

## Postprint: Assessment of High Temperature Vulnerability and Its Spatiotemporal Variation in the Guanzhong Region

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### Abstract

With global climate warming, extreme high temperature events are occurring with increasing frequency, posing serious threats to human health and socio-economic development. By comprehensively utilizing remote sensing data and socio-economic statistical data, an evaluation index system for high temperature vulnerability based on the “exposure-sensitivity-adaptive capacity” framework was established, the high temperature vulnerability index was quantified, and the spatio-temporal evolution characteristics of high temperature vulnerability in the Guanzhong region from 2005 to 2020 were revealed. The results demonstrate that: (1) From 2005 to 2020, the area of high-temperature zones in summer land surface temperature increased in the Guanzhong region, and the spatial pattern of land surface temperature remained broadly similar; sub-high temperature zones and high temperature zones exhibited patchy distribution in the central region, while sub-low temperature zones and low temperature zones were concentrated in the southern Qinling mountainous area. (2) The spatial agglomeration characteristics of high temperature vulnerability in the Guanzhong region were pronounced, with a distribution pattern similar to that of land surface temperature; areas with relatively high and high vulnerability grades were mainly concentrated in the central plains, while low and relatively low grade areas were mainly distributed in the southern Qinling mountainous area. (3) From 2005 to 2020, the high temperature vulnerability index in the Guanzhong region exhibited a decreasing trend, with the proportion of area with relatively high and high vulnerability grades decreasing from 48.20% in 2005 to 37.49% in 2020. (4) From 2005 to 2010, the scope of changes in high temperature vulnerability grades was relatively limited; from 2010 to 2020, the scope of changes in various high temperature vulnerability grades increased substantially, with vulnerability grades decreasing in most areas, primarily manifested as medium vulnerability decreasing to relatively low vulnerability, relatively high vulnerability decreasing to medium vulnerability, and high vulnerability decreasing

to relatively high vulnerability. The research results can provide reference and guidance for improving high temperature adaptive capacity and mitigating high temperature vulnerability.

## Full Text

### Assessment of Heat Vulnerability and Its Spatiotemporal Variation in the Guanzhong Region

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## Abstract

With global warming, extreme heat events have occurred more frequently, posing significant threats to human health and socio-economic development. This study integrates remote sensing data and socio-economic statistics to establish a "heat exposure-sensitivity-adaptive capacity" evaluation index system for heat vulnerability. The heat vulnerability index was quantified to reveal the spatiotemporal evolution characteristics of heat vulnerability in the Guanzhong region from 2005 to 2020. The results show that: (1) The area of high-temperature zones in summer increased in the Guanzhong region, with the spatial pattern of land surface temperature remaining broadly similar. Sub-high-temperature and high-temperature zones were distributed as continuous patches in the central region, while sub-low-temperature and low-temperature zones were concentrated in the southern Qinling Mountains. (2) The spatial clustering characteristics of heat vulnerability in the Guanzhong region were significant, with a distribution pattern similar to land surface temperature. Areas with relatively high and high vulnerability levels were mainly concentrated in the central plains, while low and relatively low vulnerability areas were primarily distributed in the southern Qinling Mountains. (3) The heat vulnerability index in the Guanzhong region showed a decreasing trend from 2005 to 2020, with the proportion of relatively high and high vulnerability areas decreasing from 48.20% to 37.49%. (4) From 2005 to 2010, the scope of changes in heat vulnerability levels was relatively small, but from 2010 to 2020, the range of changes increased significantly, with vulnerability levels decreasing in most areas. The main transformations were medium vulnerability decreasing to relatively low vulnerability, relatively high vulnerability decreasing to medium vulnerability, and high vulnerability decreasing to relatively high vulnerability. The research results can provide references for improving heat adaptation capacity and mitigating heat vulnerability.

**Keywords:** land surface temperature; heat vulnerability; spatiotemporal variation; Guanzhong region

## 1 Introduction

The IPCC Sixth Assessment Report indicates that global surface temperature has increased by 1.09°C since the period with complete meteorological observation records, marking the highest increase on record. Heat waves, as typical extreme weather events, have high probability, wide impact, and significant risk, posing a serious threat to human health. The 1995 Chicago heat wave caused approximately 700 deaths, the 2003 European summer heat wave claimed over 70,000 lives, and the 2021 Washington State heat wave caused 78 deaths in just three weeks. In addition to direct impacts on human health, extreme heat also causes economic losses by affecting labor productivity. Global economic losses are projected to reach \$2.4 trillion by 2030 due to rising temperatures. In recent years, extreme heat events in China have become increasingly severe. In the summer of 2022, southern China experienced intense heat waves, with significantly increased incidence and mortality rates of heatstroke, cardiovascular, and digestive diseases. The comprehensive intensity of heat events in China in 2022 was the strongest since 1961.

Vulnerability refers to the propensity of a system (such as natural, social, or ecological systems) to be adversely affected by external disturbances or risks (such as natural disasters and climate change). It is typically influenced by exposure to disturbances or risks, system sensitivity, and adaptive capacity. Vulnerability assessment is a crucial component of vulnerability research, helping to identify the spatial distribution of vulnerable units and provide targeted measures for disaster prevention and mitigation. Vulnerability assessment can also identify vulnerable populations and reveal their capacity to cope with risks. Therefore, applying vulnerability analysis tools to heat wave vulnerability assessment has become a hotspot in climate change vulnerability research, holding significant practical value for identifying heat-vulnerable units, formulating mitigation strategies, and enhancing disaster resilience.

International research on heat waves began relatively early, initially using pathological studies with morbidity and mortality data to analyze health outcomes caused by high temperatures, and gradually shifting toward vulnerability assessment tools that incorporate the health impacts of high temperatures. These studies construct evaluation index systems from perspectives such as natural characteristics, population distribution, and socio-economic conditions, using methods including Analytic Hierarchy Process, principal component analysis, and layer overlay methods to assess heat vulnerability and map its distribution. Representative studies include Frazier et al., who used principal component analysis to identify key variables affecting heat disaster vulnerability in U.S. census tracts for comprehensive mapping; Mushore et al., who used remote sensing and socio-economic data with layer overlay methods to assess heat vulnerability in Harare, Zimbabwe; and Tran et al., who used the Analytic Hierarchy Process to

determine indicator weights for assessing heat vulnerability across Vietnamese provinces.

Domestic research on heat waves initially focused on using meteorological station data to calculate heat wave indices such as high-temperature days, intensity, and duration to explore spatiotemporal distribution characteristics and causes. With the rapid development of remote sensing technology, research has deepened, with increasing studies using meteorological and remote sensing data combined with natural environment and socio-economic data to quantitatively assess heat risk and vulnerability. Most studies have been conducted at macro scales including national, provincial, and municipal levels. For example, Xie et al. assessed population health risk from heat stress in China based on social vulnerability; Zheng et al. evaluated heat wave vulnerability in coastal and inland cities of Fujian Province using an “exposure-sensitivity-adaptive capacity” framework; and Chen et al. used the entropy weight method to explore heat wave vulnerability distribution in central Beijing and propose planning recommendations.

Comparing international and domestic research, international studies on heat social vulnerability assessment feature early start, multi-dimensionality, rich results, and interdisciplinary integration. Domestic research started later with fewer results, requiring further improvement in vulnerability index system construction and evaluation method selection. Specific limitations include: most studies use limited meteorological station data that cannot finely represent heat distribution patterns; and from a temporal perspective, current research primarily focuses on static evaluation using single-year cross-sectional data to characterize spatial distribution patterns, with less attention to dynamic spatiotemporal evolution characteristics of heat vulnerability.

Based on this context, this study combines remote sensing data and socio-economic statistics to construct a heat vulnerability evaluation index system from the dimensions of exposure, sensitivity, and adaptive capacity. We assess heat vulnerability in the Guanzhong region from 2005 to 2020, revealing its spatiotemporal evolution characteristics and regional differences. This research provides references for heat vulnerability assessment and decision-making for enhancing heat adaptation capacity and mitigating heat vulnerability, enabling scientifically tailored response strategies.

## 2 Study Area and Methods

### 2.1 Study Area

The Guanzhong region is located in central Shaanxi Province, adjacent to the Loess Plateau in the north and the Qinling Mountains in the south, with the Wei River flowing through it. It serves as the core area of the Guanzhong Plain national urban agglomeration. The region includes Xi'an, Baoji, Xianyang, Tongchuan, Weinan, and Yangling Agricultural High-tech Industry Demonstration Zone, covering approximately  $5.54 \times 10^4 \text{ km}^2$ . By the end of 2020,

the permanent population was 25.95 million and the regional GDP reached  $1.850271 \times 10^{12}$  yuan, accounting for 65.6% and 62.1% of the province's total population and GDP, respectively. The Guanzhong region has a warm temperate semi-humid and semi-arid climate with hot, rainy summers and cold, dry winters. In recent years, influenced by global warming, subtropical high pressure control, and atmospheric circulation anomalies, heat wave events have occurred frequently. Taking Xi'an as an example, there were 49 days with daily maximum temperatures exceeding  $35^{\circ}\text{C}$  in 2022. Additionally, with rapid socio-economic development and urbanization, the urban heat island effect is pronounced, with substantial anthropogenic heat sources exacerbating ground warming. The region's special topography, high in the north and south but low in the middle, makes it difficult for heat in the central plains to dissipate quickly, further intensifying the thermal environment.

[Figure 1: see original paper] Schematic diagram of the study area

## 2.2 Heat Vulnerability Evaluation Index System

Based on existing literature and research results, this study selects relevant indicators from three dimensions—exposure, sensitivity, and adaptive capacity—to construct a heat vulnerability evaluation index system (Table 1) for assessing heat vulnerability in the Guanzhong region.

**Exposure** generally refers to the degree of danger posed by external environmental factors to the system. Meteorological stations have high temporal resolution but are typically sparse and limited in number, making it difficult to accurately capture regional thermal environment distribution patterns. Remote sensing monitoring offers wide coverage, high spatial resolution, and strong spatial continuity, enabling more comprehensive and detailed representation of thermal environment spatial distribution. Land surface temperature has been used as a heat exposure indicator in studies of heat vulnerability in cities such as Beijing and Xi'an. Research has demonstrated a high positive correlation between land surface temperature and air temperature. Therefore, this study selects land surface temperature to characterize regional heat exposure features.

**Sensitivity** refers to the degree of population response to heat disasters, typically measured through indicators of physiological conditions and socio-economic status. Studies show that elderly and children populations are more vulnerable to extreme heat, with higher hospitalization rates for heat-related illnesses including heat stroke, heat exhaustion, heat syncope, and heat cramps. Population density reflects the degree of population aggregation, with densely populated areas being more susceptible to heat impacts. This study uses population density, population density under 15 years old, and population density aged 65 and above as heat sensitivity evaluation indicators.

**Adaptive capacity** reflects a city's ability to respond, adjust, and adapt to changes through internal structural regulation when facing heat wave conditions. This can be considered from perspectives including economic development level,

medical services, and cooling facilities. Economic development level reflects regional economic capacity to cope with heat disasters, measured by per capita GDP. The number of hospital beds and health technicians per 10,000 people reflects urban medical service levels and health security capacity for heat disaster response. Vegetation, as indicated by Normalized Difference Vegetation Index (NDVI), demonstrates cooling effects at regional scales and reflects green infrastructure levels for heat adaptation.

Evaluation index system of heat vulnerability

### 2.3 Data Sources and Processing

Land surface temperature data were obtained from the MODIS 8-day land surface temperature product (MOD11A2) provided by NASA's LAADS DAAC ([adsweb.nascom.nasa.gov/data/search](https://adsweb.nascom.nasa.gov/data/search)). This product is derived using the split-window algorithm with a spatial resolution of 1 km and high accuracy. Based on the study area's tile numbers (h26v05 and h27v05), two images were downloaded. Using Modis Reprojection Tool (MRT) for batch geometric correction, mosaicking, and reprojection, the study area was clipped in ArcGIS. Raster Calculator was used to convert temperature units to Celsius ( $^{\circ}\text{C}$ ), and mean values were synthesized for monthly and seasonal scales. The temperature conversion formula is:

$$T = DN \times 0.02 - 273.15$$

where  $T$  is land surface temperature ( $^{\circ}\text{C}$ ) and  $DN$  is pixel gray value.

NDVI data were obtained from MOD13Q1 data, using maximum value composite in ArcGIS. Population density and age structure data were sourced from WorldPop (<https://hub.worldpop.org/>). Economic and medical data at the district/county scale were obtained from the Shaanxi Regional Statistical Yearbook, Shaanxi Statistical Yearbook, municipal statistical yearbooks, and National Economic and Social Development Statistical Bulletins. Due to the lack of effective spatialization methods for district/county economic and medical data, values within each district/county were assumed uniform and spatially linked with administrative boundaries for rasterization. All data were clipped using vector boundaries and reprojected to WGS\_{{1984}}\_{{UTM}}\_{{Zone}}\_{{49N}} for calculation.

### 2.4 Evaluation Methods

**2.4.1 Evaluation Method** To eliminate the influence of different data magnitudes on evaluation results, raw data were standardized before index calculation. This study employs the widely used extreme value standardization method, which includes positive and negative indicator standardization:

**Positive indicator standardization:**

$$Y_{ij} = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)}$$

**Negative indicator standardization:**

$$Y_{ij} = \frac{\max(X_j) - X_{ij}}{\max(X_j) - \min(X_j)}$$

where  $X_{ij}$  and  $Y_{ij}$  are the original and standardized values of indicator  $j$  for grid  $i$ , respectively;  $\max(X_j)$  and  $\min(X_j)$  are the maximum and minimum values of indicator  $j$ .

For weight determination, this study uses the entropy weight method, which calculates weights based solely on raw data, avoiding subjective influences and providing a straightforward calculation process.

Heat vulnerability is a function of exposure, sensitivity, and adaptive capacity, with these three dimensions comprehensively influencing heat vulnerability. Based on existing research, this study employs functional model and comprehensive index methods to construct a vulnerability assessment model. The heat vulnerability index is calculated as:

$$VI = EI + SI - AI$$

where  $VI$  is the heat vulnerability index;  $EI$  is the heat exposure index;  $SI$  is the sensitivity index; and  $AI$  is the adaptive capacity index. Exposure and sensitivity have positive effects on vulnerability (higher values increase vulnerability), while adaptive capacity offsets sensitivity. The exposure, sensitivity, and adaptive capacity indices are calculated through weighted summation:

$$EI = \sum_{j=1}^m W_j e_{ij}$$

$$SI = \sum_{j=1}^n W'_j s_{ij}$$

$$AI = \sum_{j=1}^p W''_j a_{ij}$$

where  $W_j$ ,  $W'_j$ , and  $W''_j$  are weights for exposure, sensitivity, and adaptive capacity indicators, respectively;  $e_{ij}$ ,  $s_{ij}$ , and  $a_{ij}$  are standardized values for grid  $i$  and indicator  $j$  in each dimension.

**2.4.2 Spatial Autocorrelation Analysis** Spatial autocorrelation measures the spatial distribution of attribute values and their association with neighboring regions. It includes global and local spatial autocorrelation.

**Global spatial autocorrelation** identifies the overall spatial clustering degree of variables, typically represented by the global Moran's I index. This study uses the global Moran's I to assess the average similarity of land surface temperature and heat vulnerability index values across spatial units:

$$\text{Moran's } I_{\text{global}} = \frac{n \sum_{i=1}^n \sum_{j=1}^n \omega_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n \omega_{ij} \sum_{i=1}^n (x_i - \bar{x})^2}$$

where Moran's  $I_{\text{global}}$  is the global spatial autocorrelation index;  $n$  is the total number of spatial units;  $x_i$  and  $x_j$  are land surface temperature or heat vulnerability index values for units  $i$  and  $j$ ;  $\bar{x}$  is the mean value; and  $\omega_{ij}$  is the spatial weight matrix. When Moran's  $I_{\text{global}} > 0$ , spatial units exhibit positive correlation, with values closer to 1 indicating stronger positive correlation and greater clustering. When Moran's  $I_{\text{global}} < 0$ , negative correlation exists, with values closer to -1 indicating stronger dispersion. When Moran's  $I_{\text{global}} = 0$ , attributes are randomly distributed without correlation.

**Local spatial autocorrelation** examines correlations between local spatial units and their neighbors. This study employs local Moran's I to reveal local correlations:

$$I_{\text{local}} = \frac{(x_i - \bar{x}) \sum_{j=1}^n \omega_{ij} (x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2 / n}$$

When  $I_{\text{local}} > 0$  and significant, spatial units have similar attribute values to neighbors, showing "high-high" and "low-low" clustering. When  $I_{\text{local}} < 0$  and significant, attribute values differ from neighbors, showing "high-low" and "low-high" patterns.

## 3 Results

### 3.1 Heat Exposure

Land surface temperature was classified using the standard deviation method based on the mean ( $\mu$ ) and standard deviation (SD) of regional land surface temperature. This approach divides temperature into five levels: low, sub-low, medium, sub-high, and high temperature zones (Table 2). Figure 2 shows area proportion changes for each temperature level in the Guanzhong region from 2005 to 2020.

Classification standard of land surface temperature

The low temperature zone reached its maximum area in 2015 (20.79%), while the sub-low temperature zone peaked in 2020 (16.45%). The medium temperature zone showed the most significant change, decreasing from 30.40% in 2005 to 20.10% in 2020, a reduction of 10.30 percentage points. The sub-high temperature zone reached its maximum in 2005 (28.26%), while the high temperature zone peaked in 2020 (18.75%), with its area proportion increasing by 16.36 percentage points from 2.39% in 2005.

Based on these classification standards, summer daytime average land surface temperature in the Guanzhong region was categorized, revealing spatial patterns from 2005 to 2020 (Figure 3). The spatial patterns remained broadly similar across years, with sub-high and high temperature zones primarily distributed in central and northern Xi'an, central Baoji, southern Xianyang, most of Weinan, and small parts of southern Tongchuan, forming continuous patches. These areas are mostly plains and basins with dense populations, high urbanization and industrialization levels, and strong human activity impacts. Low and sub-low temperature zones were concentrated in the southern Qinling Mountains, where higher altitude and dense vegetation coverage enhance evapotranspiration. Compared with 2005, the high temperature zone expanded significantly in 2020, with more concentrated distribution aggregating toward the central region.

Global spatial autocorrelation tests on summer daytime average land surface temperature from 2005 to 2020 showed that global Moran's I values were all positive and statistically significant ( $P < 0.01$ ), indicating significant positive spatial correlation and clear clustering. Local spatial autocorrelation analysis revealed that each year had two local spatial autocorrelation types: "high-high" and "low-low" clusters, with no "high-low" or "low-high" types. The "high-high" cluster (high temperature value aggregation) initially expanded then contracted, distributed continuously across most central areas. The "low-low" cluster (low temperature value aggregation) showed similar temporal variation, initially expanding then contracting, and was mainly distributed in the southern Qinling Mountains.

Using natural breaks in ArcGIS, heat exposure levels were divided into five grades: high, relatively high, medium, relatively low, and low (Figure 4). The spatial patterns of heat exposure remained similar across years, with relatively high and high exposure corresponding to sub-high and high temperature zones, while relatively low and low exposure corresponded to sub-low and low temperature zones.

### 3.2 Heat Sensitivity

To facilitate comparison across periods, heat sensitivity indices for 2005–2020 were uniformly classified into five grades: low, relatively low, medium, relatively high, and high (Figure 6). The spatial patterns of heat sensitivity remained similar, with relatively high and high sensitivity concentrated in Xi'an's main

urban area. Relatively high sensitivity also appeared sporadically in Yangling Agricultural High-tech Industry Demonstration Zone and Baoji's municipal district. Medium sensitivity was scattered across municipal districts of various cities. Relatively low and low sensitivity areas were widely distributed across urban peripheries and surrounding county centers, with low sensitivity covering extensive areas due to the concentration of population distribution.

### 3.3 Heat Adaptive Capacity

The spatial distribution pattern of heat adaptive capacity from 2005 to 2020 showed that relatively high and high capacity areas were small and scattered across municipal districts of Xi'an, Xianyang, Baoji, and Tongchuan. In 2005, relatively high capacity was also distributed in Linyou County in northeastern Baoji. Medium capacity areas were similarly scattered. Relatively low and low capacity areas covered extensive ranges, distributed in southwestern Xi'an and most parts of Xianyang and Weinan in 2005. In 2010, low capacity areas in northern Xianyang shifted to relatively low capacity. In 2015, low capacity areas clearly shrank in scope. In 2020, low capacity areas transferred to central Baoji.

Temporally, the heat adaptive capacity index in the Guanzhong region increased from 0.25 in 2005 to 0.43 in 2020, primarily due to continuously improving economic levels, rapid increases in per capita GDP, and increasing numbers of hospital beds and health technicians per 10,000 people, indicating improved medical conditions and health security for heat disaster response.

Global spatial autocorrelation tests on heat vulnerability from 2005 to 2020 showed that global Moran's I values were all positive and statistically significant ( $P < 0.01$ ), indicating significant positive spatial correlation and clear clustering. Local spatial autocorrelation analysis revealed that each year had two local spatial autocorrelation types: "high-high" and "low-low" clusters, with no "high-low" or "low-high" types. The "high-high" cluster (high vulnerability value aggregation) was mainly distributed across most central areas, transitioning from dispersed to concentrated distribution, showing high spatial consistency with high temperature zones, indicating that heat vulnerability patterns are largely influenced by land surface temperature and closely related to topography, altitude, and human activities. The "low-low" cluster (low vulnerability value aggregation) was mainly distributed in the southern mountainous areas, with additional distribution in northern Baoji and Tongchuan in 2020.

### 3.4 Heat Vulnerability

Heat vulnerability indices for the Guanzhong region from 2005 to 2020 were calculated using the comprehensive evaluation model. Natural breaks were used to uniformly classify vulnerability indices into five grades: low, relatively low, medium, relatively high, and high (Figure 8). The results show that heat vulnerability distribution patterns were similar to land surface temperature, with

significant spatial clustering. Relatively high and high vulnerability were concentrated in the central plains as continuous large patches. Compared with 2005, the scope of relatively high and high vulnerability decreased in 2020, with relatively high vulnerability areas in northern Xianyang shifting to medium vulnerability, and high vulnerability areas in Weinan shifting to relatively high vulnerability. Low and relatively low vulnerability areas were small, mainly distributed in the southern Qinling Mountains.

The heat vulnerability index showed a decreasing trend from 2005 to 2020, declining from 0.52 to 0.41. The proportion of relatively high and high vulnerability areas decreased from 48.20% in 2005 to 37.49% in 2020. Analysis of area proportions for different vulnerability levels using ArcGIS and Origin revealed that in 2005, areas ranked by size were: medium vulnerability (30.23%), relatively low vulnerability (24.68%), relatively high vulnerability (18.84%), low vulnerability (11.17%), and high vulnerability (2.72%). In 2010, the ranking was: medium vulnerability (31.96%), relatively low vulnerability (27.77%), relatively high vulnerability (9.84%), low vulnerability (7.82%), and high vulnerability (5.69%). In 2015, the ranking was: relatively low vulnerability (35.10%), medium vulnerability (26.32%), low vulnerability (19.85%), relatively high vulnerability (12.07%), and high vulnerability (6.17%). In 2020, the ranking was: relatively low vulnerability (35.10%), medium vulnerability (29.09%), low vulnerability (25.60%), relatively high vulnerability (8.69%), and high vulnerability (4.58%).

Transition matrix analysis of heat vulnerability levels revealed that from 2005 to 2010, the scope of changes was small (30.47% of total area), mainly involving transitions among relatively low, medium, and relatively high vulnerability levels. From 2010 to 2020, the range of changes increased significantly, primarily characterized by decreasing vulnerability levels: medium to relatively low (10.81% of area), relatively high to medium (12.77%), and high to relatively high (15.54%). This decreasing trend occurred mainly because adaptive capacity increased annually with socio-economic development and urbanization, with the increase in adaptive capacity exceeding that of exposure and sensitivity.

## 4 Discussion

This study assessed the spatiotemporal evolution patterns of heat vulnerability in the Guanzhong region, further improving dynamic evolution research on heat vulnerability. Current heat vulnerability studies often use population data from statistical sources at administrative unit levels, whereas this study uses WorldPop population data to finely represent population spatial distribution characteristics.

From 2005 to 2020, high-temperature zones in the Guanzhong region showed expansion trends, consistent with research findings that daytime average land surface temperature in the Greater Xi'an area is increasing. The spatial distribution pattern of heat vulnerability in the Guanzhong region was low in the

north and south but high in the middle, similar to the land surface temperature pattern. Studies on urban heat vulnerability in China also show similar spatial distribution patterns to urban heat exposure, indicating that heat vulnerability distribution in the Guanzhong region is mainly influenced by natural factors. The vulnerability index exhibits significant spatial clustering characteristics, consistent with spatial clustering results from heat wave risk studies in Shanghai.

The decreasing trend in heat vulnerability index from 2005 to 2020 was primarily due to continuously improving socio-economic levels and accelerating urbanization, leading to annual increases in adaptive capacity that exceeded increases in exposure and sensitivity.

Therefore, targeted measures are needed to improve regional heat adaptation capacity and reduce heat vulnerability: (1) For relatively high and high exposure areas, rationally plan blue-green spaces according to local urban characteristics to improve the thermal environment. Specific measures include vertical greening, cool roofs, light-colored roofing, optimized building design and construction, reduced anthropogenic heat emissions, promotion of green and low-carbon buildings, and avoidance of high-density construction. (2) For relatively high and high sensitivity areas, focus on high-sensitivity groups including the elderly, children, outdoor workers, and chronic disease patients. Improve health early warning systems, categorize risk levels, disseminate heat avoidance knowledge through television, radio, and internet, and enhance public awareness. Medical institutions should implement emergency response measures during extreme heat events. At the community level, track sensitive groups' health conditions during heat wave periods through phone calls, registration, and health records. (3) For low and relatively low adaptive capacity areas, local governments should focus on public facility and space renovation, improve planning for cooling shelters, extend operating hours, comprehensively enhance heat adaptation capacity, increase financial investment, and gradually address resource allocation inequalities during heat disasters.

## 5 Conclusion

This study reveals that: (1) From 2005 to 2020, the area of high-temperature zones in the Guanzhong region increased during summer, with broadly similar spatial patterns. Sub-high-temperature and high-temperature zones were distributed as continuous patches in the central region, while sub-low-temperature and low-temperature zones were concentrated in the southern Qinling Mountains. (2) The spatial pattern of heat sensitivity remained similar, with relatively high and high sensitivity concentrated in Xi'an's main urban area and medium sensitivity scattered across municipal districts. Heat adaptive capacity showed no obvious spatial clustering characteristics. (3) The spatial distribution pattern of heat vulnerability was similar to land surface temperature, with significant spatial clustering. Relatively high and high vulnerability were concentrated in the central plains, while low and relatively low vulnerability were

mainly distributed in the southern Qinling Mountains. (4) The summer heat vulnerability index decreased from 0.52 to 0.41, with the proportion of relatively high and high vulnerability areas decreasing from 48.20% to 37.49%. From 2005 to 2010, the scope of vulnerability level changes was small, but from 2010 to 2020, the range increased significantly, mainly manifested as decreasing vulnerability levels.

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