in socioeconomic vulnerability to humid-heat risk, a socioeconomic vulnerability index (VI) was constructed for each of the 21 prefecture-level administrative units in Sichuan Province [42–44]. In the integrated humid-heat risk framework, vulnerability is not a measure of the climatic hazard itself. It describes how easily an urban socioeconomic system may be affected by humid-heat events, and how well it can respond, recover, and adjust afterward. Under a similar level of humid-heat hazard, cities may still face different outcomes because they differ in economic strength, fiscal capacity, medical services, infrastructure, and industrial structure. Including VI therefore helps distinguish intercity differences in risk and characterize changes in the socioeconomic vulnerability component across the six selected assessment years.

The VI was constructed using socioeconomic data from the 21 cities and prefectures of Sichuan Province for the six assessment years of 2000, 2005, 2010, 2015, 2020, and 2024. The socioeconomic data for 2024 were obtained primarily from the 2025 statistical yearbooks, which report official statistics for the 2024 statistical year. Missing or incomplete records were supplemented using officially published 2024 Statistical Communiqués on National Economic and Social Development and other statistical reports issued by the relevant prefecture-level governments and statistical bureaus. An initial pool of 34 socioeconomic indicators was established based on previous studies and the theoretical framework of socioeconomic vulnerability. After preliminary screening based on theoretical relevance, data availability, temporal continuity, and comparability across cities and study years, 11 candidate indicators were retained. Real-estate development investment per 10,000 people was subsequently excluded because some early-year records required cross-year supplementation, which reduced temporal continuity and data comparability. Consequently, 10 indicators were included in the final principal component analysis (PCA).

As shown in Table 2, the selected indicators were classified as negative indicators associated with adaptive capacity and positive indicators associated with sensitivity [43,44]. Before PCA, the nine negative indicators were multiplied by -1 , whereas the positive indicator was retained in its original direction so that higher values consistently represented greater socioeconomic vulnerability.

Table 2. Indicator system for socioeconomic vulnerability assessment.

Relationship with Vulnerability	Indicator	Indicator Dimension
Negative	Per capita gross regional product (CNY)	Economic development level
	Total retail sales of consumer goods (CNY 10,000 per 10,000 people)	Economic vitality
	Fiscal revenue (CNY 10,000 per 10,000 people)	Fiscal capacity
	Fixed-asset investment (CNY 10,000 per 10,000 people)	Infrastructure investment
	Hospital beds (beds per 10,000 people)	Medical service capacity
	Private and self-employed workers (persons per 10,000 people)	Employment and economic vitality
	Physicians (persons per 10,000 people)	Medical service capacity
	Fiscal expenditure (CNY 10,000 per 10,000 people)	Public-service capacity
	Freight volume (10,000 tons per 10,000 people)	Transportation and circulation capacity
Positive	Share of primary industry in GDP (%)	Industrial structure sensitivity

Overall, cities with stronger adaptive capacity are better able to reduce the consequences of humid-heat shocks through medical assistance, public services, infrastructure provision, and fiscal investment. In contrast, cities with a less diversified industrial structure, weaker public-service capacity, or a relatively limited economic foundation tend to exhibit higher socioeconomic vulnerability [45–47].

To reduce information redundancy while retaining the main socioeconomic information, PCA was jointly applied to the direction-adjusted data from all 126 city-year observations after z-score standardization [45,48]. PCA transforms multiple correlated socioeconomic variables into a smaller number of uncorrelated principal components, thereby extracting the dominant structural information related to socioeconomic vulnerability. The first principal component (PC1) had an eigenvalue of 6.7427 and explained 67.43% of the total variance, while the second principal component (PC2) had an eigenvalue of 1.4056 and explained 14.06%. Because both components satisfied the Kaiser criterion, with eigenvalues greater than 1, and together explained 81.48% of the total variance, PC1 and PC2 were retained to construct the composite socioeconomic vulnerability score.

The variance-weighted composite score obtained from PCA was denoted as VI_{raw} , and was calculated as follows [45,47,49]:

$$VI_{raw} = 0.8275 \times PC1 + 0.1725 \times PC2 \quad (10)$$

where PC1 and PC2 represent the scores of the first and second principal components, respectively. The weights of 0.8275 and 0.1725 were derived from the normalized explained-variance contributions of PC1 and PC2. VI_{raw} denotes the unnormalized composite socioeconomic vulnerability score. Its numerical range is not fixed, and negative values or differences in magnitude across observations may occur. Because the signs of principal components are mathematically arbitrary, the directions of the retained component scores were checked and reversed where necessary so that higher scores consistently indicated greater socioeconomic vulnerability. Variance-based weighting was used because it assigns greater influence to the component that retains a larger proportion of the original

information while avoiding equal weighting of components with substantially different explained-variance contributions.

To make the VI compatible with the HI and EI in the calculation of the comprehensive heat–humidity risk index, VI_{raw} was further normalized to the range of 0.05–0.95 using the minimum–maximum method:

$$VI = 0.05 + \frac{VI_{raw} - VI_{raw, min}}{VI_{raw, max} - VI_{raw, min}} \times 0.90 \quad (11)$$

where $VI_{raw, min}$ and $VI_{raw, max}$ represent the minimum and maximum values of VI_{raw} , respectively, calculated across all 126 city-year observations pooled from the six study years. A higher normalized VI indicates stronger socioeconomic vulnerability and relatively weaker adaptive capacity under humid-heat risk. Conversely, a lower VI indicates lower socioeconomic vulnerability and stronger capacity to cope with humid-heat risk.

2.6. Comprehensive Heat–Humidity Risk Index and Statistical Analysis

After HI, EI, and VI were directionally aligned and normalized to the common range of 0.05–0.95, the comprehensive urban heat–humidity risk index was calculated using an equally weighted geometric mean [50,51]:

$$HHRI = \sqrt[3]{(HI \times EI \times VI)} \quad (12)$$

The equally weighted geometric mean assigns the same exponent of 1/3 to HI, EI, and VI and limits the complete compensatory effect among humid-heat hazard, population-density exposure, and socioeconomic vulnerability. Compared with an additive weighted model, in which a high value in one dimension may compensate for a low value in another, the geometric mean places greater emphasis on the joint occurrence of high values across the three risk components [50,51]. Accordingly, HHRI reaches a relatively high level only when humid-heat hazard, population-density exposure, and socioeconomic vulnerability are all relatively high. If one of the three dimensions remains low, the overall risk is correspondingly constrained. To ensure consistent classification and direct comparison among the six assessment years, the 20th, 40th, 60th, and 80th percentile thresholds were calculated from the pooled HHRI values of all 126 city-year observations rather than separately for each year. The same thresholds were then applied to all assessment years to classify the prefecture-level administrative units into five risk levels: very low, low, moderate, high, and very high [52].

2.7. Spatial Autocorrelation Analysis

To examine the spatial dependence and clustering characteristics of HHRI, spatial autocorrelation analysis was conducted using Global Moran's I and Local Moran's I, also known as Local Indicators of Spatial Association (LISA).

A first-order Queen contiguity spatial weights matrix was constructed for the 21 prefecture-level administrative units of Sichuan Province. Two spatial units were considered neighbors if they shared either a common boundary or a vertex. The initial binary spatial weights were defined as follows:

$$w_{ij} = \begin{cases} 1, & \text{if spatial units } i \text{ and } j \text{ are adjacent,} \\ 0, & \text{otherwise,} \end{cases} \quad (13)$$

where $w_{ii} = 0$. The spatial weights matrix was subsequently row-standardized so that the weights associated with each spatial unit summed to one. This treatment reduces the influence of differences in the number of neighboring units.

Global Moran's I was used to evaluate the overall spatial autocorrelation of HHRI for each study year:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_{i=1}^n (x_i - \bar{x})^2} \quad (14)$$

where n is the number of spatial units, x_i and x_j are the HHRI values of spatial units i and j , respectively, $\bar{x}$ is the mean HHRI value, w_{ij} is the spatial weight between units i and j , and $S_0 = \sum_i \sum_j w_{ij}$. A positive Moran's I indicates that spatial units with similar HHRI values tend to cluster together, whereas a negative value indicates spatial dispersion or adjacency between dissimilar values.

Local Moran's I was further calculated to identify the location and type of local spatial associations:

$$I_i = \frac{z_i}{m_2} \sum_{j=1}^n w_{ij} z_j \quad (15)$$

where $z_i = x_i - \bar{x}$, $z_j = x_j - \bar{x}$, and $m_2 = n^{-1} \sum_i z_i^2$. Based on the sign of the standardized HHRI value and its spatial lag, statistically significant spatial units were classified into four types: High–High, representing a high-value unit surrounded by high-value neighbors; Low–Low, representing a low-value unit surrounded by low-value neighbors; High–Low, representing a high-value unit surrounded by low-value neighbors; and Low–High, representing a low-value unit surrounded by high-value neighbors. Units that did not pass the significance test were classified as not significant.

For both Global Moran's I and Local Moran's I , statistical significance was evaluated using 999 random permutations, with $p < 0.05$ adopted as the significance threshold. The analyses were implemented in Python 3.13.2 using the Queen contiguity weights and Moran statistics provided by the PySAL framework.

2.8. Contribution Decomposition Analysis of HHRI Changes

To identify the main components associated with changes in comprehensive heat–humidity risk, this study decomposed changes in the HHRI into the contributions of humid-heat hazard, population exposure, and socioeconomic vulnerability. This analysis was based on the multiplicative structure of the HHRI and was used to quantify the relative role of each component in the observed risk changes rather than to establish strict causal relationships.

Because the HHRI is calculated as the geometric mean of HI, EI, and VI, its logarithmic change between two consecutive study years can be exactly decomposed into the logarithmic changes in the three component indices:

$$\Delta \ln(HHRI) = \ln \left(\frac{HHRI_{t_1}}{HHRI_{t_0}} \right) = \frac{1}{3} \ln \left(\frac{HI_{t_1}}{HI_{t_0}} \right) + \frac{1}{3} \ln \left(\frac{EI_{t_1}}{EI_{t_0}} \right) + \frac{1}{3} \ln \left(\frac{VI_{t_1}}{VI_{t_0}} \right) \quad (16)$$

where t_0 and t_1 denote two consecutive study years, and $\Delta \ln(HHRI)$ represents the logarithmic change in comprehensive heat–humidity risk between the two periods. The three terms on the right-hand side represent the respective contributions of humid-heat hazard, population exposure, and socioeconomic vulnerability to the change in HHRI. A positive value indicates that the corresponding component was associated with an increase in HHRI, whereas a negative value indicates that it was associated with a decrease. The larger the absolute value of a component contribution, the greater its relative importance in explaining the observed HHRI change. Accordingly, the component with the largest absolute contribution was identified as the dominant source of change during the corresponding period.

Based on the above methodological procedures, the overall analytical framework and technical workflow of this study are summarized in Figure 2.

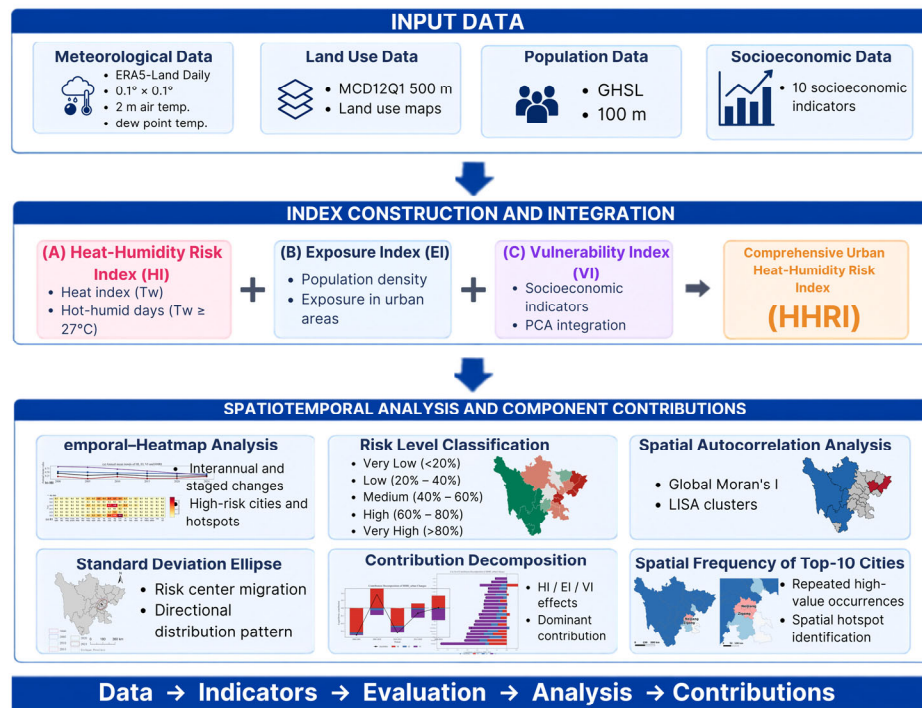


Figure 2. Methodological framework for assessing the spatiotemporal evolution and component contributions of urban heat-humidity risk in Sichuan Province from 2000 to 2024. The arrows indicate the sequence of the research workflow, the plus signs represent the integration of the three component indices, and the different colors distinguish the main analytical modules. The embedded images are schematic excerpts from the corresponding figures presented in the main text.

3. Results

3.1. Temporal Evolution of Urban HHRI and Its Component Indices

As shown in Figure 3, across the six assessment years from 2000 to 2024, urban heat-humidity risk in Sichuan Province showed an overall decline, although higher values reappeared in some assessment years. The comprehensive HHRI decreased over the study period, but higher values appeared again in 2010 and 2024. This pattern indicates that the differences in risk among the assessment years were not linear and were associated with changes in humid-heat hazard, population-density exposure, and socioeconomic vulnerability.

The three sub-indices followed different trajectories. HI varied markedly among the six assessment years and reached relatively high levels in 2010 and 2024. The contribution decomposition further showed that changes in HI were a major contributor to the increases in HHRI observed in these assessment years. EI showed an overall decline across the assessment years, indicating a decrease in population-density exposure intensity within urban built-up areas. This pattern may occur when built-up area expansion outpaces population growth and should not be interpreted as a reduction in the total exposed population. VI showed a larger overall decrease across the six assessment years, consistent with improvements in socioeconomic conditions, fiscal capacity, medical resources, and public-service provision at the prefecture level. This reduction in vulnerability played a major role in the long-term decline in HHRI.

These results suggest that improvements in socioeconomic conditions and adaptive capacity were associated with a lower HHRI, whereas increases in humid-heat hazard

could still contribute to higher risk in individual assessment years. Therefore, prefecture-level risk management should continue to consider changes in climatic hazard even where socioeconomic vulnerability has declined.

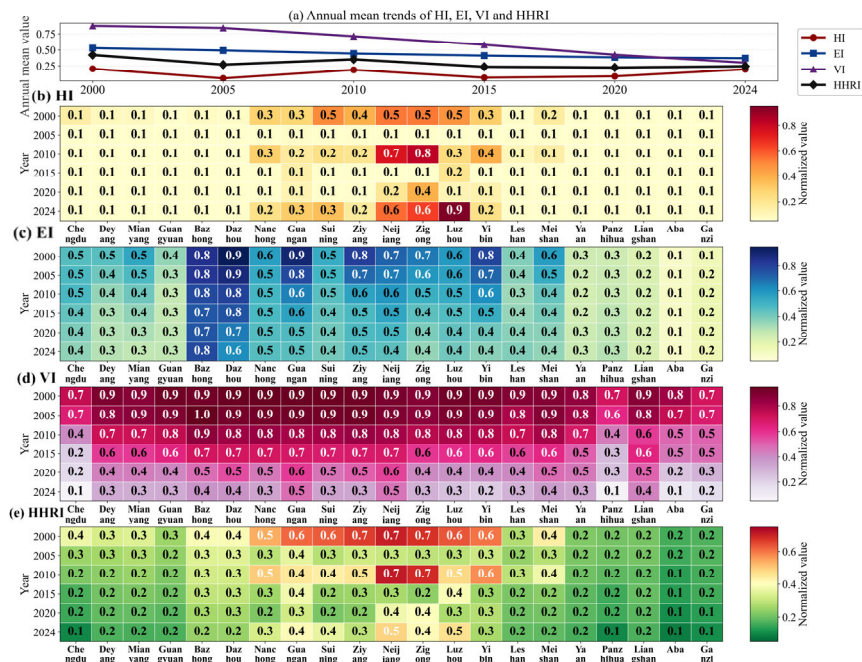


Figure 3. Integrated temporal evolution of urban heat–humidity risk and its sub-indices in Sichuan Province from 2000 to 2024.

3.2. Spatiotemporal Variations in HI, EI, and VI

To examine the spatial variation in urban humid-heat risk across Sichuan Province, the index results for 2000, 2005, 2010, 2015, 2020, and 2024 were mapped at the prefecture level. The calculated index values for each prefecture-level administrative unit were joined to the corresponding administrative boundaries and displayed together with the terrain background of Sichuan Province. For each index, the 20th, 40th, 60th, and 80th percentile thresholds were calculated from the pooled values of all 126 city-year observations, and the same thresholds were applied to all six assessment years to classify the results into five levels. The resulting maps illustrate the prefecture-level spatial patterns of regional background humid-heat conditions sampled at urban built-up locations, population-density exposure, socioeconomic vulnerability, and HHRI across Sichuan Province.

As shown in Figure 4, HI showed clear topographic differentiation. Southern Sichuan, southeastern Sichuan, and the central-eastern part of the Sichuan Basin were more prone to higher humid-heat levels, whereas the western Sichuan Plateau remained at consistently low levels. The extent of high-value areas contracted in 2005 and 2015, while concentrated high values re-emerged along the southern and southeastern margins of the basin in 2010 and 2024. In 2024, Luzhou recorded an HI value of 0.95, the highest among all samples, while Zigong and Neijiang also ranked among the high-value cities in the same year.

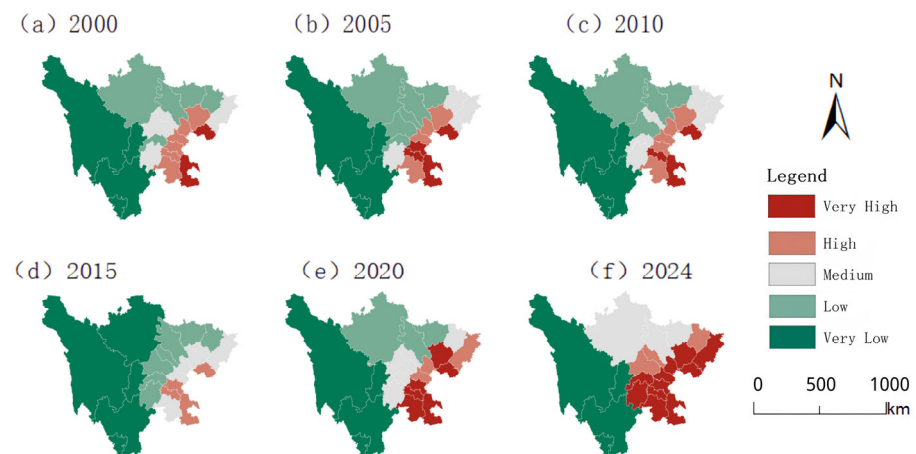


Figure 4. Spatiotemporal patterns of urban HI levels in Sichuan Province from 2000 to 2024.

As shown in Figure 5, High EI values were mainly observed in the early years of the study period, especially in Dazhou, Guang'an, and Bazhong. In later years, many cities moved from high exposure to medium or low exposure levels. Among all city-year samples, Dazhou had the highest EI value, reaching 0.95 in 2000.

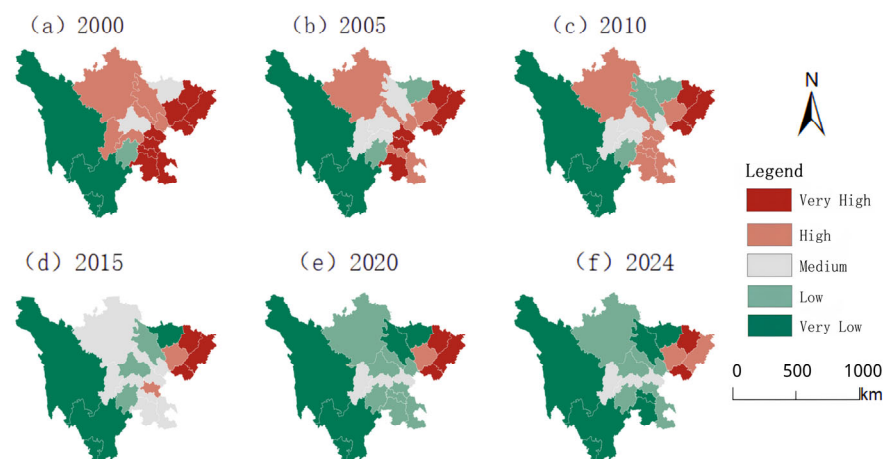


Figure 5. Spatiotemporal patterns of EI levels in Sichuan Province from 2000 to 2024.

As shown in Figure 6, VI values were relatively high in 2000 and 2005. After that, vulnerability declined in many cities and prefectures, especially in the eastern and southern parts of the Sichuan Basin. By 2024, most cities and prefectures had shifted to the low or very low vulnerability categories. Bazhong reached the highest VI value, 0.95, in 2005. Nanchong, Dazhou, Guang'an, and Suining also showed high vulnerability in 2000. The broad decline in VI did not mean that humid-heat risk disappeared; instead, it weakened the possible impacts of similar climatic shocks.

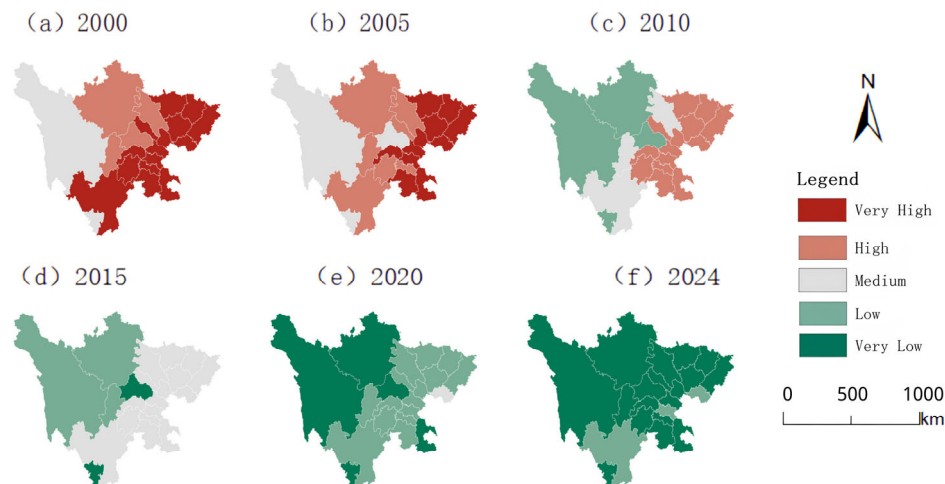


Figure 6. Spatiotemporal patterns of urban VI levels in Sichuan Province from 2000 to 2024.

3.3. Spatial Pattern and Terrain Differentiation of Urban HHRI

As shown in Figure 7, HHRI showed a relatively stable spatial pattern, with higher risk concentrated in the Sichuan Basin and lower risk mainly found in the plateau areas. In 2000, high-risk areas were widely distributed in eastern and southern Sichuan. These areas shrank clearly in 2005, but some cities showed a rebound in 2010. From 2015 to 2020, low- and moderate-risk areas expanded, while high HHRI values appeared again in southern and southeastern Sichuan in 2024. Among all 126 city-year samples, Neijiang had the highest HHRI value, reaching 0.71 in 2010. High comprehensive risk did not simply follow the distribution of HI. Instead, it was shaped by humid-heat hazard, population-density exposure, and socioeconomic vulnerability together.

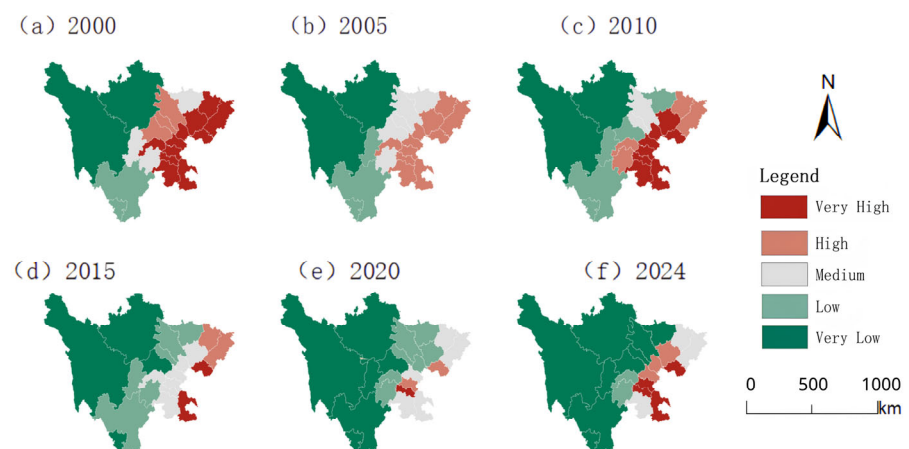


Figure 7. Spatiotemporal patterns of urban risk levels in Sichuan from 2000 to 2024.

To examine how terrain influenced the spatial pattern of urban humid-heat risk in Sichuan Province, bar charts of HI, EI, VI and HHRI were overlaid on the provincial terrain background. This made it possible to compare basin, plateau, and mountainous areas over the period of 2000–2024. As shown in Figure 8, The comparison shows a clear terrain-related pattern. Higher bars were concentrated mainly in the Sichuan Basin, especially in its eastern, southern, and southeastern cities, whereas the western Sichuan Plateau and

mountainous areas generally showed lower values. Together, these features form a stable pattern of higher risk in the basin and lower risk in the plateau. This suggests that terrain plays an important role in shaping urban humid-heat risk in Sichuan Province. Low-elevation basin areas contain more cities, stronger hot-humid conditions, and denser populations, which together contribute to higher overall risk. By contrast, the high-elevation plateau and mountainous areas in western Sichuan have weaker thermal conditions, fewer urban settlements, and lower population exposure; so, their risk levels remained relatively low over the long term.

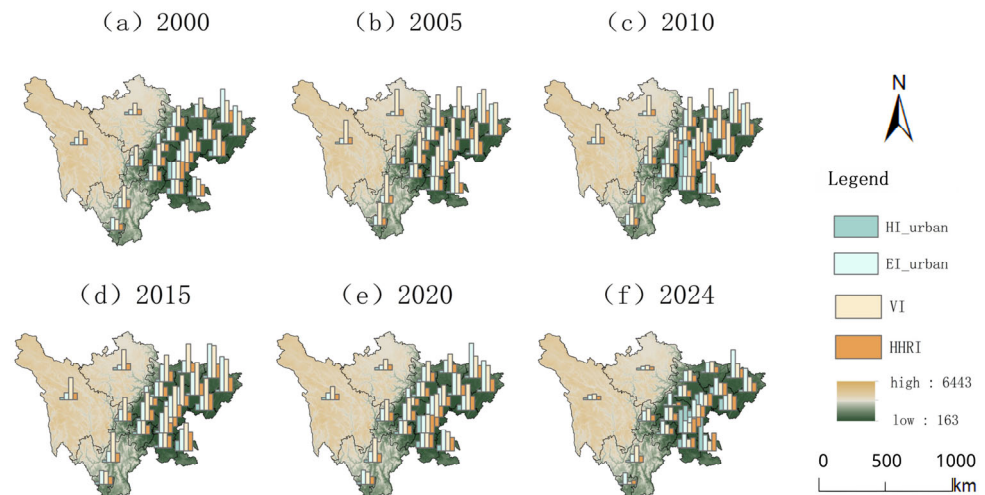


Figure 8. Spatiotemporal patterns of HI, EI, VI and HHRI over the terrain of Sichuan Province from 2000 to 2024.

Across the six assessment years from 2000 to 2024, urban HHRI in Sichuan Province consistently exhibited a clear basin–plateau contrast. Higher values were mainly found in the Sichuan Basin, especially in eastern and southern basin cities such as Neijiang, Zigong, Ziyang, Luzhou, and Suining. The western Sichuan Plateau and adjacent mountainous areas, by contrast, remained at relatively low risk levels across the six assessment years. The differences among the assessment years were uneven rather than strictly linear. HHRI was relatively high in 2000, declined noticeably in 2005, increased again in some cities in 2010, and remained relatively low in the 2015 and 2020 assessment years. By 2024, high values reappeared in several areas, indicating that the overall decline across the assessment years was accompanied by a localized increase in risk in the final assessment year. The sub-indices help explain this pattern. HI fluctuated strongly, with higher values in 2010 and 2024; EI declined gradually as population exposure per unit of built-up land weakened; and VI showed the largest overall decrease across the assessment years, reflecting improvements in socioeconomic conditions and public services. Thus, the contribution decomposition indicated that the decrease in VI was the dominant component associated with the overall reduction in HHRI across the selected assessment years, whereas increases in HI contributed to localized increases in HHRI in some assessment intervals.

3.4. Stability of the Risk Center and Basin Clustering Mechanism

As shown in Figure 9, based on the standard deviation ellipses, the main body of the ellipse in each year was located within and around the Sichuan Basin. This indicates that the spatial center of urban comprehensive heat–humidity risk remained concentrated in and around the Sichuan Basin across the six assessment years. The ellipses also showed a

clear directional pattern, with their major axes broadly extending along the urban belt within the Sichuan Basin. This directional pattern indicates that HHRI was spatially concentrated along the main urban belt of the Sichuan Basin rather than being evenly distributed across the province. This pattern was spatially consistent with the concentration of cities, population-density exposure, and relatively high humid-heat conditions within the basin. Although the size and position of the ellipses varied slightly across years, their overall spatial orientation remained relatively stable, indicating that the dominant spatial pattern of urban heat–humidity risk in Sichuan Province did not undergo a fundamental shift during the study period.

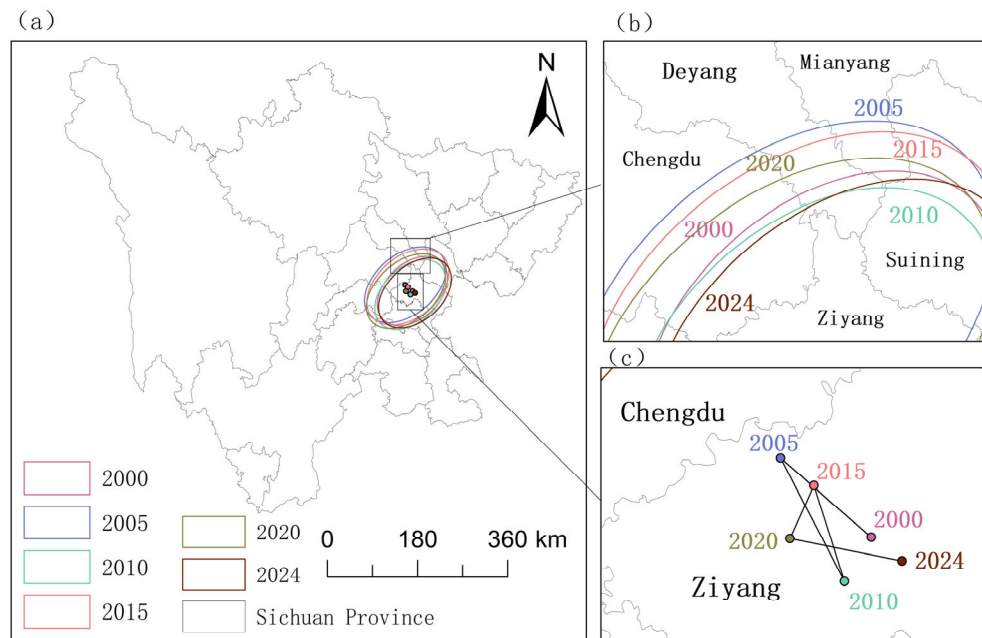


Figure 9. Spatial autocorrelation, directional distribution, and centroid migration of urban HHRI in Sichuan Province from 2000 to 2024. (a) Spatial distribution of the standard deviation ellipses of urban HHRI in Sichuan Province from 2000 to 2024. (b) Enlarged view showing the interannual changes in the size, orientation, and position of the HHRI standard deviation ellipses. (c) Migration trajectory of the HHRI spatial center from 2000 to 2024.

At the city-point scale, the basin-centered pattern shown by the standard deviation ellipses was not produced by all basin cities evenly. Several cities played a stronger role in shaping the position and direction of the ellipse. Ziyang, Suining, Neijiang, and Zigong were close to the risk-weighted center, helping keep the ellipse center relatively stable. Chengdu, Deyang, and Meishan were distributed on the western side of the ellipse and generally exhibited relatively high population-density exposure. In southern and south-eastern Sichuan, Zigong, Luzhou, and Yibin pulled the ellipse slightly southeastward when risk increased in 2010 and 2024. Nanchong, Guang'an, and Dazhou mainly affected the northeastern extension of the ellipse. By contrast, Aba, Garze, Liangshan, and other plateau or mountainous areas in western Sichuan had only limited influence on the ellipse center and major-axis direction. This means that the spatial structure of urban HHRI in Sichuan Province is more complex than a simple “high in the basin and low in the periphery” pattern. More specifically, central Sichuan cities were located close to the risk-weighted center, Chengdu Plain cities generally showed relatively high population-density exposure, southern Sichuan cities were associated with the southeastward extension

observed in some assessment years, and northeastern Sichuan cities were distributed along the peripheral extension of the ellipse.

The migration trajectory of the risk center further shows that the weighted center of HHRI from 2000 to 2024 was generally located in the central-eastern part of the Sichuan Basin, with only limited movement over time. This reflects strong spatial stability in the comprehensive risk center. Minor shifts in different periods were associated with changes in the contribution of high-risk cities in specific years. For example, relatively high HHRI values in some southern and southeastern basin cities in 2010 and 2024 coincided with a slight shift in the risk-weighted center toward these areas. The Global Moran's I results further indicate that Moran's I values were positive and statistically significant in all study years from 2000 to 2024. This confirms the persistent presence of significant positive spatial autocorrelation in HHRI across Sichuan Province. In other words, prefecture-level units with high HHRI values tended to be adjacent to other high-value units, while low-value units also tended to cluster spatially, revealing a clear spatial agglomeration pattern of urban heat-humidity risk.

3.5. Local Spatial Clustering and Identification of Joint Risk-Prevention Areas

Global Moran's I provides an overall measure of spatial autocorrelation, but it cannot show which specific cities form clusters. Therefore, LISA was used to identify local spatial associations in urban HHRI across Sichuan Province. As shown in Figure 10, across the six assessment years, the statistically significant LISA results were dominated by two cluster types: High-High and Low-Low. High-High clusters were mainly located in the eastern, southern, and southeastern parts of the Sichuan Basin. These cities not only had relatively high HHRI values themselves, but were also surrounded by neighboring cities with similarly high risk levels. This suggests that humid-heat risk in the basin was spatially connected rather than isolated in single cities. Low-Low clusters were mostly distributed in the western Sichuan Plateau and mountainous areas, where both local cities and their neighboring areas maintained low HHRI levels. The contrast between basin clusters and plateau clusters indicates that the local spatial pattern of urban heat-humidity risk was closely related to Sichuan's terrain, population distribution, and urban development differences. Compared with Global Moran's I, the LISA results further reveal where the clustering occurred and help identify priority areas for differentiated risk management.

The Low-Low clusters were relatively stable over time and were mainly located in western and southwestern Sichuan, including Aba, Ganzi, and Liangshan. These areas are mainly located on the western Sichuan Plateau and in adjacent mountainous regions and generally exhibited relatively low population-density exposure and HHRI values across the assessment years. The High-High clusters changed more noticeably among the six assessment years. They were most evident in the southern and southeastern parts of the Sichuan Basin in 2000, 2010, and 2024, showing that high-risk cities in these years tended to be spatially connected with other high-risk neighbors. In 2015, the High-High clusters became less extensive, but they appeared again in the southern and southeastern basin areas in 2020 and 2024. This pattern suggests that local high-risk clustering was not constant, but fluctuated with changes in humid-heat hazard, population-density exposure, and socioeconomic vulnerability. In general, the LISA results point to a persistent west-basin contrast in Sichuan Province, with low-risk clustering in the plateau and mountainous areas and high-risk clustering mainly within the basin.

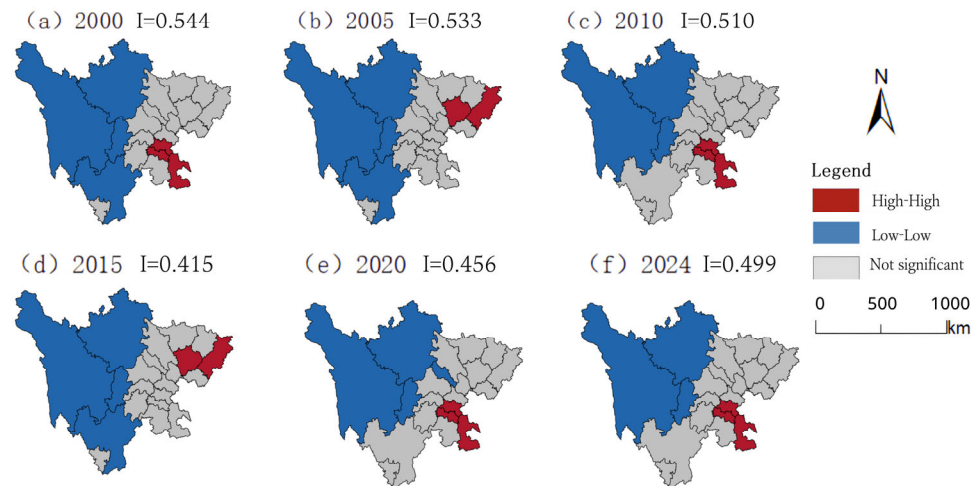


Figure 10. LISA cluster maps of urban heat-humidity risk in Sichuan Province from 2000 to 2024. No statistically significant High–Low or Low–High clusters were detected in any of the six study years at the $p < 0.05$ significance level; spatial units that did not pass the significance test were classified as “Not significant”.

No statistically significant High–Low or Low–High clusters were identified in any of the six study years. This may be related to the relatively continuous spatial clustering pattern of HHRI across Sichuan Province. High-value cities and prefectures generally formed contiguous clusters within the Sichuan Basin, whereas low-value areas were concentrated in the western plateau and mountainous regions. Consequently, local spatial outliers characterized by a high-value unit surrounded by low-value neighbors or a low-value unit surrounded by high-value neighbors were not sufficiently pronounced to reach statistical significance. The positive Global Moran’s I values in all study years further indicate that the spatial distribution of HHRI was dominated by the clustering of similar values rather than an alternating arrangement of high and low values.

4. Discussion

4.1. Dominant Sources of HHRI Change Based on Contribution Decomposition

At the assessment-interval scale, changes in HHRI were mainly associated with fluctuations in HI and the overall decline in VI, as shown in Figure 11. From 2000 to 2005, both HI and VI made negative contributions and were the main components associated with the marked decrease in HHRI. From 2005 to 2010, HI shifted to a strong positive contribution, leading to a temporary rebound in comprehensive risk. From 2010 to 2015, both HI and VI again contributed negatively, resulting in a decline in HHRI. During 2015–2020, although HI made a positive contribution, the negative contribution of VI still constrained the increase in comprehensive risk. From 2020 to 2024, the positive contribution of HI strengthened, becoming a major contributor of the renewed increase in HHRI. These results indicate that changes in HI were the dominant contributors to increases in HHRI during individual assessment intervals, whereas the overall decline in VI was the main contributor to the reduction in comprehensive risk across the selected assessment years.

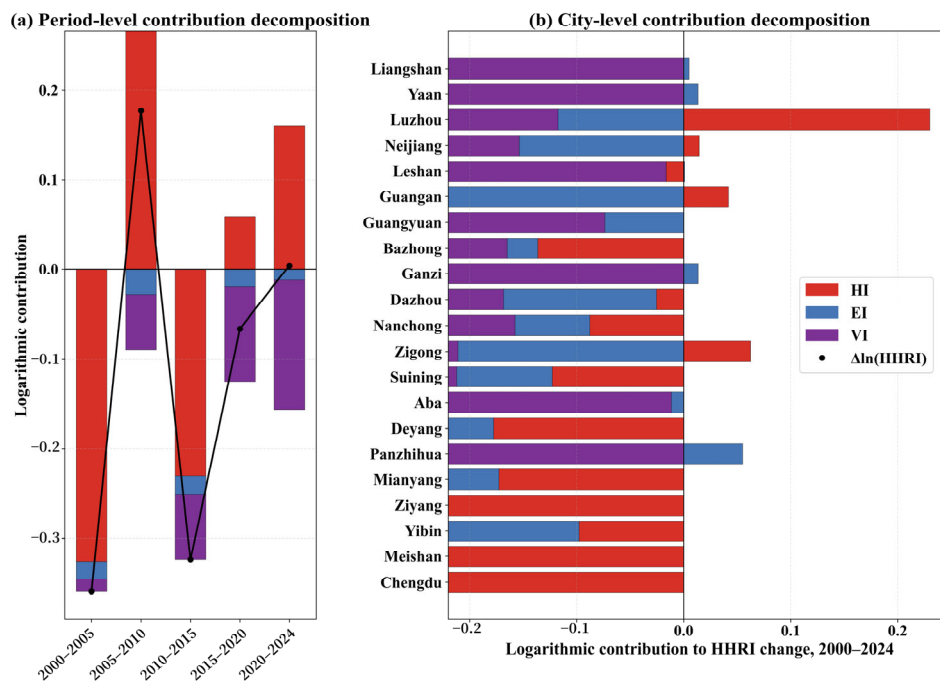


Figure 11. Contribution decomposition of changes in urban heat–humidity risk in Sichuan Province from 2000 to 2024.

At the prefecture level, the net changes in HHRI between 2000 and 2024 varied substantially among administrative units. Most cities showed a negative total change from 2000 to 2024, indicating an overall decline in comprehensive heat–humidity risk. The declines in HHRI were particularly evident in Chengdu, Meishan, Yibin, Ziyang, Mianyang, and Panzhihua, and were mainly associated with the negative contributions of VI and EI. This suggests that reductions in vulnerability and changes in population-density exposure played important roles in lowering risk. In contrast, cities such as Luzhou, Neijiang, Zigong, and Guang’an showed relatively strong positive contributions from HI. These positive HI contributions partly offset the risk-reduction contribution associated with declining VI. Overall, the contribution decomposition indicates that the decline in VI was the dominant contributor to the overall reduction in HHRI across the selected assessment years, whereas increases in HI were the main contributors to the increases observed in several assessment intervals.

4.2. High-Risk City-Year Samples and Component-Specific Adaptation Priorities

To summarize the cities that repeatedly appeared at the upper end of each index, spatial frequency maps were created from the top 10 city-year records of HI, EI, VI, and HHRI during 2000–2024. For each index, all city-year values from the 21 cities and prefectures across the six study years were ranked, and the ten highest records were selected. The frequency for each city was then calculated by counting how often it appeared in these top 10 records, as summarized in Table 3.

Table 3. Top 10 city-year records of HI, EI, VI, and HHRI in Sichuan Province from 2000 to 2024.

Indicator	Rank	Year	City/Prefecture	Value
HI	1	2024	Luzhou	0.95
	2	2010	Zigong	0.83
	3	2010	Neijiang	0.75

EI	4	2024	Zigong	0.65
	5	2024	Neijiang	0.56
	6	2000	Neijiang	0.54
	7	2000	Zigong	0.54
	8	2000	Suining	0.50
	9	2000	Luzhou	0.48
	10	2010	Yibin	0.40
	1	2000	Dazhou	0.95
	2	2000	Guang'an	0.90
	3	2005	Dazhou	0.88
VI	4	2000	Bazhong	0.85
	5	2005	Bazhong	0.83
	6	2000	Ziyang	0.80
	7	2010	Dazhou	0.80
	8	2000	Yibin	0.79
	9	2024	Bazhong	0.78
	10	2010	Bazhong	0.78
	1	2005	Bazhong	0.95
	2	2000	Nanchong	0.94
	3	2000	Dazhou	0.94
HHRI	4	2000	Guang'an	0.94
	5	2000	Suining	0.93
	6	2005	Ziyang	0.93
	7	2000	Ziyang	0.93
	8	2000	Guangyuan	0.92
	9	2000	Bazhong	0.92
	10	2000	Luzhou	0.92
	1	2010	Neijiang	0.71
	2	2000	Neijiang	0.70
	3	2010	Zigong	0.70
HHRI	4	2000	Zigong	0.68
	5	2000	Ziyang	0.64
	6	2000	Luzhou	0.64
	7	2000	Suining	0.63
	8	2000	Guang'an	0.62
	9	2000	Yibin	0.60
	10	2010	Yibin	0.57

Thus, the mapped values represent repeated high-value occurrence rather than the absolute index value. The frequency results were joined to the prefecture-level boundaries of Sichuan Province, and enlarged inset maps were used to show high-frequency areas in the Sichuan Basin, especially the southern, northeastern, and central-eastern basin regions.

The four indices did not share the same high-frequency pattern. HI occurred most often in the southern Sichuan Basin, particularly in Neijiang, Zigong, Yibin, and Luzhou. High-frequency EI values were concentrated in northeastern and eastern Sichuan, mainly in Bazhong, Dazhou, and Guang'an. For VI, frequent high values were found in the northeastern and central-eastern basin, including Bazhong, Nanchong, Dazhou, Guang'an, Suining, and Ziyang. This distribution reflects regional differences in economic conditions, public services, medical resources, and adaptive capacity. HHRI was more concentrated in the central-southern basin, especially around Neijiang, Zigong, Ziyang, and Yibin. Its spatial pattern did not correspond to any single component index, but instead reflected

the repeated overlap of humid-heat hazard, population-density exposure, and socioeconomic vulnerability.

The results suggest that adaptation priorities should vary across regions, as shown in Figure 12. The central-southern and southeastern Sichuan Basin deserves particular attention because high HI and HHRI values occurred repeatedly there. In northeastern and eastern basin cities, including Bazhong, Dazhou, Guang'an, Nanchong, and Suining, more attention should be paid to population-density exposure and socioeconomic vulnerability. Prefecture-level units with relatively high EI or VI should improve heat-health preparedness, early-warning and emergency-response capacity, public-service provision, and medical-resource support.

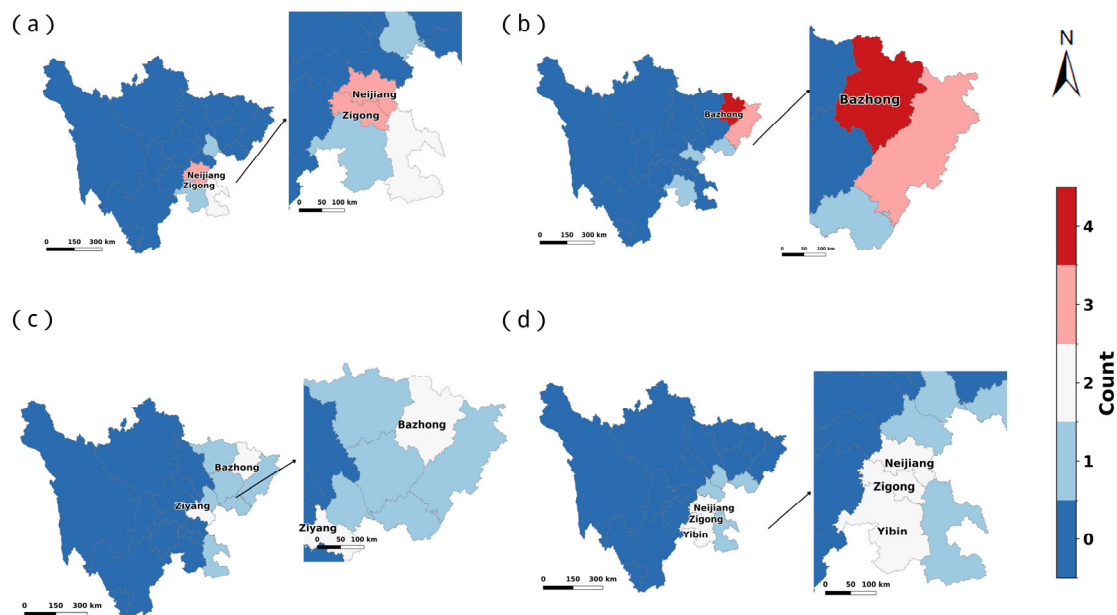


Figure 12. Spatiotemporal hotspot frequency of top 10 ranked cities for HI, EI, VI, and HHRI: (a) HI; (b) EI; (c) VI; and (d) HHRI.

The western plateau and mountainous areas, including Aba, Ganzi, Liangshan, and parts of western Sichuan, appeared less often among the highest-ranked records. Their relatively low high-value frequencies, however, do not mean that future risk can be disregarded, particularly as climatic and socioeconomic conditions continue to change.

Humid-heat risk should also be considered in territorial spatial planning and urban renewal, particularly when regional development and public services are arranged. Prefecture-level units that repeatedly ranked high in HHRI should receive priority in integrated risk assessment, heat-health adaptation, and public-service improvement.

4.3. Limitations and Future Research

Several limitations should be acknowledged. ERA5-Land represents regional background humid-heat conditions at urban locations rather than fine-scale urban microclimates, and validation against meteorological station observations showed a systematic cold bias of approximately -1.47 °C. Accordingly, hazard-day counts may be underestimated in absolute terms, and the HI is intended primarily for inter-prefecture and inter-year comparisons rather than precise estimation of absolute hazard-day counts. In addition, the Stull (2011) [37] approximation for wet-bulb temperature was developed under standard sea-level pressure and may introduce additional uncertainty in the high-elevation western prefectures. However, these areas remain well below the 27 °C threshold; so,

this limitation is unlikely to affect the spatial patterns or the main conclusions of this study. HI values and detailed rankings were also affected by the selected wet-bulb temperature threshold, although the main spatial pattern remained stable under the 26 °C and 27 °C settings. The use of adjacent-year urban masks and interpolated 2024 population data may introduce temporal mismatch. In addition, EI measures population-density exposure rather than the total exposed population, while prefecture-level VI cannot identify neighborhood differences or specific vulnerable groups. The six selected years support comparison among sampled years but cannot establish continuous annual trends or precise turning points. HHRI may also vary with normalization, weighting, and aggregation choices. Future research should use higher-resolution data, expand station and mobile validation, combine density- and person-based exposure measures, and conduct CMIP6-based scenario assessments.

5. Conclusions

- (1) Across the six assessment years from 2000 to 2024, the mean urban HHRI in Sichuan Province declined from 0.42 to 0.24. HHRI was relatively high in 2000, decreased in 2005, increased again in some cities in 2010, remained comparatively low in 2015 and 2020, and rose locally in 2024. The contribution decomposition showed that the decline in VI made the largest contribution to the overall reduction in HHRI, whereas increases in HI contributed to rebounds during several assessment intervals.
- (2) HHRI consistently exhibited a clear basin–plateau contrast. Relatively high values were concentrated in southern and southeastern Sichuan and the central-eastern Sichuan Basin, whereas the western plateau and mountainous areas generally remained at low risk levels. The standard deviation ellipses located the risk-weighted center within and around the Sichuan Basin, while Global Moran's I and LISA indicated significant positive spatial autocorrelation and local clustering in all six assessment years. High–High clusters occurred mainly within the basin, and Low–Low clusters were concentrated in the western plateau and mountainous areas.
- (3) Prefecture-level results revealed substantial differences among administrative units. Neijiang, Zigong, and Ziyang recorded relatively high HHRI values in several assessment years, indicating repeated overlap among humid-heat hazard, population-density exposure, and socioeconomic vulnerability. Luzhou recorded the highest HI value in 2024. EI reflected changes in population-density exposure intensity within urban built-up areas, while VI declined from 0.87 to 0.30 and became the dominant contributor to the overall reduction in HHRI.
- (4) The first two principal components explained 81.48% of the total variance in the socioeconomic indicator system. Their loadings showed that VI captured differences in economic development, fiscal capacity, infrastructure investment, medical resources, public-service provision, and transportation conditions. Overall, HHRI reflected the joint contributions of humid-heat hazard, population-density exposure, and socioeconomic vulnerability. Future adaptation should therefore emphasize integrated risk governance, with priority given to the central-southern and southeastern Sichuan Basin. Prefecture-level units with relatively high HI or repeatedly high HHRI values should strengthen regional heat-health preparedness, early-warning, emergency response, public-service provision, medical-resource capacity, and socioeconomic adaptive capacity.

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visualization, M.W.; supervision, Y.W.; project administration, M.W. All authors have read and agreed to the published version of the manuscript.

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