

# Divergence between physical and emotional heat resilience in Chinese cities

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## A. Supplementary Notes

### **Note S1: Socio-economic stratification and spatial inequity of urban heat resilience**

The Lorenz curves and Gini coefficients collectively reveal that the distribution of resilience components is consistent yet diagnostically distinct across economic, demographic, and spatial weighting contexts (Supplementary Fig. 4). Under GDP weighting, the Emotional Recovery Time ( $RT_e$ ) exhibits the strongest inequality (Gini = 0.68). Its curve remains significantly below the line of equality for most of the range before rising steeply at the tail, suggesting that a minority of high-GDP units contribute a disproportionate share of the  $RT_e$  burden. In contrast, shock and cumulative load indicators show moderate concentration ( $IMAX_e = 0.43$ ,  $RP_e = 0.38$ ), whereas physical metrics like  $RT_h$  (0.32) and  $IMAX_h$  (0.26) are less concentrated. Notably, the concentration of aggregated indices is significantly compressed by the "aggregation effect," with HGI at 0.16 and EGI recording the lowest value (0.09). This proximity to the line of equality implies that composite emotional resilience is distributed nearly broadly in economic terms.

Weighting by population maintains the overall ranking, indicating that concentration is not driven solely by economic scale.  $RT_e$  remains the highest (0.57), confirming its high concentration even within the context of social equity. While  $IMAX_e$  (0.42) and  $RP_e$  (0.22) maintain moderate deviation,  $RT_h$  rises to 0.26, suggesting a stronger demographic clustering of recovery rhythms. Meanwhile,  $RP_h$  drops to 0.19, and the

composite indices remain low ( $HGI = 0.17$ ,  $EGI = 0.07$ ), indicating that inequality in comprehensive resilience diminishes significantly under demographic weighting. When weighted by area, spatial agglomeration features become more explicit. Although  $RT_e$  dips slightly, it remains high (0.65). The most critical shift occurs in shock intensity ( $IMAX_e$ ), which rises to 0.39—surpassing its levels under GDP and population weighting—pointing to a distinct "spatially clustered" risk profile for extreme shocks.  $RP_e$  (0.33) and  $RT_h$  (0.30) also show slight increases. Conversely,  $RP_h$  is lowest under area weighting, indicating the weakest spatial clustering. Overall, the three weighting schemes confirm a robust conclusion:  $RT_e$  is consistently the most unequal component, EGI is consistently the most equal, whereas  $IMAX_e$  is most sensitive to spatial weighting, reflecting its stronger geographic agglomeration.

The Local Disparity Index (LDI) results reveal that local inequality is characterized by distinct regional differentiation and transitional zones (Supplementary Fig. 3). In the physical dimension, high values of  $IMAX_h$  tend to form patchy hotspots in the arid Northwest and inland basins, with local abrupt changes appearing at several eastern coastal endpoints, manifesting as a "shock intensity fracture" relative to surrounding units. By contrast, medium-to-high values of  $RT_h$  are more commonly distributed in bands or sheets across the Southwest mountain-basin transition zone, extending toward the Central-North China climatic transition belt. This suggests that recovery rhythm differences unfold continuously along regional gradients rather than being driven by isolated cities.  $RP_h$  is generally more fragmented with fewer high values, indicating weaker local disparity. At the composite level, the LDI for HGI is

noticeably smoother, with high values concentrated in transitional zones where topographic and developmental gradients overlap. The emotional dimension presents a "multi-centered, weakly continuous" pattern: while generally low,  $IMAX_e$  still exhibits identifiable high-value patches in the Northeast and along the eastern urbanization corridor. Disparities in  $RT_e$  and  $RP_e$  appear more frequently at urban agglomeration edges, rural-urban interfaces, and around inland nodes, manifesting as scattered hotspots against a weak gradient background. Ultimately, EGI is the smoothest, indicating that peak-like local differences are significantly dampened after aggregation.

Although  $RT_e$  showed clear concentration under GDP, population and area weighted schemes, with Gini coefficients of approximately 0.64, 0.63 and 0.59, the composite HGI and EGI remained low and stable across weighting schemes. Under GDP weighting, HGI = 0.12 and EGI = 0.09; under population weighting, HGI = 0.13 and EGI = 0.08; and under area weighting, EGI remained within approximately 0.08 – 0.09. These results indicate that the inequality structure of the composite HGI and EGI was not dominated by a small number of high-GDP, high-population or high-posting-density cities.

These regional variations can be attributed to distinct spatial control mechanisms governing physical versus social processes. Hotspots and gradients in physical metrics are dominated by climatic and topographic contexts: in the arid Northwest and basin environments, low-moisture substrates and strong sensible heat accumulation amplify

peak shocks, creating abrupt mutations between neighborhoods. Similarly, the banded disparities in the Southwest basins align with mechanisms where recovery is constrained by ventilation efficiency and heat dissipation difficulties in high-humidity backgrounds, leading recovery times to follow continuous gradients along transition zones. In comparison, inequality on the emotional side is more readily triggered by abrupt shifts within the urban system—specifically in population exposure, development levels, public service accessibility, and social support networks—resulting in discrete "anomaly patches" at urban fringes and rural-urban transitions. Methodologically, the composite indices (HGI, EGI) aggregate shock, cumulative load, and recovery processes, thereby attenuating the peak disparities of single process variables and rendering spatial patterns more continuous. Thus, the dual characteristic of "physical gradients versus social fractures" revealed by the LDI provides direct evidence for tailoring governance priorities and adaptation strategies across different regions.

**Note S2: Structural decomposition and component-level analysis of physical and emotional resilience**

To dissect the structural underpinnings of HGI and elucidate adaptive mechanisms obscured by aggregate analysis, we decomposed the metric into  $IMAX_h$ ,  $RT_h$ , and  $RP_h$ , employing multi-dimensional diagnostics across climate zones and spatial mapping (Extended Fig.1; Supplementary Fig. 6-7). Statistical analysis revealed a core resistance-recovery trade-off across environmental gradients. Constrained by inherent humidity barriers and latent heat retention, TSC regions exhibited a typical chronic exposure mode where  $RT_h$  was significantly prolonged despite  $IMAX_h$  being moderated by maritime influences. Conversely, CTC and PC regions displayed characteristics of acute shock, with resilience deficits stemming primarily from extremely high  $IMAX_h$  reflecting a lack of load-handling capacity for episodic heatwaves. Along the urban-rural gradient, megacities leveraged an infrastructure bonus to effectively blunt immediate heat peaks resulting in low  $IMAX_h$ , yet the immense thermal inertia of high-density built environments incurred a significant heat island penalty causing  $RT_h$  to lag far behind rural areas that lacked defense but possessed superior natural ventilation. This mechanistic trade-off projected a distinct pattern of geographical decoupling.  $IMAX_h$  followed a pronounced North-High South-Low gradient, with inland basins and arid Northwest regions forming deep red shock-susceptible zones. Mirroring this,  $RT_h$  exhibited a South-High North-Low distribution where the Yangtze River Basin and South China coast constituted persistence-susceptible zones due to the dual lock-in effect of high humidity and

urban heat islands, while high  $RP_h$  bands precisely delineated climate transition zones. Collectively, these findings confirmed that physical resilience was not uniformly distributed but represented a dynamic spatial separation between resistance capacity and recovery efficiency across climatic and urbanization contexts.

The structural decomposition of EGI further confirmed the existence of a prosperity penalty at the micro-mechanistic level, revealing the non-linear breakdown of psychosocial adaptation under extreme climate (Extended Fig.2; Supplementary Fig. 6-8). Unlike the dynamic balance seen in physical resilience, the three components of emotional resilience  $IMAX_e$ ,  $RT_e$ , and  $RP_e$  exhibited a synchronous double deficit effect across the urban-rural gradient. Megacities not only encountered the highest  $IMAX_e$  indicating that negative emotional outbursts among high-density populations were more intense and prone to breaching psychosocial thresholds, but also recorded the longest  $RT_e$ . This extended recovery reflected how rapid social metabolism and hyper-competitive environments severely compressed the psychological repair window, causing negative emotions to linger long after heatwaves subsided. Climatic heterogeneity further modulated this response, with TSC regions again emerging as the core of emotional vulnerability. Physiological discomfort driven by humid heat and continuous nocturnal exposure created a potent emotional hysteresis effect, elevating  $RT_e$  significantly above arid or cold zones. Spatially, this mechanism projected a characteristic Core-Periphery dual structure. In sharp contrast to the physically robust eastern coastal clusters, dense agglomerations like YRD, PRD, and BTH appeared as extensive low-value emotional heat islands within the EGI map,

characterized by high-intensity emotional oscillation or high  $RP_e$  and sustained suppression or high  $RT_e$ . Conversely, the ecological southwest periphery and less developed small-to-medium cities retained higher emotional elasticity, serving as green sanctuaries for psychological adaptation. This significant spatial mismatch between physical buffering and psychological experience profoundly underscored that technical adaptation alone could not neutralize the psychosocial impact of climate change, suggesting that high-density urban morphology was itself becoming a structural stressor that eroded human emotional resilience.



### **Note S3: Log-Scale Joint Density Analysis of Resilience–Development Relationships**

To quantify the nonlinear links between resilience indicators and development drivers across socio-economic gradients spanning multiple orders of magnitude, this study constructed log-scale joint density plots (Extended Fig.5). The framework combined bivariate kernel density estimation with marginal histograms, and applied base-10 log transforms to the highly skewed population and GDP data to correct their heavy-tailed distributions. This treatment reduced the leverage of extreme outliers from mega-cities on the inferred patterns and, with a nonlinear smoothed regression overlay, robustly revealed the underlying structure of how urban resilience varied with development scale in log space.

The joint-density diagnostics showed that physical and emotional resilience responded to city size in fundamentally different ways. Physical resilience (HGI) exhibited only weak, relatively flat associations with log-transformed population and GDP, with the high-density core concentrated around mid-range values, indicating scale neutrality in physical heat adaptation—large cities did not display a clear per-capita defensive advantage despite resource agglomeration. By contrast, emotional resilience (EGI) showed a pronounced, monotonic negative relationship, with the fitted curve declining steeply as population density and economic mass increased. This pattern pointed to a latent prosperity penalty, or density penalty, in which high-density environments produced by rapid urbanisation concentrated material wealth while materially eroding psychological buffering capacity against

214 climate stress, leaving affluent metropolitan areas as hotspots of emotional  
215 vulnerability. Together with the component-level evidence in Supplementary Note S2,  
216 the log-scale density results indicate that the prosperity penalty is an observed  
217 recovery-side pattern, not an a priori assumption imposed on the data.

218 Prosperity penalty should not be interpreted as a deterministic claim that economic  
219 development directly reduces emotional resilience. Rather, it describes an empirical  
220 pattern in which the physical benefits of development do not translate proportionally  
221 into publicly expressed emotional recovery. This interpretation is consistent with  
222 three theoretical traditions. Scitovsky's joyless economy distinguishes material  
223 comfort from subjective recovery. Wilkinson's inequality-anxiety framework links  
224 affluent and unequal urban contexts to chronic status pressure and reduced  
225 psychological buffering. Evans' cumulative environmental stressors framework  
226 further suggests that density, commuting, noise, housing pressure and heat exposure  
227 can jointly amplify emotional burden. Together, these theories support the  
228 interpretation that dense and prosperous cities may retain strong physical adaptive  
229 capacity while showing weaker expressed emotional recovery under heatwave stress.

**Note S4: Decoupling of resilience patterns revealed by bivariate density plots**

Kernel density scatter plots derived from global urban annual means (2010–2024) reveal that HGI and EGI exhibit only a weak negative correlation across the full sample—statistically significant yet negligible in effect size (Extended Fig.10-11).

With regression slopes and explanatory power approaching zero, this pattern indicates that these two resilience dimensions do not form a stable linear coupling at the annual scale; rather, their relationship is better characterized by structural decoupling and a multi-modal distribution. The density peak centers on a region where HGI is slightly positive and EGI hovers near zero. Furthermore, quadrant decomposition shows that approximately two-thirds of the city-year units record positive HGI values; notably, a substantial portion of these coincide with negative EGI, suggesting that improvements on the physical side do not necessarily translate into synchronous emotional recovery.

Stratification by climate zone isolates the Arid and Semi-arid regions as having the most pronounced negative correlation, whereas associations in WTC, TSC, and CTC zones remain generally weaker. Structural differences also emerge across quadrants: the CTC zone exhibits the highest proportion of dual-positive outcomes (positive HGI and EGI), whereas WTC regions tend to cluster in the combination of positive HGI but negative EGI. This implies that the climatic background systematically modulates the synchronization—or desynchronization—between physical and emotional resilience.

Further grouping by urbanization level reveals steeper negative slopes in both megacities and rural areas. In megacities specifically, distinct emotional divergence occurs even under conditions of positive HGI, reflecting that high-intensity physical adaptation fails to mitigate psychosocial stress and may instead reinforce adaptive disparities. Conversely, small and medium-sized cities show near-zero or weak positive correlations. Collectively, these findings suggest that the HGI–EGI relationship is co-modulated by climate zones and urbanization processes; thus, it is more accurately interpreted as evidence of stratified decoupling rather than synchronous evolution summarized by a single correlation coefficient.

## **Note S5: Robustness checks and trend analysis of emotional time series**

To diagnose the stability of emotional shifts across varying temporal aggregation scales, we employed the Mann–Kendall test to detect monotonic trends within city-level emotional time series, quantifying their magnitude and direction via Sen’s slope estimator (Supplementary Table 1; Supplementary Fig.12). The screening process yielded 1,013 optimal series, all satisfying the 95% significance threshold. With p-values ranging from 0 to 0.0498 (median: 0.0185; interquartile range: 0.0065–0.0328), these results confirm that the observed trends are not artifacts of stochastic fluctuation. Directionally, the trends exhibit a near-equilibrium at the national scale: 513 series (50.6%) show an upward trajectory, while 500 (49.4%) exhibit a decline. This split suggests that emotional evolution is not characterized by a uniform, unidirectional drift across the country. Temporal resolution within the "optimal series" displays a distinct hierarchy, with the 3-hour scale dominating (41.6%), followed by 6-hour (21.1%), 24-hour (20.1%), and 12-hour (17.2%) intervals; consequently, 3-hour emotional data were selected for constructing resilience indices. While the overall magnitude of Sen’s slopes is modest, the distribution range broadens significantly with coarser temporal aggregation. Extreme values in 24-hour series reach from  $-0.0222$  to  $0.0196$ , indicating that while temporal smoothing enhances the detection of long-term drifts, it may simultaneously amplify the influence of persistent local deviations on trend estimation.

Despite the balanced dichotomy nationwide, a sharp adaptive divergence emerges within densely populated metropolitan areas. Traditional core cities—typified by Beijing ( $\text{Sen} \approx -3.3 \times 10^{-5}$ ), Guangzhou ( $\text{Sen} \approx -3.4 \times 10^{-4}$ ), and Chongqing—exhibit a significant erosion of resilience, reflecting the cumulative toll of high-density heat stress and fast-paced social burdens. Conversely, Shenzhen ( $\text{Sen} \approx +2.7 \times 10^{-4}$ ) and Shanghai ( $\text{Sen} \approx +9.0 \times 10^{-5}$ ) display an encouraging positive trajectory, potentially attributable to superior coastal ventilation or more effective adaptive governance, such as "park city" initiatives. Notably, the most extreme rates of change are confined to peripheral zones. Resource-depleted or arid cities like Shuangyashan ( $\text{Sen} = -0.0223$ ) and Hami ( $\text{Sen} = -0.0094$ ) constitute "vulnerability traps" requiring urgent intervention, highlighting the compound shock of economic contraction and extreme climate exposure on socio-psychological capital. In contrast, high-ecological-function areas such as Ledong ( $\text{Sen} = +0.0197$ ) and Shannan ( $\text{Sen} = +0.0109$ ) serve as "oases" of rapidly improving resilience, leveraging their superior natural baselines. This differentiation underscores that the long-term trajectories of urban emotional resilience are not random walks; rather, they are heavily constrained by path dependencies rooted in urban function, economic transition pathways, and the stock of ecological capital.

For each city, we calculated the total number of heatwave-related Weibo posts and tested its correlation with city-level EGI. The association between EGI and post count was weakly negative, with Pearson's  $r = -0.190$  and  $p = 3.377 \times 10^{-4}$ . Although this relationship was statistically significant, the effect size was small and the

direction was negative, indicating that cities with more posts did not systematically obtain higher EGI values. Because  $|r| < 0.3$ , the two variables showed no strong linear dependence. This result indicates that EGI was not mechanically driven by city-level posting density. Together with the long-tailed post-count distribution shown in Supplementary Fig. 20, this test supports the interpretation that EGI mainly reflects the relative intensity, persistence and recovery capacity of emotional response trajectories, rather than absolute posting volume.

**Note S6: Indicator considerations for the estimation models employed in this study**

To attribute the driving mechanisms underlying urban resilience and its spatial heterogeneity this study developed two categories of non-linear estimation models specifically designed for the Physical Resilience Index (HGI) and the Emotional Resilience Index (EGI). Both modeling frameworks are anchored in a standardized set of explanatory variables capable of robustly characterizing urban structural conditions and morphological variations at a national scale. This comprehensive feature set encompasses socio-economic status represented by Gross Domestic Product (GDP) and Population Count (PopC) topographic context via Elevation (DEM) vegetation and land cover composition including the Normalized Difference Vegetation Index (NDVI) alongside fractional cover indicators for Forest (FT) Barren land (BN) Grassland (GD) Built-up areas (UP) Water bodies (WR) and Cropland (CD) as well as built environment morphology metrics such as Building Height (BH) Building Density (BD) and Floor Area Ratio (FAR) thereby capturing the geographic constraints surface composition and spatial form differences defining distinct urban environments in a unified framework (Supplementary Table 2).

The configuration of these variables adheres to the critical physical pathways governing thermal environment formation. Topography and land surface characteristics constitute the physical baseline where Elevation (DEM) captures the background modulation of thermal lapse rates and local circulation. Regarding surface energy partitioning the Normalized Difference Vegetation Index (NDVI) alongside



specific land use categories characterizes variances in canopy structure and evapotranspiration cooling while Water bodies (WR) reflect regulation via high specific heat capacity and Built-up areas (UP) represent impervious substrates characterized by low moisture availability and high heat storage potential. Beyond surface characteristics the three-dimensional morphological structure reshapes the local thermal environment by altering aerodynamic roughness and radiative transfer paths. Grid-average Building Height (BH) and Building Density (BD) signify vertical wind blockage potential and horizontal heat storage surface area respectively while Floor Area Ratio (FAR) serves as a comprehensive metric of development intensity directly associated with longwave radiation trapping efficiency. Finally, Population Count (PopC) and Gross Domestic Product (GDP) were employed as critical proxies for anthropogenic heat emissions representing the intensity of metabolic heat release and waste heat discharge associated with high-energy economic activities.

As illustrated by the correlation heatmap (Supplementary Fig.19), the pairwise Pearson correlation coefficients ( $r$ ) among the selected independent variables were predominantly low. Specifically, the absolute correlation values ( $|r|$ ) for all variable pairs remained well below the strict threshold of 0.8, signifying a lack of strong linear dependence across the morphological, climatic, and socio-economic predictors. Complementing this diagnostic, the Variance Inflation Factor (VIF) analysis offered a quantitative evaluation of multicollinearity severity. As detailed in Supplementary Table 2, the VIF values for all input features consistently fell beneath the conservative threshold of 5. Collectively, these findings confirm the satisfactory orthogonality of

354 the feature set, validating its suitability for attributing the drivers of urban resilience

355 without significant interference.

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## **Note S7: Cross-regional generalizability and model calibration**

We utilized "city-year" observational units from 2010–2024 to validate the model, partitioning the dataset into 80% training and 20% validation subsets. Kernel density scatter plots were generated for 19 distinct city clusters to visualize the agreement between predicted and actual values; in these plots, color gradients represent sample density, while linear regression fits are superimposed on the 1:1 identity line to characterize directional deviation (Extended Fig. 5). Overall, the point clouds adhere closely to the 1:1 line with high-density regions clustering along the diagonal, indicating robust model calibration across the full value spectrum. Validation metrics for the full sample yield an  $R^2$  of 0.91, a mean absolute error (MAE) of 0.014, and a bias of  $-0.002$ , reflecting minimal error magnitudes and negligible systematic bias. Importantly, these performance patterns remain consistent across disaggregated city clusters, demonstrating that LightGBM maintains stable generalizability in cross-regional contexts. This consistency underscores the algorithm's capacity to precisely capture the localized emotional baselines and fluctuation dynamics intrinsic to diverse geographical units.

Temporal hold-out validation. To assess whether the temperature–resilience relationship learned by LightGBM generalizes across time rather than merely across cities within the same window, we conducted a strict temporal hold-out: the model was trained on city-year observations from 2010–2022 and used to blind-predict 2023–2024. Across all 19 city clusters, validation  $R^2$  ranged from 0.75 to 0.84, with

378 mean absolute error below 0.06 and bias below 0.03. This time-ordered validation  
379 substantially strengthens the cross-regional in-sample evidence and confirms that the  
380 empirical relationships are stable enough to support out-of-sample projection

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## **Note S8: Attribution of driving mechanisms for Best Lag (BL)**

The Best Lag (BL) parameter directly quantifies the temporal delay between heat exposure peak and emotional response recovery, making it a critical diagnostic of why emotional recovery may not synchronize with physical cooling. SHAP-based attribution analysis (Supplementary Fig. 16) revealed that land cover characteristics, geo-environmental context, and heat hazard intensity jointly governed BL, with no single category dominating. Forest cover fraction (FT) emerged as the largest single contributor at 19.42%, followed by elevation (DEM, 9.65%), heat hazard primitives ( $RP_h$  9.43%;  $IMAX_h$  8.33%), and built-environment density (BD 8.23%). Socio-economic variables such as GDP (6.87%) and population density (PopC 5.65%) contributed at moderate levels, while urban morphology variables (BH, FAR) and minor land cover fractions provided smaller stable adjustments.

Dependence analysis further elucidated the distinct operational modes of these key factors. FT exhibited a strong monotonic negative relationship with BL (spline  $R^2 = 0.78$ ), where higher forest cover progressively shortened the optimal lag, consistent with the microclimatic buffering role of vegetation in dampening cumulative thermal stress and accelerating physiological and emotional recovery.  $IMAX_h$  showed the most pronounced non-linear dependence ( $R^2 = 0.80$ ): at low peak intensities,  $IMAX_h$  strongly extended BL, but its effect attenuated rapidly and became weakly negative beyond the moderate-intensity range, suggesting that once peak heat shock surpassed a critical threshold, additional intensity no longer prolonged the lag but instead

triggered abrupt emotional responses with shorter recovery windows.  $RP_h$  displayed a non-linear positive pattern ( $R^2 = 0.72$ ), where cumulative heat load progressively increased BL through a sigmoidal transition from low to high values, indicating that sustained thermal accumulation extended the recovery window through a dose-response mechanism. GDP exhibited an inverted-U dependence ( $R^2 = 0.67$ ), peaking at intermediate GDP levels around 100 to 150 and declining at both lower and higher ends, suggesting that economic capacity influences BL through a combination of infrastructure provisioning at low income levels and rapid lifestyle adaptation at high income levels.

Taken together, the SHAP attribution of BL provides empirical evidence for the asynchrony between physical and emotional resilience identified in Notes S2 and S3. The 'prosperity penalty' is quantitatively confirmed by megacities receiving mixed effects on HGI (lower  $IMAX_h$  but prolonged  $RT_h$ ) yet a unidirectional double deficit on EGI (higher  $IMAX_e$  and longer  $RT_e$ ; Lederbogen et al., 2011). The 'accelerated social metabolism' is signalled by  $RT_e$  showing the highest scenario sensitivity among all EGI primitives (+33.5%, 90% CI: 13.2–53.8% under SSP5-8.5; Supplementary Note S9), reflecting how rapid urban tempo compresses the psychological repair window (Obradovich et al., 2018). The fact that no single physical heat-hazard variable dominated BL, together with the inverted-U dependence of GDP and the substantial contribution of land cover and geo-environmental factors, suggests that emotional response lag is shaped by a combination of ecological buffering, heat-stress dose-response dynamics, and socio-economic conditions rather than physical heat

intensity alone. This multi-factor structure is consistent with information–cognitive amplification effects, in which media and social-media coverage may independently prolong public emotional response beyond direct thermal exposure (Coombs, 2007). However, our current dataset does not include variables that directly capture information-exposure intensity (e.g., search-engine query indices, news-coverage metrics, or social-media trending-topic ranks). Future research integrating such information-environment variables, together with micro-scale data on air-conditioning prevalence and individual-level longitudinal psychological surveys, will be needed to test this information–cognitive pathway directly and to elevate the BL attribution from a strong indirect signal to a causal-mediation estimate

**Note S9: Temporal trajectories and component-level drivers of physical and emotional resilience (2025–2100)**

Time series reconstructions derived from an ensemble of 13 CMIP6 models indicated that under three SSP pathways, both HGI and EGI evolved with a distinct non-linear morphology characterized by moderate mid-term changes followed by accelerated late-term shifts (Extended Fig.7-9; Supplementary Fig.16-17). However, a temporal mismatch existed in their sensitivity to emission intensities. EGI exhibited quasi-plateau characteristics between 2025 and 2050, with relative changes of  $-1.4\%$  (90% CI:  $-10.0\%$  to  $+7.7\%$ ) under SSP1-2.6,  $-6.3\%$  (90% CI:  $-14.5\%$  to  $+1.4\%$ ) under SSP2-4.5, and  $-10.9\%$  (90% CI:  $-17.1\%$  to  $-2.0\%$ ) under SSP5-8.5; only the SSP5-8.5 trajectory crossed zero with statistical confidence in this early window. It was only after 2050 that a deep downward trajectory initiated under the higher-emission pathways, resulting in cumulative declines relative to 2025 of  $-5.9\%$  (90% CI:  $-18.2\%$  to  $+4.4\%$ ),  $-18.2\%$  (90% CI:  $-26.4\%$  to  $-10.0\%$ ), and  $-22.4\%$  (90% CI:  $-31.5\%$  to  $-20.1\%$ ) under SSP1-2.6, SSP2-4.5 and SSP5-8.5, respectively, by 2100. The SSP1-2.6 confidence interval continued to span zero, while the SSP2-4.5 and SSP5-8.5 declines were statistically robust.

In contrast, the attenuation of HGI displayed a marked early onset. Cumulative declines of  $3.3\%$  (90% CI:  $1.2\%$ – $10.5\%$ ) to  $8.3\%$  (90% CI:  $4.2\%$ – $18.5\%$ ) emerged within the first half of the century, accelerating further in the latter half as high-emission pathways locked in; by 2100, reductions reached  $-3.8\%$  (90% CI:  $-1.2\%$  to  $-17.4\%$ )



under SSP1-2.6,  $-14.1\%$  (90% CI:  $-6.6\%$  to  $-26.0\%$ ) under SSP2-4.5, and  $-28.5\%$  (90% CI:  $-20.4\%$  to  $-34.0\%$ ) under SSP5-8.5. These scenario-dependent trajectories suggested that high-emission pathways not only significantly amplified the magnitude of long-term decay but also widened the uncertainty bandwidth of predictions — a divergence directly visible in the broadening 90% CI bands of Extended Fig. 7–9 after 2060, especially under SSP5-8.5. Consequently, the structure of systemic risk diverged drastically in the second half of the century driven by scenario disparities.

The evolution of six structural components further elucidated the micro-dynamic sources of this index attenuation. Across all scenarios, the sustained rise in  $IMAX_h$ ,  $RT_h$ , and  $RP_h$  confirmed a synchronous deterioration in physical heat shock intensity, recovery lag, and process volatility, while the parallel elevation of  $IMAX_e$ ,  $RT_e$ , and  $RP_e$  signaled a systemic amplification of negative emotional peaks and hysteresis effects. This deteriorating trend presented a clear gradient differentiation across scenarios, driven primarily by incremental changes post-2050. Under SSP5-8.5, the magnitude of deterioration for physical and emotional components reached its zenith:  $IMAX_h$  and  $RT_h$  rose by  $35.6\%$  (90% CI:  $12.0 - 53.4\%$ ) and  $42.7\%$  (90% CI:  $21.0 - 64.5\%$ ) respectively, while  $IMAX_e$  and  $RT_e$  rose by  $24.4\%$  (90% CI:  $5.5 - 43.4\%$ ) and  $33.5\%$  (90% CI:  $13.2 - 53.8\%$ ); the corresponding cumulative-load components,  $RP_h$  and  $RP_e$ , increased by  $36.2\%$  (90% CI:  $15.5 - 57.0\%$ ) and  $33.4\%$  (90% CI:  $13.1 - 53.7\%$ ). These values far exceed the moderate increases observed under SSP1-2.6, where most component-level 90% CIs span zero — for example,  $IMAX_h +13.8\%$  (90% CI:  $-8.4\%$  to  $+33.3\%$ ) and  $IMAX_e +9.2\%$  (90% CI:  $-10.8\%$  to  $+29.2\%$ ) —

indicating that low-emission pathways yield no statistically distinguishable component-level deterioration. Notably, among all components,  $RT_h$  and the SSP2-4.5  $RT_h$  in particular (+47.0%, 90% CI: 19.7 – 74.2%) exhibited the highest scenario sensitivity. This revealed that structural degradation at the recovery end, rather than mere peak elevation, constituted the dominant channel driving resilience collapse in a high-emission future. Furthermore, the physical and emotional linkages displayed stronger synergistic amplification characteristics in the latter half of the century.

**Note S10: Positioning HGI–EGI findings within the IPCC AR6 framework**

AR6 WGII Chapter 16 distinguishes soft limits, beyond which current adaptation measures become insufficient under prevailing constraints, from hard limits, beyond which no feasible adaptation can preserve system functioning. The dominance of recovery-end degradation under SSP5-8.5, with  $RT_e$  rising by 33.5% (90% CI: 13.2 to 53.8%) and showing the highest scenario sensitivity among all EGI primitives (Supplementary Note S9), provides a quantitative signature of cities approaching the soft limits of emotional adaptation. This signature is characterized by the gradual, compounding erosion of inter-event recuperation capacity, in which each successive heatwave leaves the population incompletely recovered before the next event begins. By the 2050s under SSP5-8.5, a substantial fraction of Chinese cities may cross this emotional soft limit well before comparable transitions occur in the physical HGI dimension.

AR6 WGII Chapter 8 emphasizes that non-economic losses, including harms to mental health, cultural identity, and community cohesion, constitute a systematically under-quantified dimension of climate-induced L&D, primarily due to the lack of scalable measurement frameworks. The EGI framework directly addresses this gap by providing a spatio-temporally resolved, population-scale, and cross-event-comparable metric of emotional harm. The faster decline of EGI relative to HGI, with a relative decline ratio of approximately 1.25 (90% CI: 1.07 to 1.46), implies that even as physical infrastructure adapts, climate-induced harm progressively accumulates in the

non-economic L&D dimension, which is precisely the dimension least represented in current national and international assessments. Following the COP27 Loss and Damage Fund decision, indicators such as EGI warrant consideration for inclusion in future L&D monitoring and attribution efforts.

Whether the prosperity penalty reflects a universal feature of urban heat adaptation or an East Asian specific product warrants explicit assessment. The underlying mechanism, which involves densification-driven compression of psychological recovery, reduced access to recuperative environments, and amplification of social metabolism, does not rely on culturally or institutionally specific assumptions and has been independently documented in European and North American contexts, suggesting qualitative universality across high-density metropolitan regions. The quantitative intensity we observe in Chinese cities may, however, be amplified by East Asian features that include exceptionally rapid densification, the prevalence of super-tall residential developments, and patterns of long working hours that erode baseline psychological resources. Cross-continental comparative analyses extending the HGI and EGI framework to Europe, South Asia, and Latin America are identified as a priority direction for future research.

## B. Supplementary Tables

**Supplementary Table 1.** *Statistical significance and magnitude of emotional trends in 40 representative cities: Z-values, P-values, Sen's slopes and Best lag days derived from 3-hour scale observations.*

| City      | Z Value | P Value  | Sen Slope | Best Lag days |
|-----------|---------|----------|-----------|---------------|
| Beijing   | -2.3683 | 0.0179   | -0.000023 | 3.6           |
| Shanghai  | 7.8170  | 5.33e-15 | 0.000078  | 2.9           |
| Guangzhou | -4.0572 | 0.00005  | -0.000059 | 2.5           |
| Shenzhen  | 2.3623  | 0.0182   | 0.000028  | 2.9           |
| Tianjin   | 3.0763  | 0.0021   | 0.000054  | 4.0           |
| Chongqing | -1.9819 | 0.0475   | -0.000037 | 3.4           |
| Nanjing   | 3.8714  | 0.0001   | 0.000025  | 2.6           |
| Suzhou    | 9.5870  | 0.0000   | 0.000146  | 3.0           |
| Hangzhou  | -2.7953 | 0.0052   | -0.000041 | 2.6           |
| Wuhan     | -2.3090 | 0.0209   | -0.000032 | 3.0           |
| Xian      | -2.0535 | 0.0400   | -0.000035 | 3.2           |
| Wuxi      | -4.4134 | 0.00001  | -0.000073 | 2.9           |
| Ningbo    | -5.6040 | 2.09e-08 | -0.000114 | 2.9           |
| Changsha  | -6.0617 | 1.35e-09 | -0.000033 | 2.8           |
| Hefei     | -6.8170 | 9.30e-12 | -0.000183 | 3.4           |
| Fuzhou    | 3.0925  | 0.0020   | 0.000086  | 2.4           |
| Jinan     | -2.3610 | 0.0182   | -0.000054 | 3.5           |
| Shenyang  | 2.3145  | 0.0206   | 0.000044  | 3.3           |

|                  |         |          |           |     |
|------------------|---------|----------|-----------|-----|
| <b>Haerbin</b>   | 2.0689  | 0.0386   | 0.000019  | 2.9 |
| <b>Dalian</b>    | -4.8353 | 1.33e-06 | -0.000072 | 3.1 |
| <b>Xiamen</b>    | -3.2981 | 0.0010   | -0.000042 | 2.2 |
| <b>Foshan</b>    | 2.3862  | 0.0170   | 0.000023  | 2.8 |
| <b>Nanning</b>   | -2.5295 | 0.0114   | -0.000054 | 2.0 |
| <b>Haikou</b>    | 2.5018  | 0.0124   | 0.000115  | 2.2 |
| <b>Guiyang</b>   | 2.6206  | 0.0088   | 0.000032  | 2.6 |
| <b>Lanzhou</b>   | -2.7202 | 0.0065   | -0.000124 | 3.3 |
| <b>Nanchang</b>  | -2.7852 | 0.0053   | -0.000040 | 3.2 |
| <b>Huhehaote</b> | -3.7197 | 0.0002   | -0.000084 | 3.5 |
| <b>Wulumuqi</b>  | 2.3429  | 0.0191   | 0.000055  | 3.8 |
| <b>Changzhou</b> | -8.4626 | 0.0000   | -0.000326 | 3.3 |
| <b>Dongguan</b>  | 3.5582  | 0.0004   | 0.000072  | 3.1 |
| <b>Huizhou</b>   | -2.9159 | 0.0035   | -0.000088 | 2.5 |
| <b>Jiaxing</b>   | -2.3576 | 0.0184   | -0.000031 | 2.8 |
| <b>Nantong</b>   | -2.5822 | 0.0098   | -0.000045 | 2.5 |
| <b>Quanzhou</b>  | -4.8088 | 1.52e-06 | -0.000094 | 2.3 |
| <b>Wenzhou</b>   | -2.0244 | 0.0429   | -0.000042 | 2.2 |
| <b>Xuzhou</b>    | 3.4753  | 0.0005   | 0.000111  | 3.4 |
| <b>Yantai</b>    | 2.0603  | 0.0394   | 0.000037  | 2.7 |
| <b>Zhongshan</b> | 2.2163  | 0.0267   | 0.000070  | 2.6 |

**Supplementary Table 2.** *Summary of explanatory variables, physical mechanisms, and variance inflation factors (VIF)*

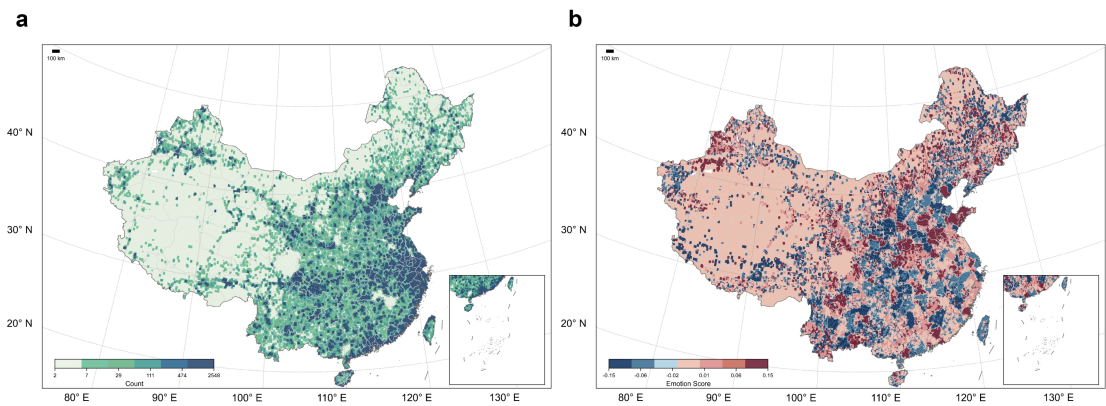
| Category                     | Variable                               | Abbreviation      | Physical Mechanism & Rationale                                             | VIF                      |
|------------------------------|----------------------------------------|-------------------|----------------------------------------------------------------------------|--------------------------|
| Physical Resilience Metrics  | Heat Recovery Time                     | RT <sub>h</sub>   | Duration required for the thermal environment to return to baseline levels | 1.11                     |
|                              | Peak Heat Severity                     | IMAX <sub>h</sub> | Maximum intensity of the heatwave event relative to the baseline           | 1.40                     |
|                              | Cumulative Heat Magnitude              | RP <sub>h</sub>   | Total accumulated thermal stress (area under the curve) during the event   | 1.33                     |
| Emotional Resilience Metrics | Emotion Recovery Time                  | RT <sub>e</sub>   | Duration for public sentiment to recover to baseline levels after heat     | 1.11                     |
|                              | Peak Emotional Severity                | IMAX <sub>e</sub> | Maximum intensity of negative emotional expression during the heatwave     | 1.16                     |
|                              | Cumulative Emotional Perturbation      | RP <sub>e</sub>   | Total accumulated emotional stress load during the event                   | 1.19                     |
| Socio-economic Status        | Gross Domestic Product                 | GDP               | Proxy for anthropogenic waste heat discharge from economic activities      | 2.94                     |
|                              | Population Count                       | PopC              | Represents metabolic heat release and human activity intensity             | 3.26                     |
| Topographic Context          | Elevation                              | DEM               | Background modulation of thermal lapse rates and local circulation         | 2.32                     |
| Vegetation & Land Cover      | Normalized Difference Vegetation Index | NDVI              | Characterizes vegetation vitality and surface energy partitioning          | 4.76                     |
|                              | Forest / Grassland / Cropland          | FT / GD / CD      | Capture canopy structures and evapotranspiration cooling capacities        | 4.88 /<br>4.27 /<br>4.94 |
|                              | Water Bodies                           | WR                | Reflects thermal regulation via high specific heat capacity                | 1.34                     |
|                              | Barren Land / Built-up Areas           | BN / UP           | Impervious substrates with low moisture and high heat storage              | 4.17 /<br>4.60           |
|                              | Grid-average Building Height           | BH                | Signifies vertical wind blockage potential and aerodynamic                 | 4.75                     |
| Built Environment            | Grid-average Building Density          | BD                | Horizontal surface area available for solar heat storage                   | 4.55                     |
|                              | Floor Area Ratio                       | FAR               | Metric of development intensity                                            | 4.42                     |

**Supplementary Table 3.** *The CMIP6 models used in the analysis. Listed are the ensemble size of the ALLforcing, NAT-forcing, GHG-forcing, segments of piControl simulations, SSP1-2.6, SSP2-4.5, and SSP5-8.5 experiments, and the equilibrium climate sensitivity (ECS) of climate models. The ECS estimates are from Zelinka et al. (2020)*

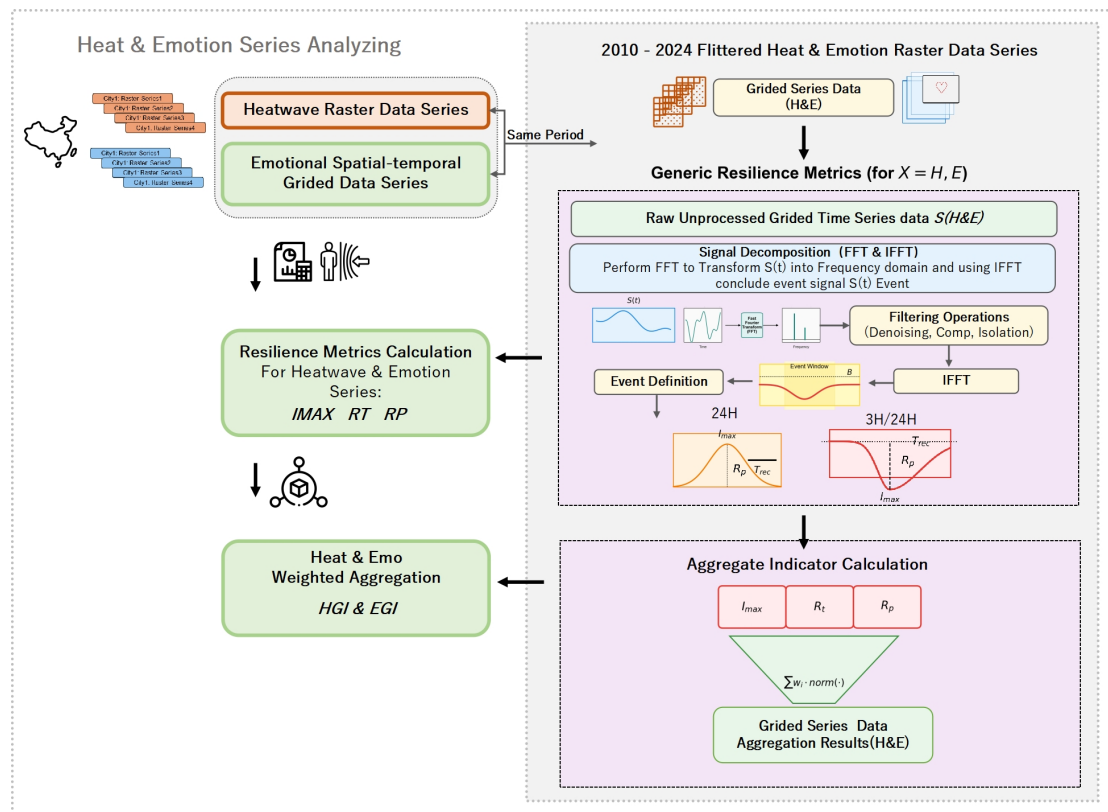
| MODEL         | ALL | NAT | GHG | piControl | SSP 1-2.6 | SSP 2-4.5 | SSP 5-8.5 | ECS (K) |
|---------------|-----|-----|-----|-----------|-----------|-----------|-----------|---------|
| ACCESS-CM2    | 3   | 3   | 3   | 1         | 3         | 3         | 3         | 4.72    |
| ACCESS-ESM1-5 | 3   | 3   | 3   | 1         | 3         | 3         | 3         | 3.88    |
| BCC-CSM2-MR   | 3   | 3   | 3   | 1         | 1         | 1         | 1         | 3.02    |
| CanESM5       | 10  | 10  | 10  | 1         | 25        | 25        | 25        | 5.64    |
| CESM2         | 3   | 3   | 3   | 1         | 3         | 3         | 3         | 5.15    |
| CNRM-CM6-1    | 6   | 6   | 6   | 1         | 6         | 6         | 6         | 4.83    |
| FGOALS-g3     | 3   | 3   | 3   | 1         | 1         | 1         | 1         | 2.87    |
| GFDL-ESM4     | 3   | 3   | 3   | 1         | 1         | 1         | 1         | 2.65    |
| GISS-E2-1-G   | 5   | 5   | 5   | 1         | 5         | 5         | 5         | 2.72    |
| IPSL-CM6A-LR  | 6   | 6   | 6   | 1         | 6         | 6         | 6         | 4.56    |
| MIROC6        | 3   | 3   | 3   | 1         | 3         | 3         | 3         | 2.60    |
| MRI-ESM2-0    | 3   | 3   | 3   | 1         | 1         | 1         | 1         | 3.15    |
| NorESM2-LM    | 3   | 3   | 3   | 1         | 1         | 1         | 1         | 2.54    |
| SUM (runs)    | 54  | 54  | 54  | 13        | 59        | 59        | 59        | —       |



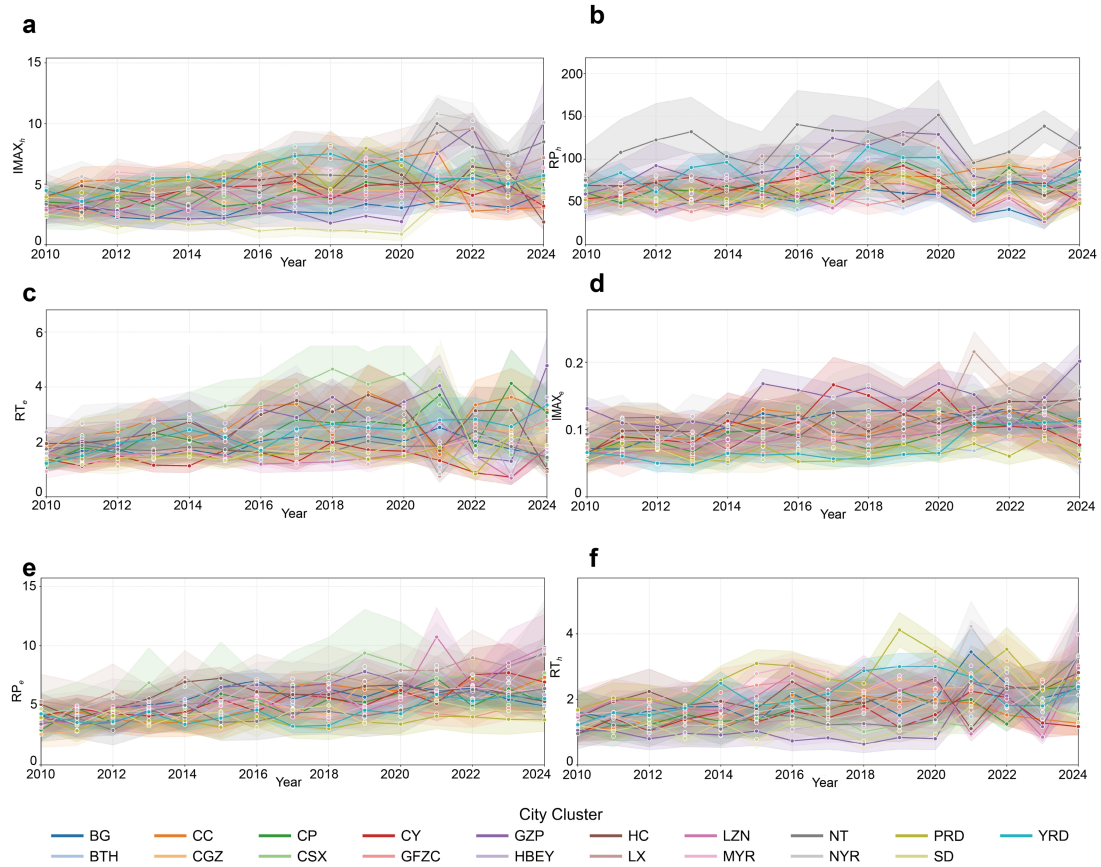
C. Supplementary Figures



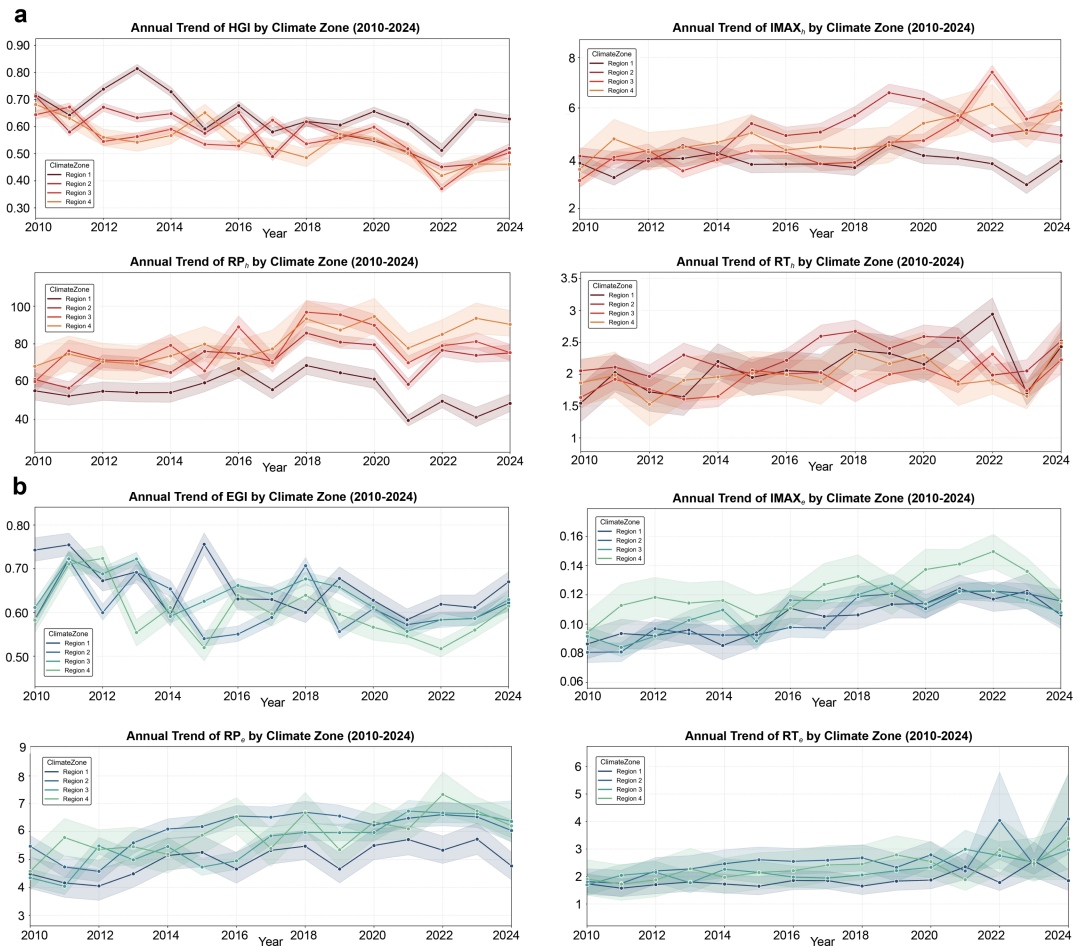
**Supplementary Fig. 1. Spatial coverage of social emotion data.** a, Density of geolocated Weibo comments used in the analysis. b, Spatial distribution of calculated sentiment scores.



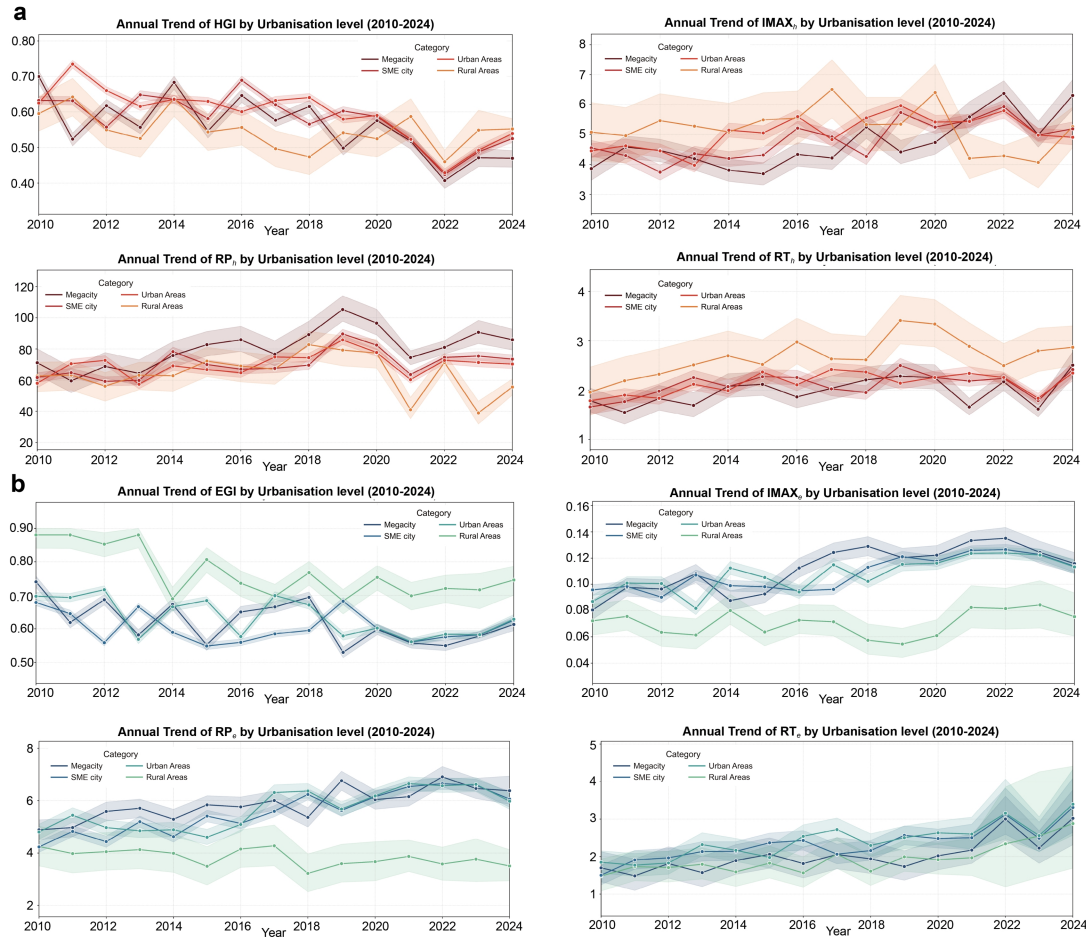
**Supplementary Fig. 2. Computational framework for quantifying heat and emotional resilience metrics.**



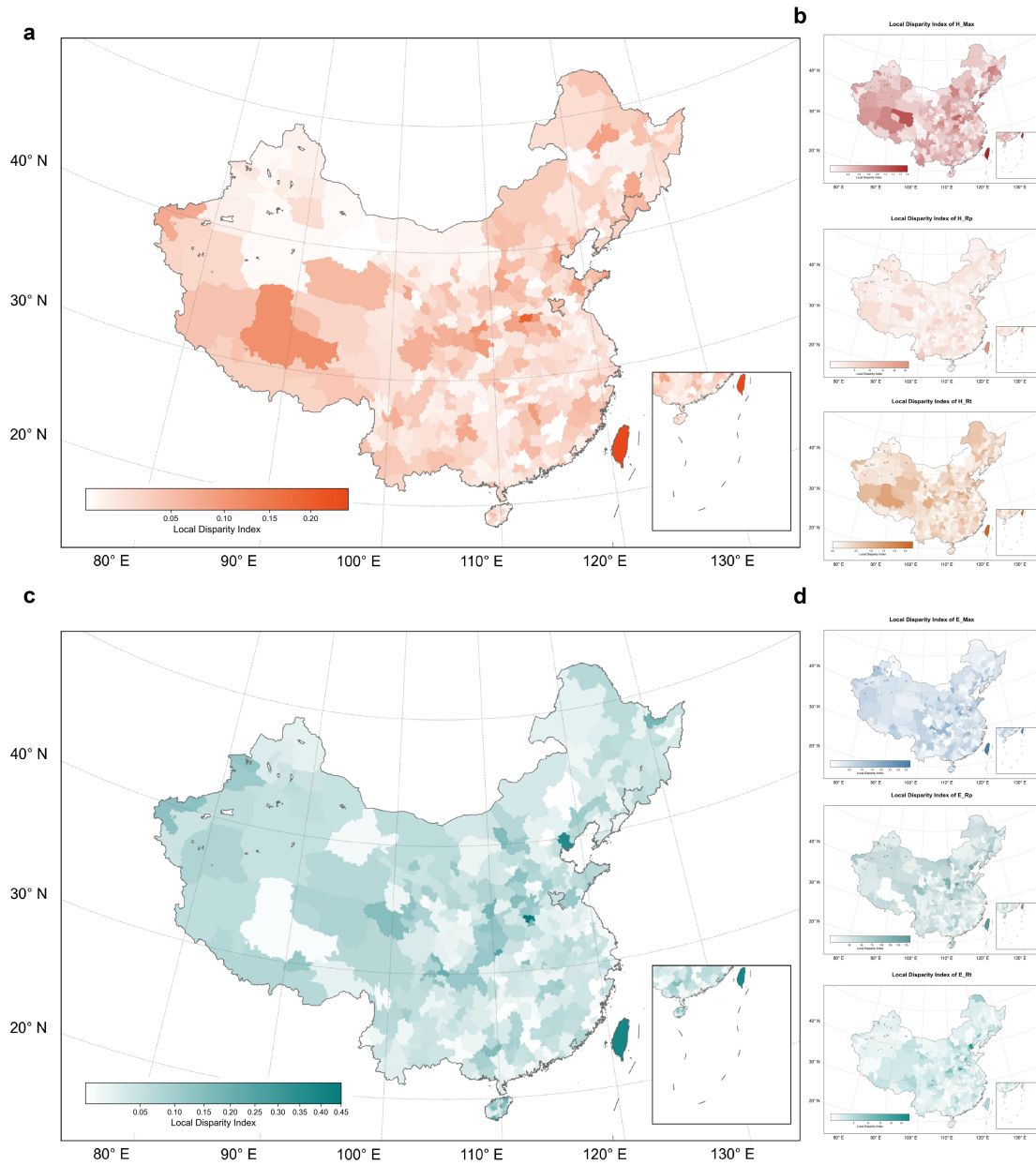
**Supplementary Fig. 3. Interannual variability of resilience components across city clusters (2010 – 2024).** a – c, Heat components:  $IMAX_h$  (a),  $RP_h$  and  $RT_h$  (c). d – f, Emotion components:  $IMAX_e$  (d),  $RP_e$  (e), and  $RT_e$  (f). Coloured lines represent individual city clusters; shaded areas denote 95% confidence intervals.



**Supplementary Fig. 4. Interannual variability of resilience metrics across climate zones (2010 – 2024).** a, Heat metrics: HGI,  $IMAX_h$ ;  $RP_h$ , and  $RT_h$ . b, Emotion metrics: EGI,  $IMAX_e$ ;  $RP_e$ , and  $RT_e$ . Coloured lines represent climatic regions (TSC, WTC, CTC, PC); shaded areas denote 95% confidence intervals.

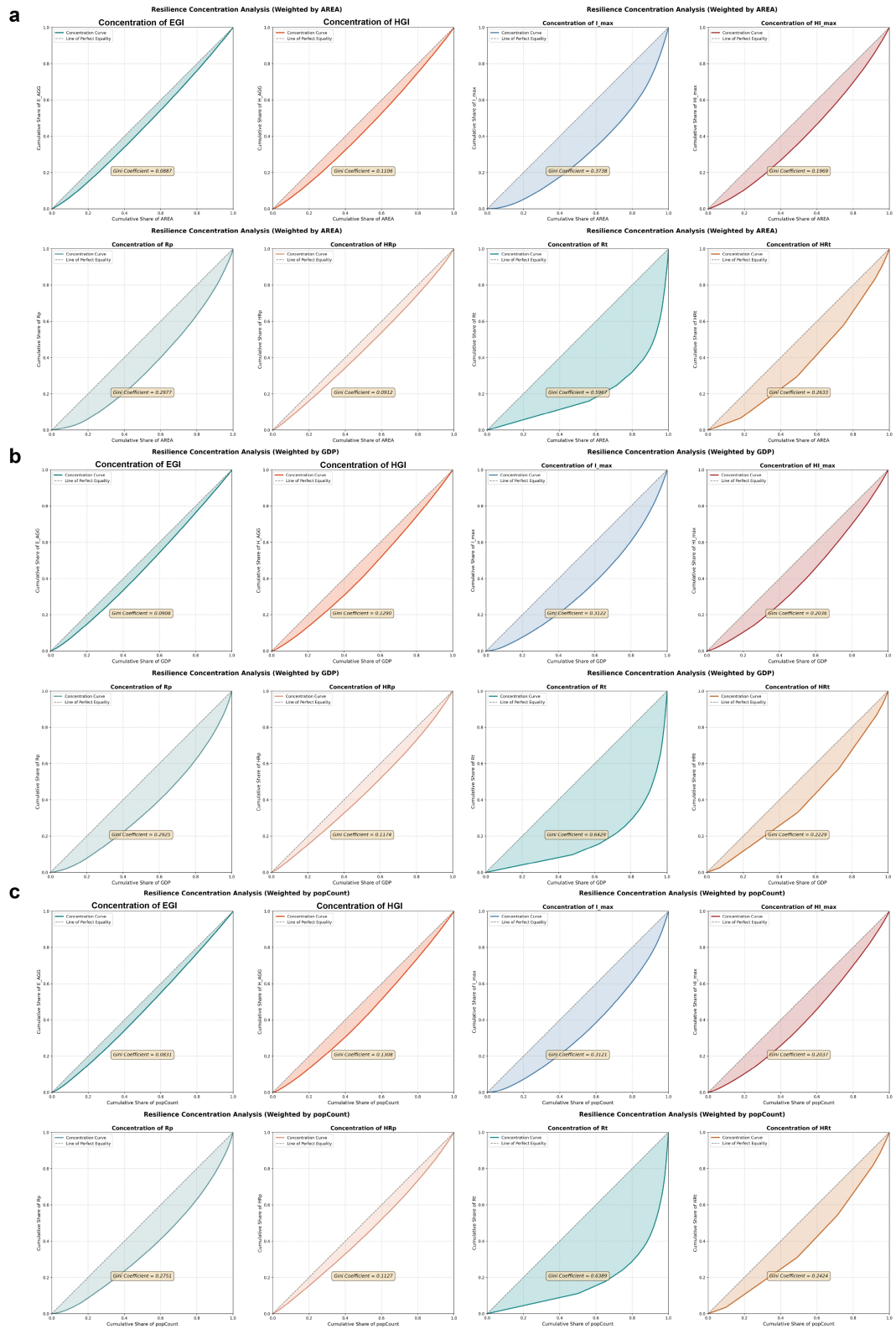


**Supplementary Fig. 5. Interannual variability of resilience metrics across urbanization levels (2010 – 2024).** a, Heat metrics:  $HGI$ ,  $IMAX_h$ ,  $RP_h$ , and  $RT_h$ . b, Emotion metrics:  $EGI$ ,  $IMAX_e$ ,  $RP_e$ , and  $RT_e$ . Coloured lines represent urbanization categories (Megacity, SME City, Urban Areas, Rural Areas); shaded areas denote 95% confidence intervals.



**Supplementary Fig. 6. Spatial patterns of local inequality characterized by the Local Disparity Index (LDI).** a, c, HGI (a) and EGI (c). b, Heat components ( $IMAX_h$ ;  $RP_h$ , and  $RT_h$ ). d, Emotion components ( $IMAX_e$ ;  $RP_e$ , and  $RT_e$ ). Darker shades indicate higher disparity.

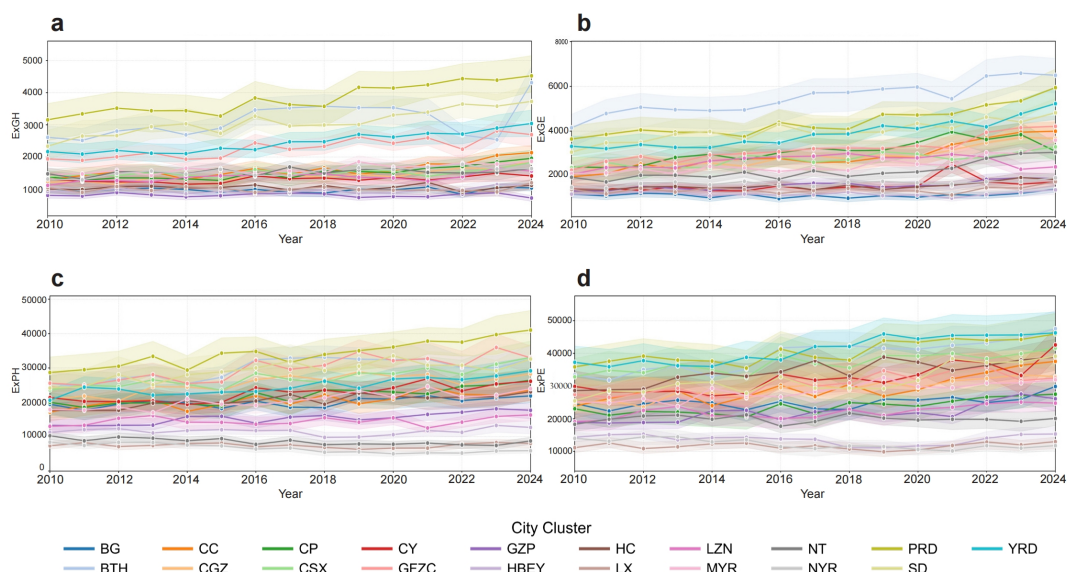




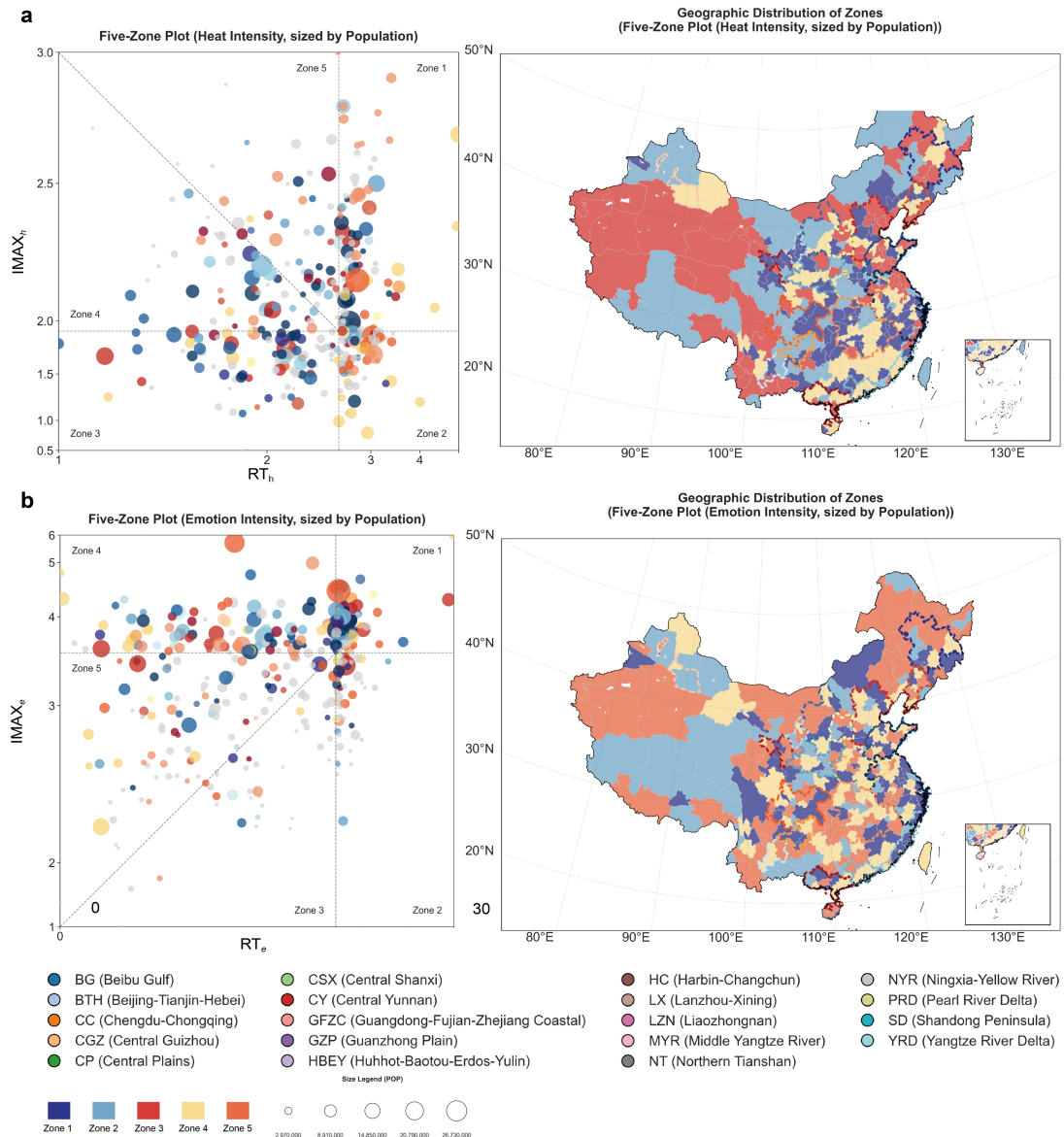
**Supplementary Fig.7. Lorenz curves quantifying inequality in resilience metrics.**  
a, Population-weighted; b, GDP-weighted; and c, Area-weighted. The diagonal line represents perfect equality.



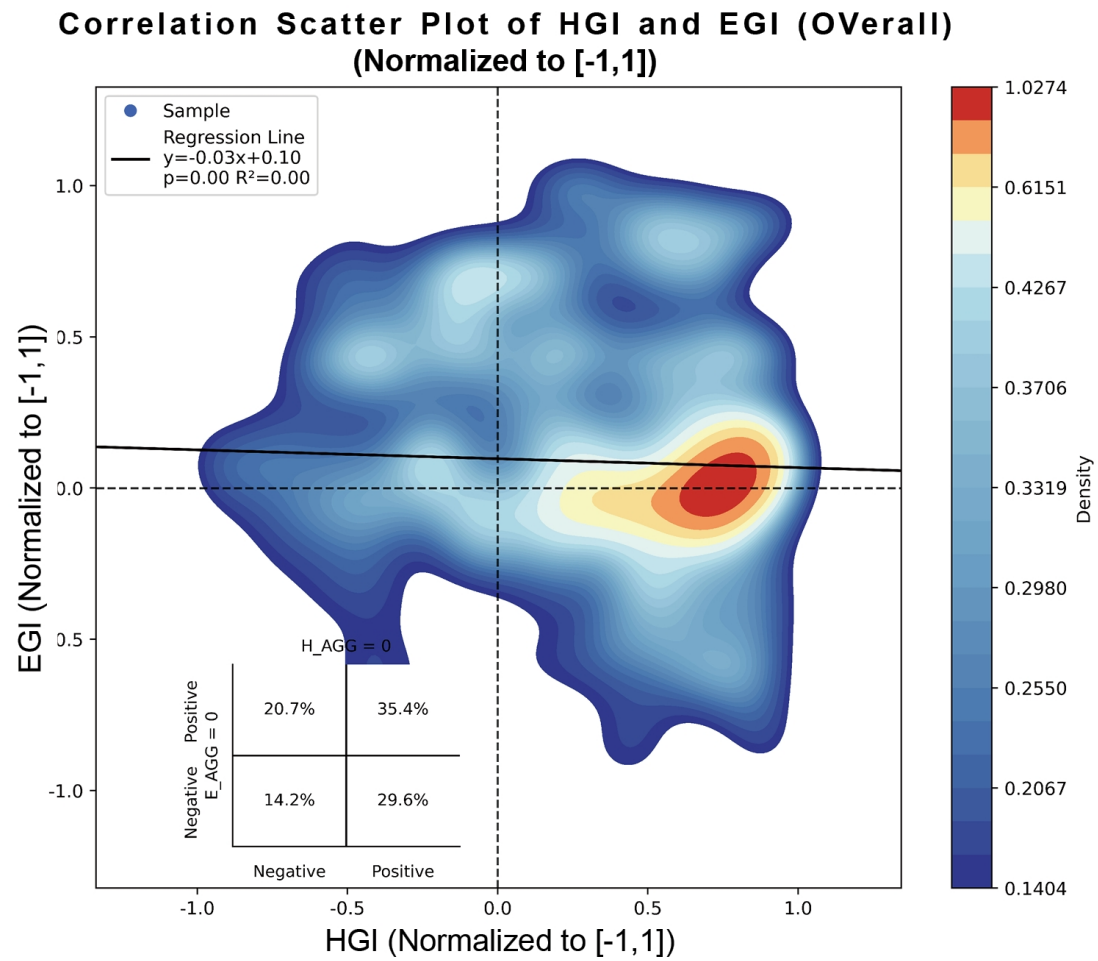




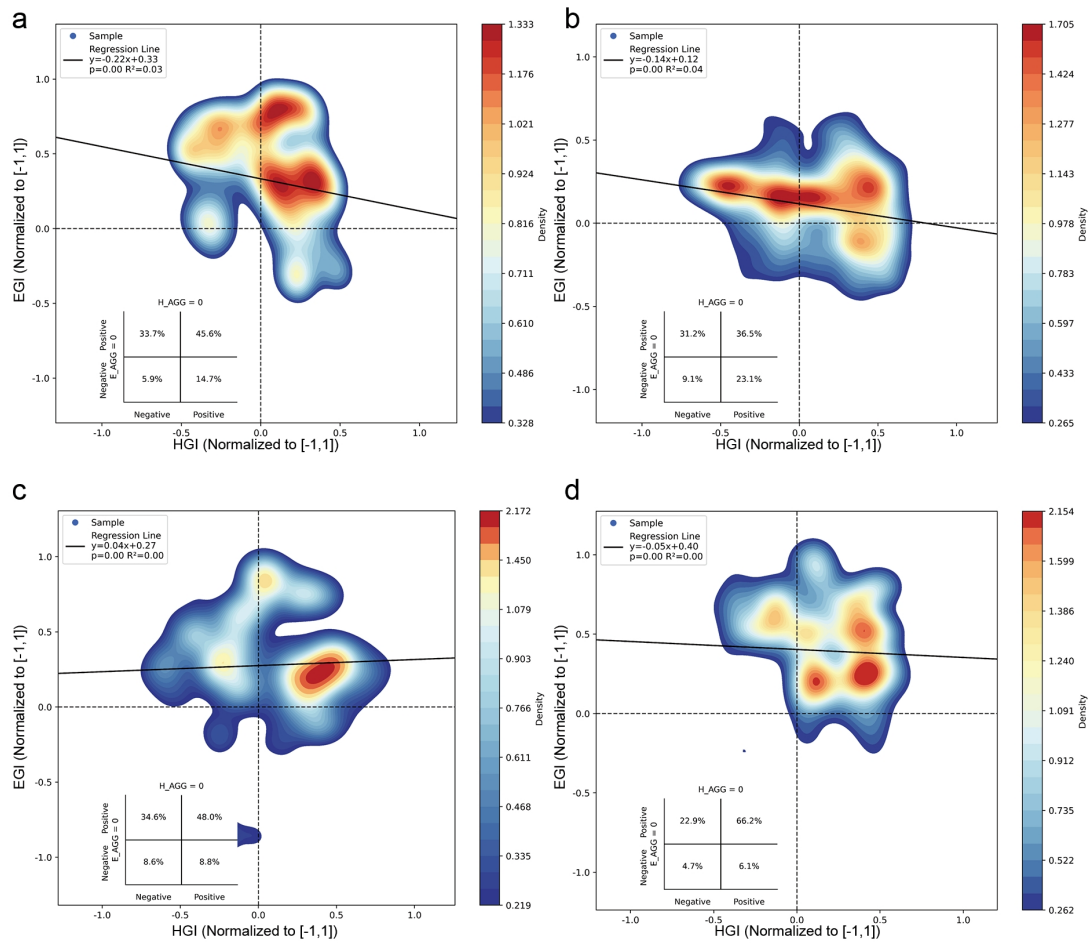
**Supplementary Fig. 9. Temporal trajectories of socioeconomic exposure to physical heat and emotional stress.** a,b, Annual trajectories of GDP exposure to physical heat (E\_GH; a) and emotional stress (E\_GE; b) across 19 Chinese city clusters from 2010 to 2024. c,d, Corresponding trajectories of population exposure to physical heat (E\_PH; c) and emotional stress (E\_PE; d). Coloured solid lines represent annual cluster means, filled circles indicate observed annual values and semi-transparent bands show 90% confidence intervals obtained by bootstrapping across constituent cities.



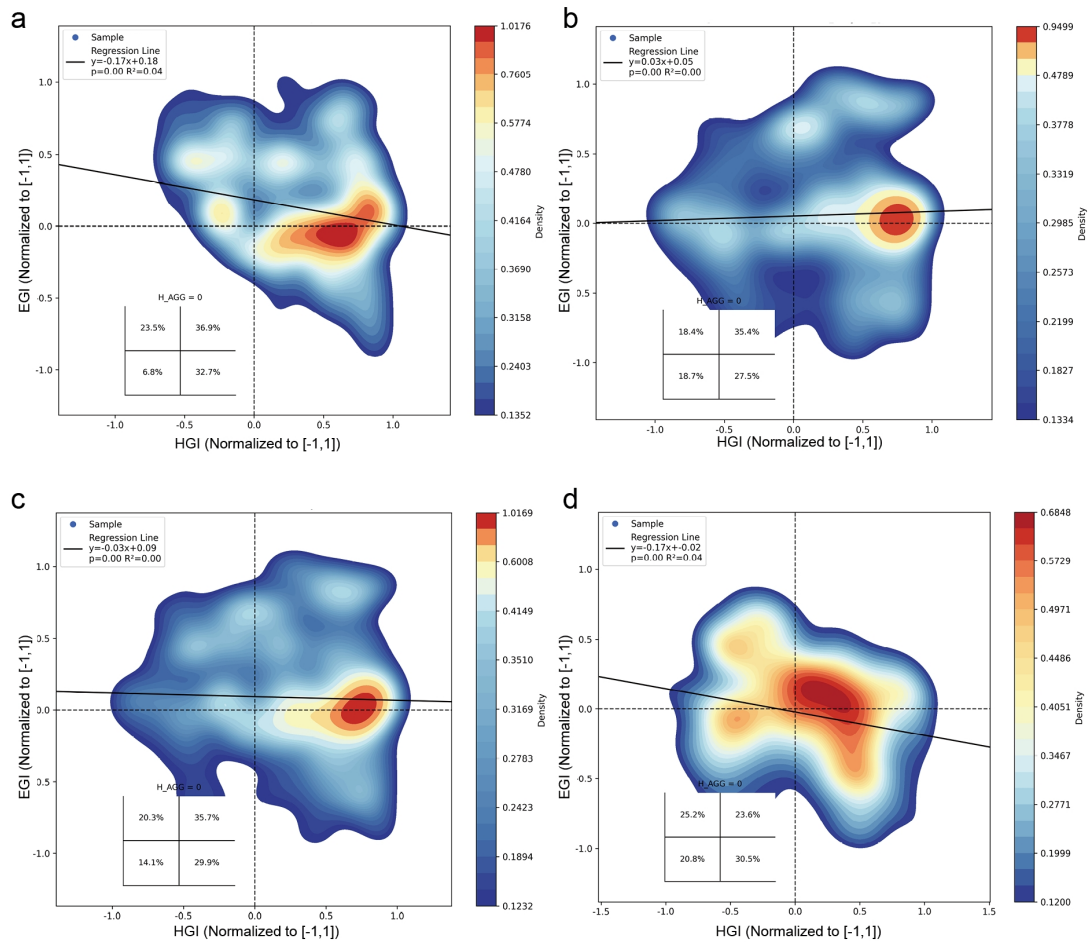
**Supplementary Fig. 10. Pentagonal scatter plots mapping 357 cities based on population weighting.** a, b, Classification of Heat Intensity (a) and Emotion Intensity (b). Bubble sizes indicate population magnitude, while colours represent the 19 city clusters.



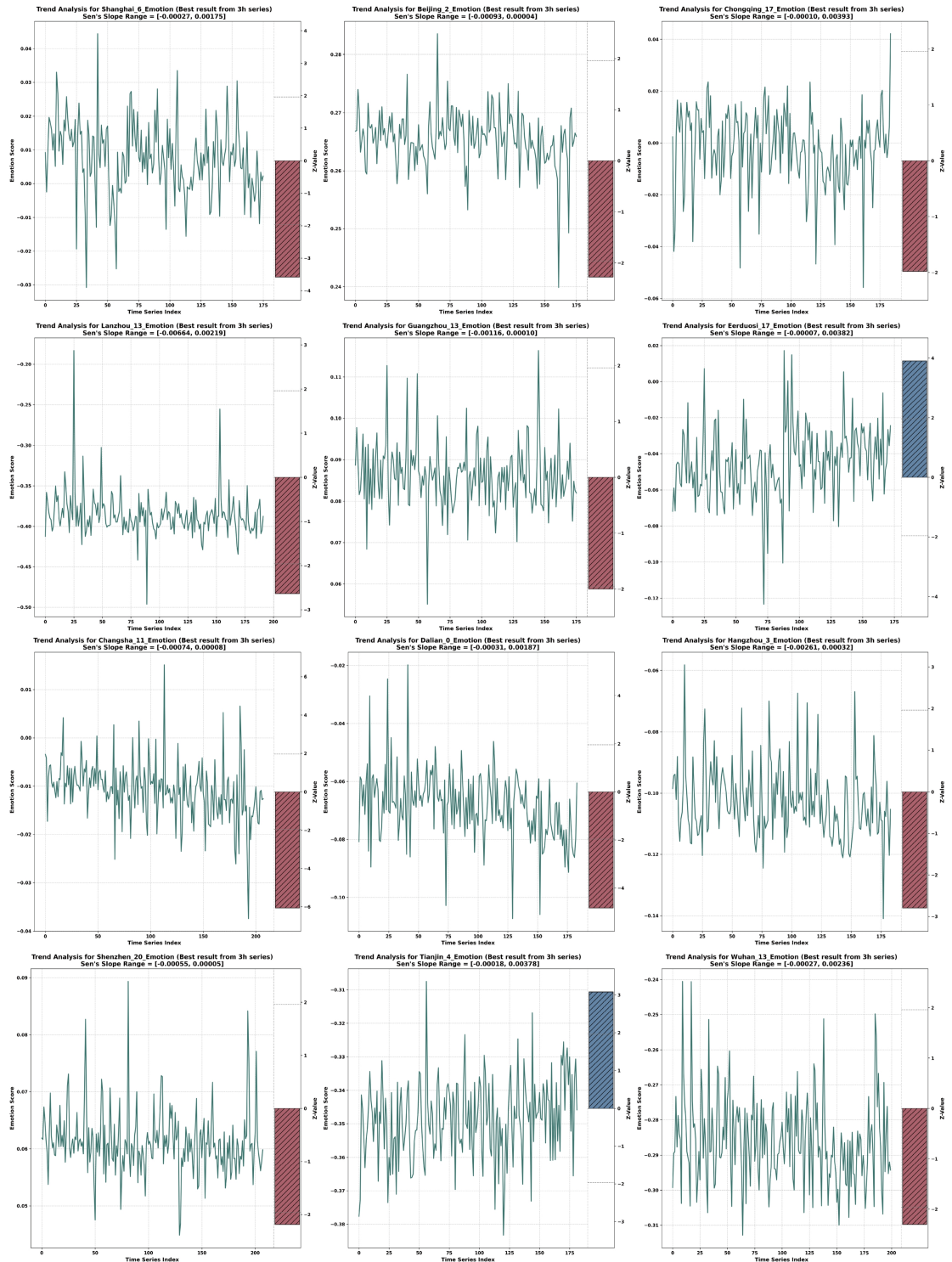
**Supplementary Fig.11. Bivariate KDE analysis of HGI and EGI decoupling.**



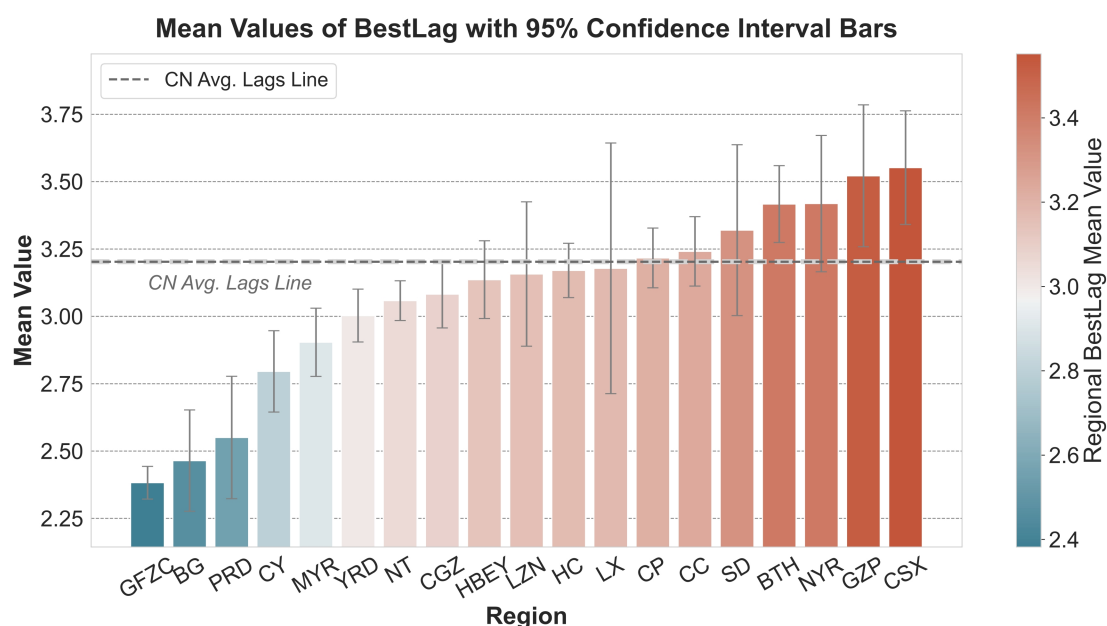
**Supplementary Fig.12. Bivariate KDE analysis of HGI and EGI decoupling across climatic zones.** a, Climatic regions: tropical – subtropical (TSC); b, warm temperate (WTC); c, cold temperate (CTC); d, plateau climate (PC).



**Supplementary Fig.13. Bivariate KDE analysis of HGI and EGI decoupling across city scale and urban contexts. a, megacity; b, SME City; c, urban areas; d, rural areas.**

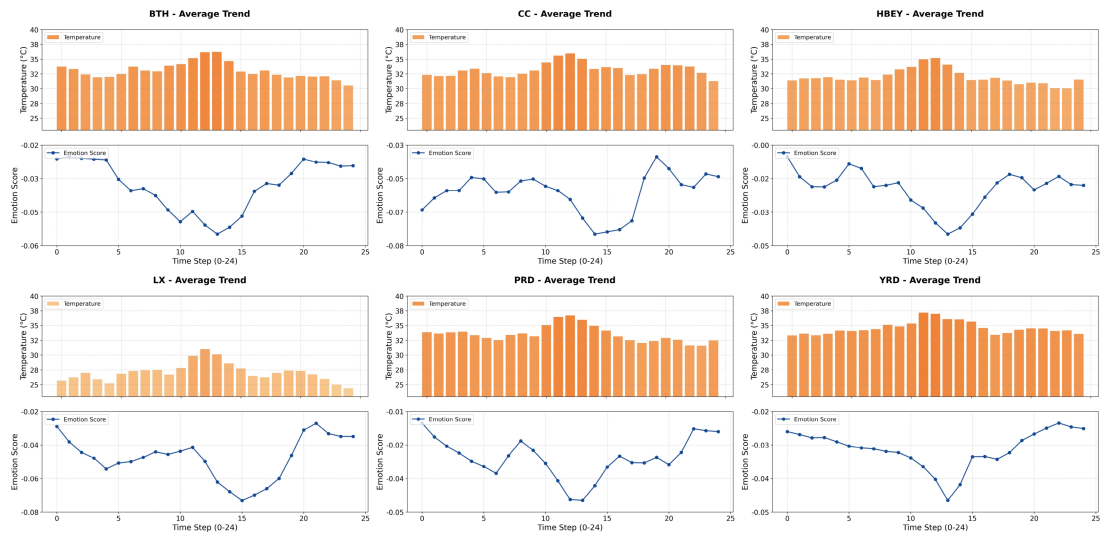


**Supplementary Fig.14. Mann - Kendall trend detection and Sen ' s slope quantification for twelve representative cities.** Bars are colour-coded to indicate the trend direction: red represents a positive Sen ' s slope (associated with active recovery or increasing resilience), whereas blue represents a negative Sen ' s slope (indicating persistent stress accumulation or decreasing resilience). The asterisk (\*) denotes statistical significance at the 0.05 level.



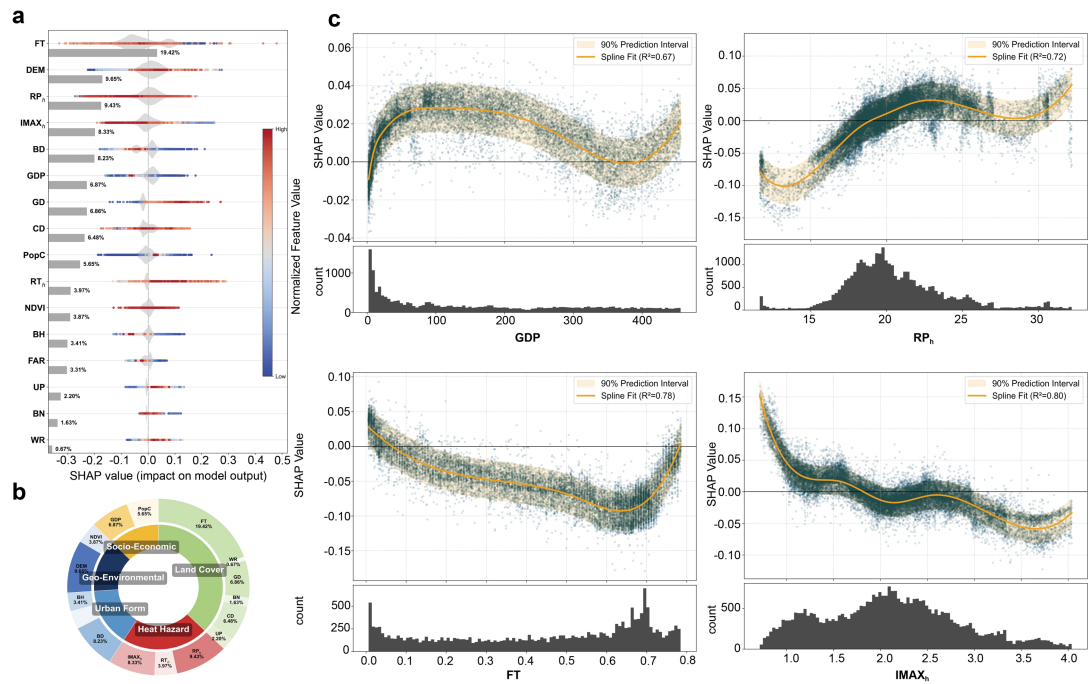
**Supplementary Fig.15. Regional heterogeneity in the lag response of emotional sentiment across 19 major urban agglomerations.** The bar chart displays the estimated Best Lag (BL) days for each city cluster, derived from Distributed Lag Non-linear Models (DLNM). The height of each bar represents the regional mean, while error bars denote the 95% confidence intervals (95% CI).



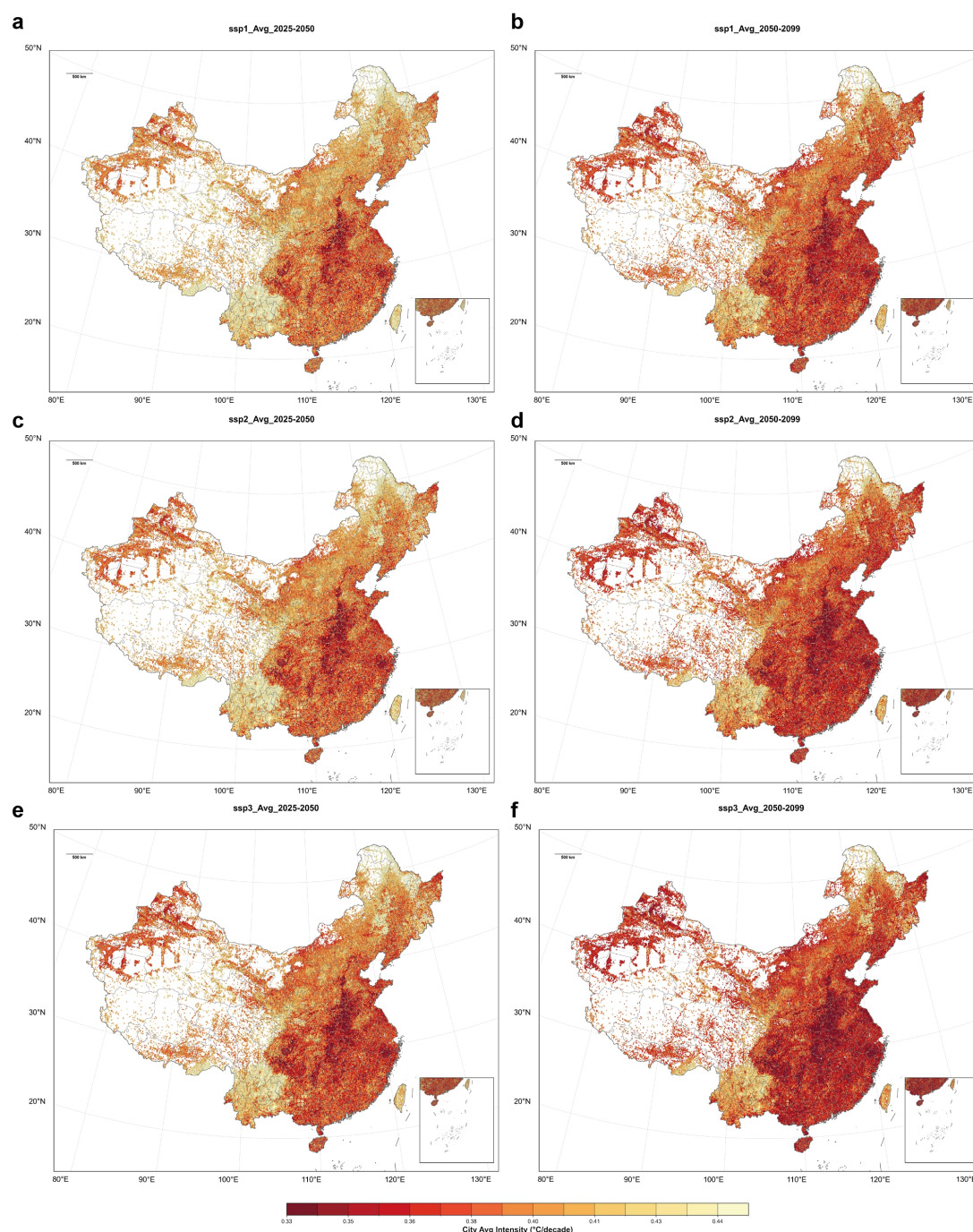


**Supplementary Fig.16. Daily time series of maximum temperature and emotion scores across six representative urban agglomerations.**

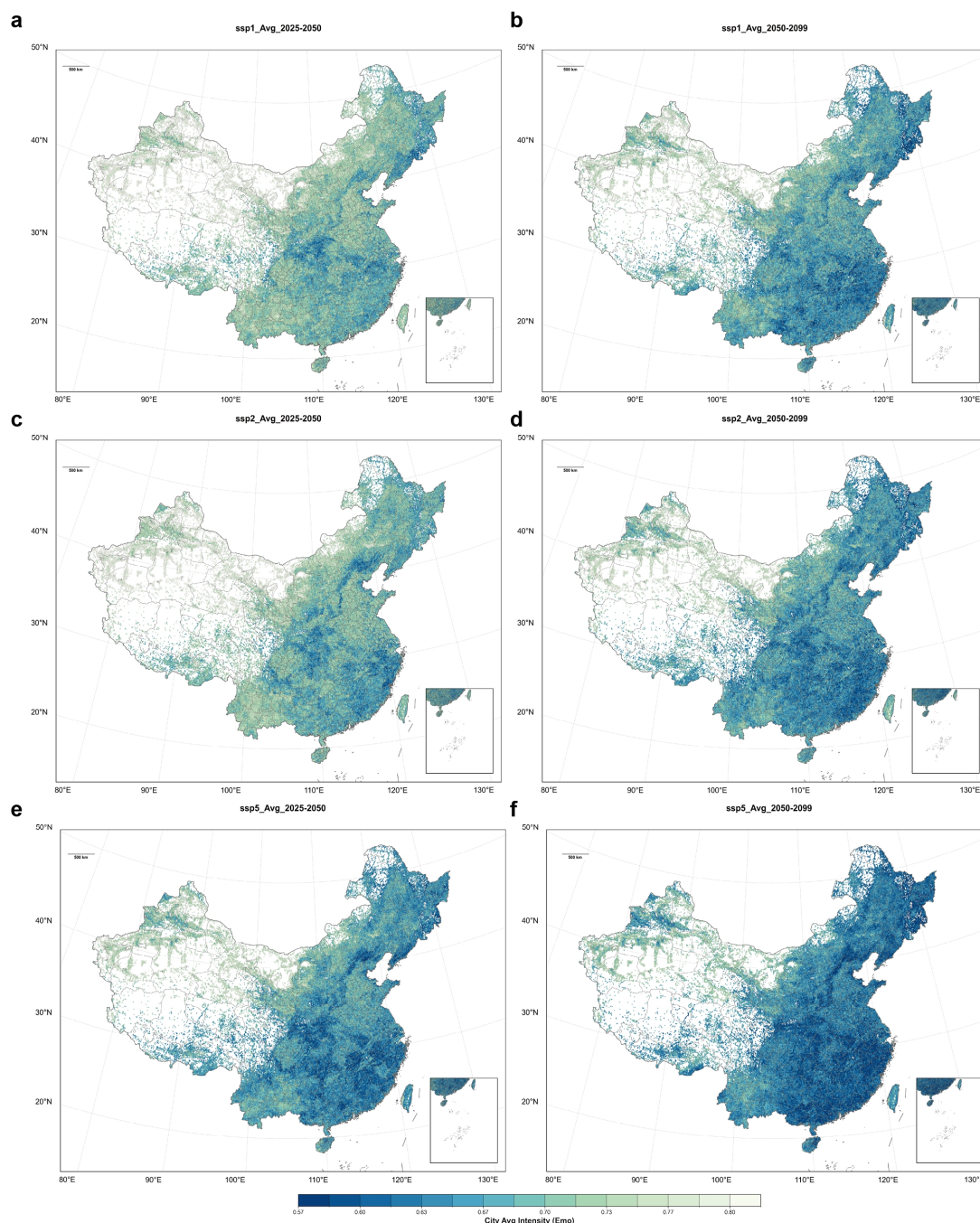




**Supplementary Fig.17. Global importance and local effect of each feature in the ensemble learning models for BL.**

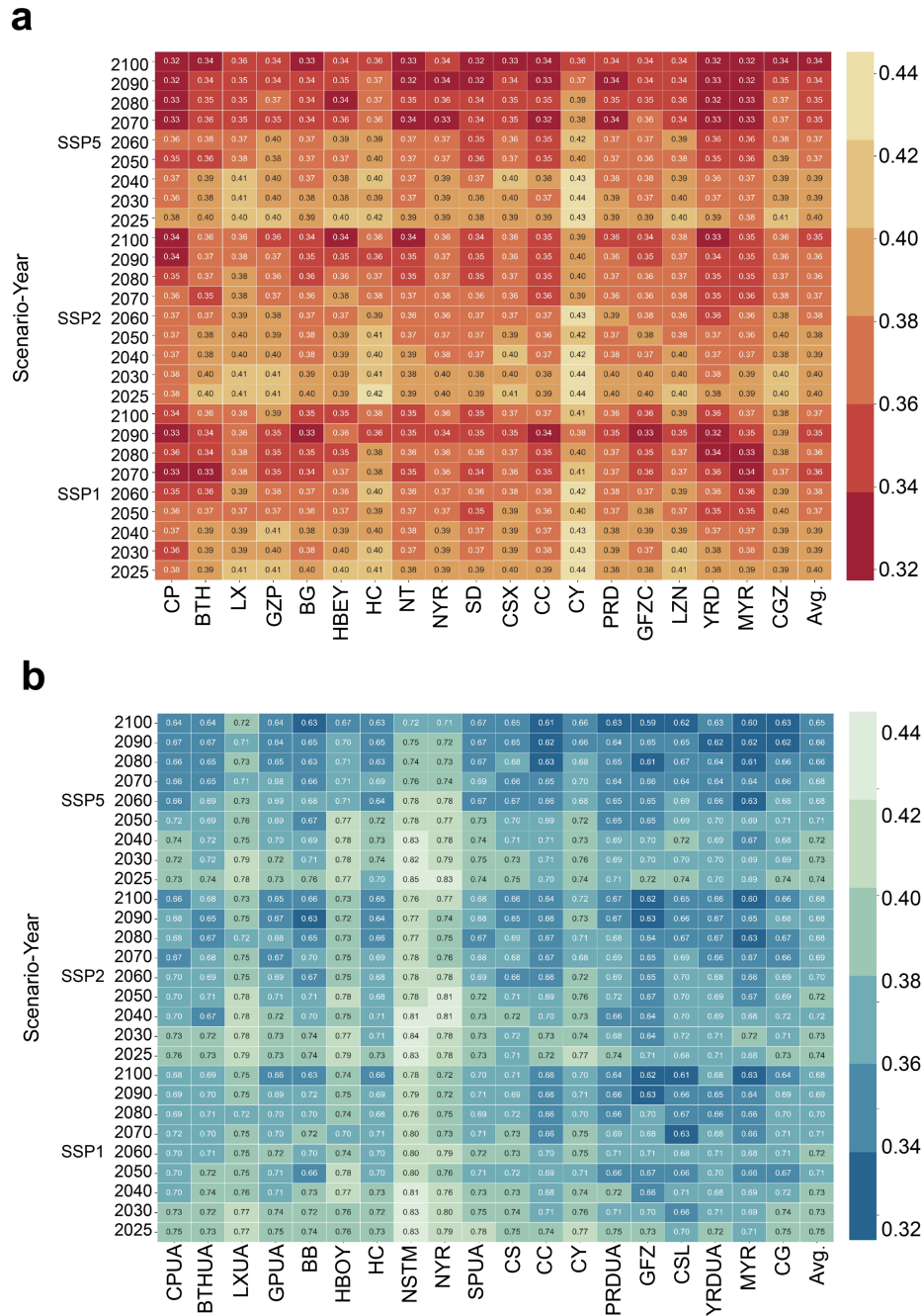


**Supplementary Fig.18. Projected spatiotemporal evolution of HGI under different SSP - RCP scenarios.** The maps visualize the projected mean HGI across Chinese cities for the near-term (2025 - 2050) and long-term (2050 - 2100) periods. a, b, Spatial distribution of mean HGI under the SSP1-2.6 scenario for 2025 - 2050 (a) and 2050 - 2100 (b). c, d, Projections under the SSP2-4.5 scenario for the same time periods. e, f, Projections under the SSP5-8.5 scenario.

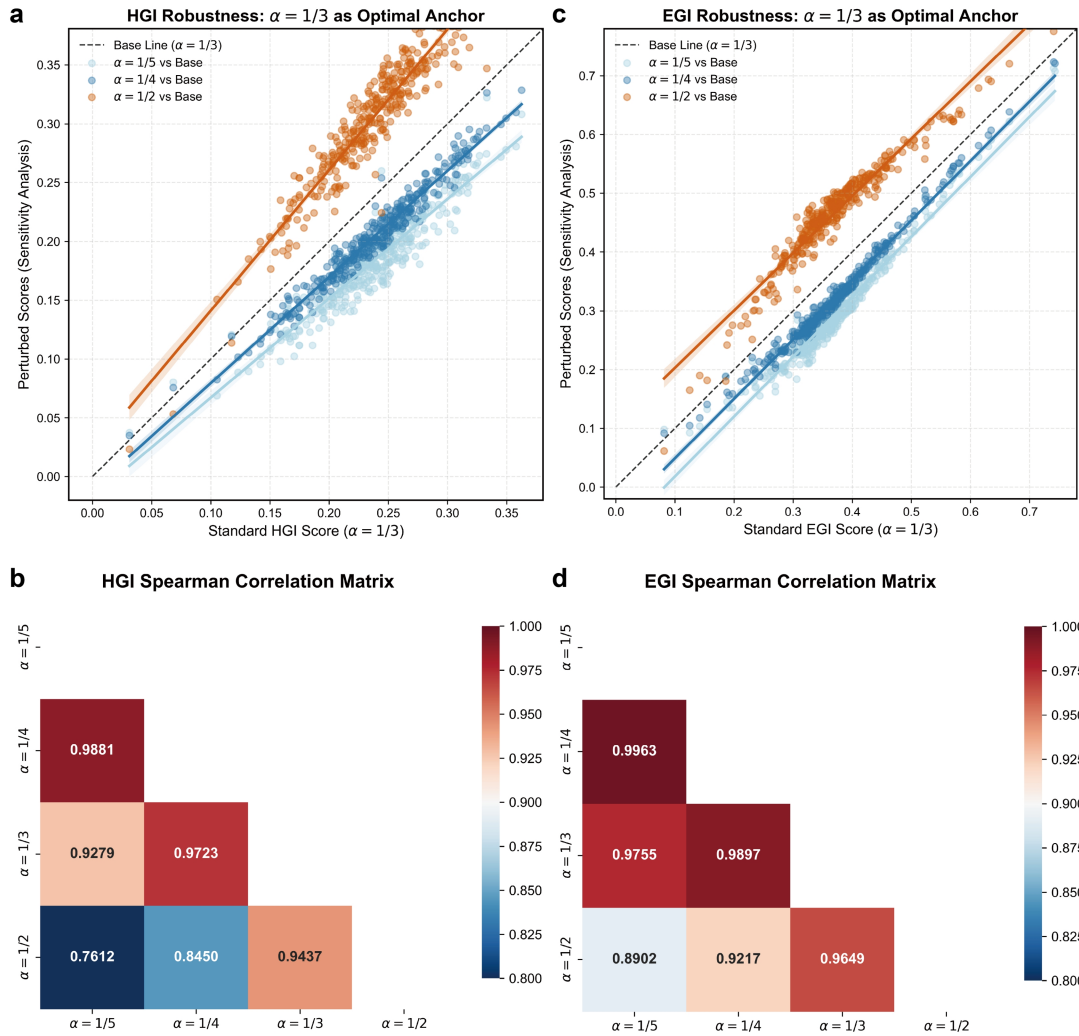


**Supplementary Fig.19. Projected spatiotemporal evolution of EGI under different SSP - RCP scenarios.** The maps visualize the projected mean EGI across Chinese cities for the near-term (2025 - 2050) and long-term (2050 - 2100) periods. a, b, Spatial distribution of mean EGI under the SSP1-2.6 scenario for 2025 - 2050 (a) and 2050 - 2100 (b). c, d, Projections under the SSP2-4.5 scenario for the same time periods. e, f, Projections under the SSP5-8.5 scenario.



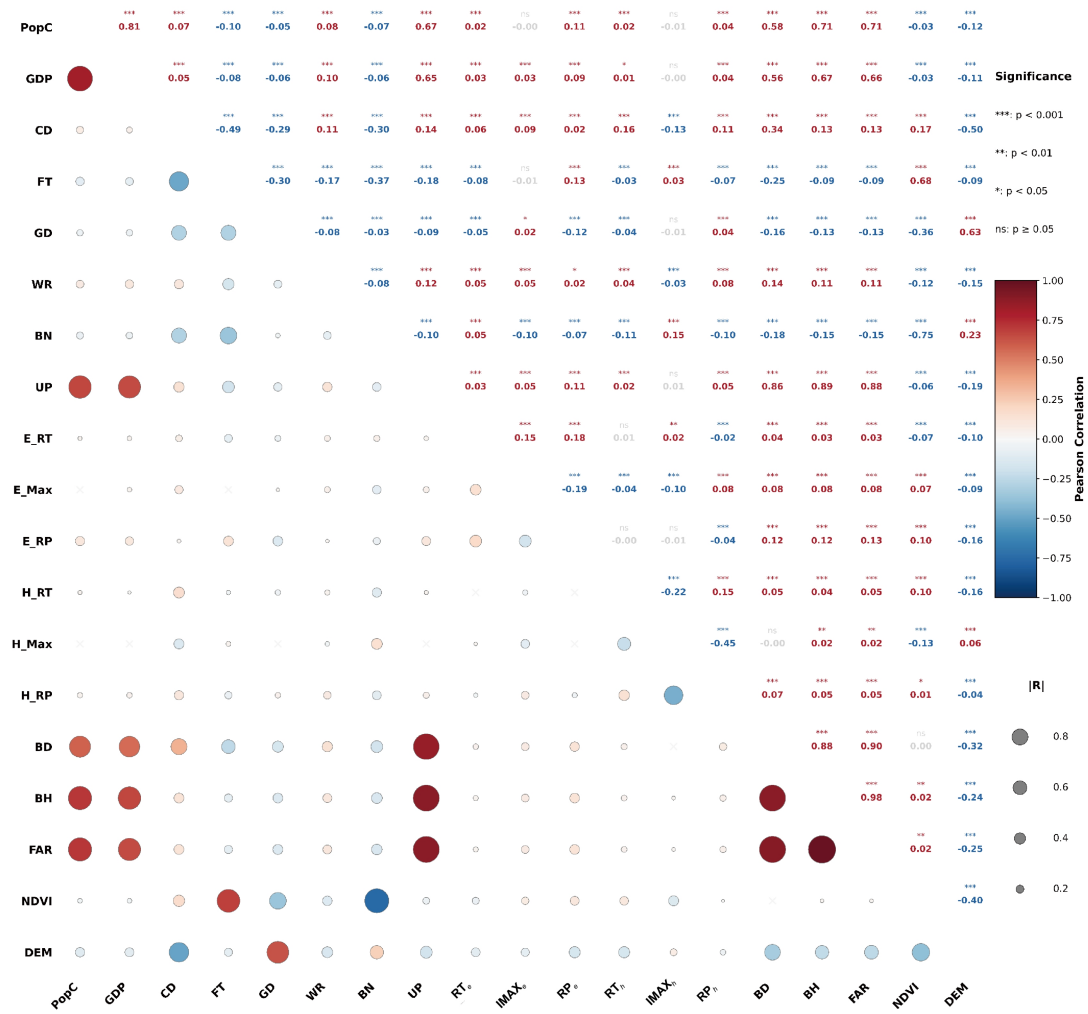


**Supplementary Fig. 20. Projected evolution of physical and emotional heat resilience across major Chinese urban agglomerations.** a,b, Multi-model ensemble (MME) mean values of the heatwave resilience index (HGI; a) and emotional resilience index (EGI; b) across 19 major urban agglomerations at selected years from 2025 to 2100 under SSP1–2.6, SSP2–4.5 and SSP5–8.5. Rows denote scenario–year combinations, columns denote urban agglomerations, and the final column (Avg.) shows the mean across all agglomerations. Numbers within cells indicate MME mean values derived from 13 CMIP6 models. Warm and blue–green colour scales indicate increasing HGI and EGI values, respectively. Urban-agglomeration abbreviations are defined in Fig. 1.

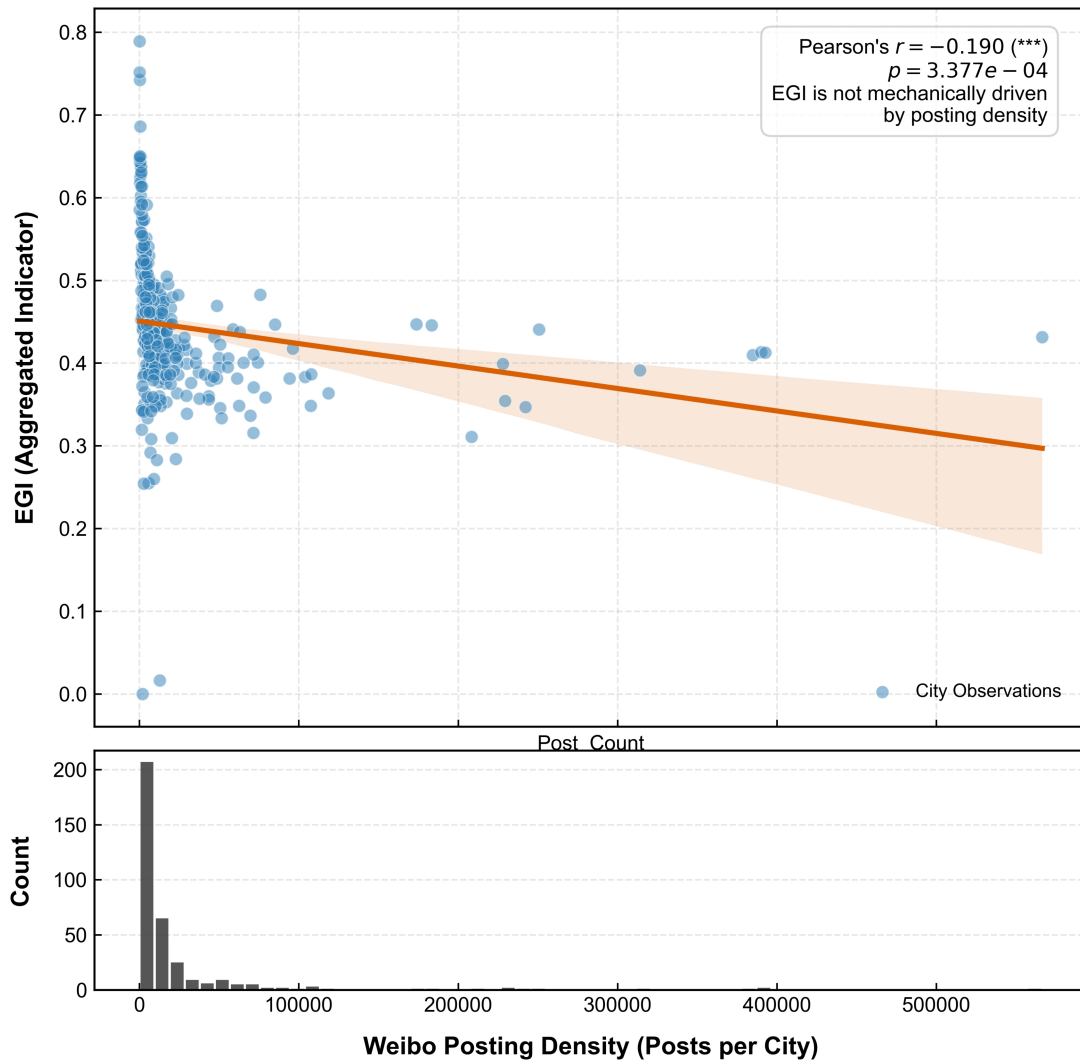


**Supplementary Fig. 21.  $\alpha = 1/3$  as the robustness anchor of HGI and EGI.** (a, c) Scatter plots of perturbed HGI (a) and EGI (c) scores under  $\alpha = 1/5$ ,  $1/4$ , and  $1/2$  against the  $\alpha = 1/3$  baseline; all perturbed series remain tightly linear and parallel to the  $y = x$  reference, indicating that only absolute score levels shift while cross-city relative rankings remain stable. (b, d) Spearman rank correlation matrices for HGI (b) and EGI (d) across the four  $\alpha$  values;  $\alpha = 1/3$  yields the highest average pairwise correlation with all alternative weights (mean  $\rho = 0.948$  for HGI; mean  $\rho = 0.977$  for EGI), confirming its role as the most robust central anchor.

Correlation Matrix with Significance Levels



Supplementary Fig.22. Pearson correlation matrix of urban drivers and resilience metrics.



**Supplementary Fig.23. Sensitivity of EGI to Weibo posting density.** The upper panel shows the city-level relationship between EGI and the total number of heatwave-related Weibo posts, with the fitted regression line and 95% confidence interval. The lower panel shows the marginal distribution of city-level post counts.