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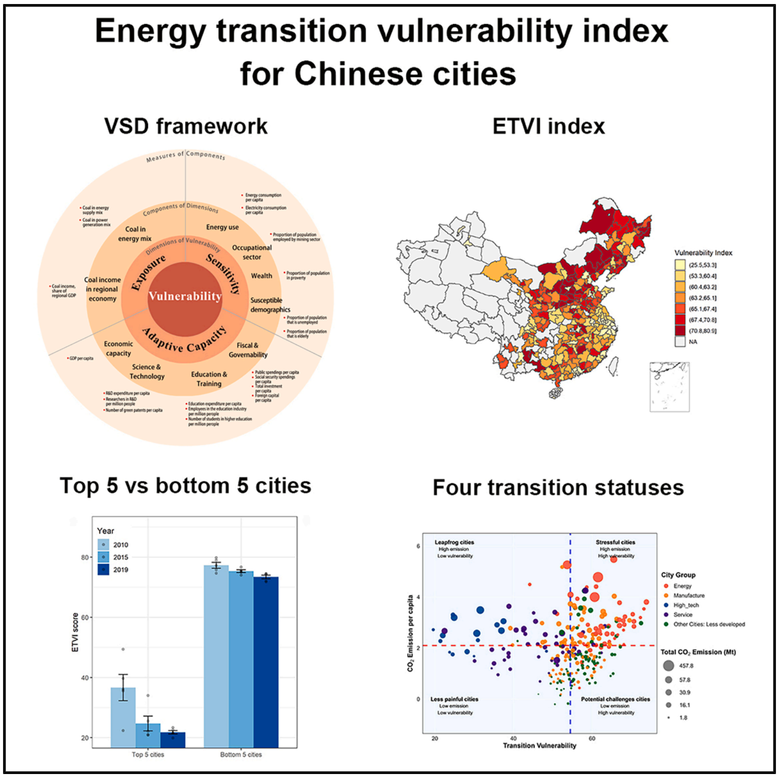
Evaluating regional disparities in socio-economic vulnerability to coal phase-out across Chinese cities

Graphical abstract



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In brief

Shen et al. develop a city-level index to assess vulnerability to coal phase-out across China. They reveal widening regional disparities and identify tailored decarbonization pathways to support a just energy transition.

Highlights

- Energy transition vulnerability index (ETVI) is developed for 281 Chinese cities
- Nearly 90% of cities reduced vulnerability from 2010 to 2019
- Regional disparities in vulnerability persist and have widened over time
- Urgent need for tailored policies to ensure a just, inclusive transition

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Evaluating regional disparities in socio-economic vulnerability to coal phase-out across Chinese cities

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SCIENCE FOR SOCIETY Achieving a low-carbon energy transition is essential for meeting global climate goals but introduces uneven socio-economic challenges across regions. Focusing on coal phase-out in China, this study develops a multidimensional energy transition vulnerability index (ETVI) to assess the vulnerability of 281 cities to this transition. We show that while many cities are becoming less vulnerable overall, disparities between regions are growing, with the most vulnerable cities concentrated in Northern and Western China and the least vulnerable along the southeastern coast. By identifying which cities are most at risk and why, the research provides valuable insights for policymakers to design targeted support measures. This study underscores the importance of interdisciplinary collaboration—integrating insights from economics, environmental science, and energy systems—to ensure that the transition to low-carbon energy is just and inclusive for all stakeholders.

SUMMARY

Phasing out coal is central to China's low-carbon transition but entails uneven socio-economic impacts across regions. Here, we develop a multidimensional energy transition vulnerability index (ETVI) to assess city-level vulnerability to coal phase-out across 281 Chinese cities from 2010 to 2019. The results show that although overall vulnerability has declined, regional disparities have widened, with the most vulnerable cities concentrated in Northern and Western China and the least vulnerable along the southeastern coast. Spatial clustering analysis reveals persistent high-high and low-low vulnerability patterns. By integrating ETVI with per capita CO_2 emissions, we identify differentiated decarbonization pathways that align mitigation priorities with local energy transition capacities. These findings highlight the need for regionally adaptive policies to support a just and inclusive energy transition within China's national climate strategy.

INTRODUCTION

The transition from fossil-based to low-carbon energy systems is essential for mitigating the impacts of climate change and ensuring a sustainable future.[1] However, this transition can lead to complex adverse economic, social, and environmental impacts, such as extreme price shocks, energy supply disruptions, and socio-economic hardships. These impacts are unlikely to be evenly distributed, often affecting some groups more than others.[2,3] For example, regions heavily reliant on fossil fuels, sensitive to energy price changes, and with limited financial or technological capability are likely to face greater challenges. Therefore, distributional justice is considered a key tenet of energy justice.[2,4,5] At COP 28, a historic agreement was reached to speed up the transition away from fossil fuels by tripling renewable energy capacity, with a strong emphasis on ensuring that this shift is just, orderly, and equitable.

Measuring the socio-economic vulnerability to low-carbon transition is fundamental to addressing the equity implications of such a shift. While existing studies on energy transition vulnerability cover various scales—ranging from countries and cities to communities, households, and relevant sectors[6–10]—many have

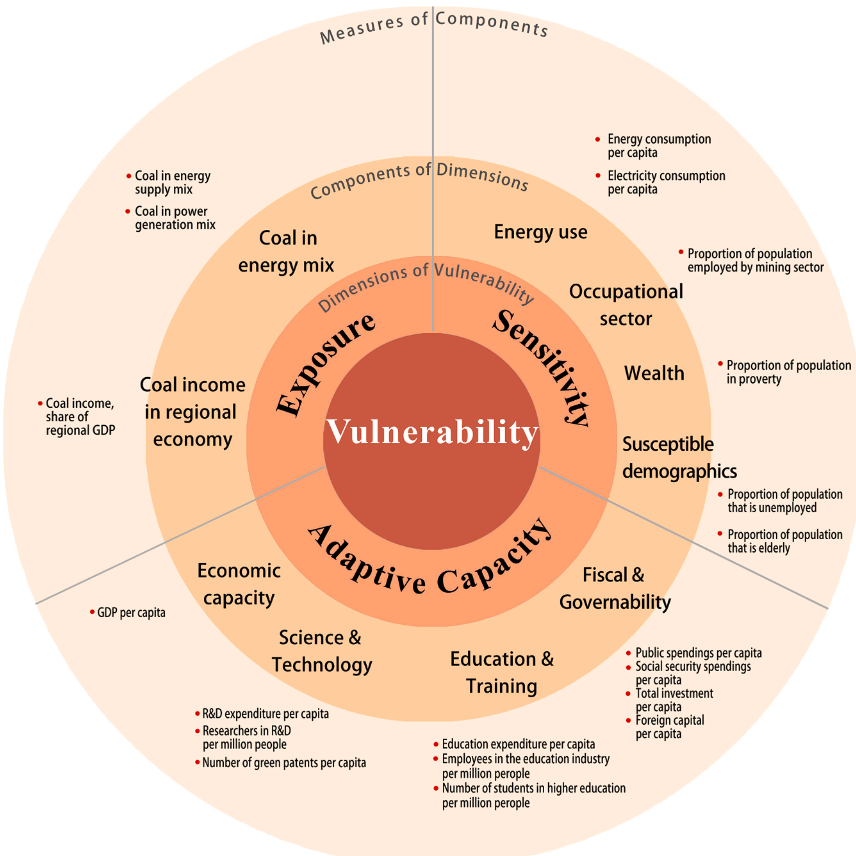

Figure 1. Energy transition vulnerability scoping diagram for Chinese cities

Vulnerability in the context of energy transition is defined as a function of exposure, sensitivity, and adaptive capacity. For each dimension, related concepts (components of dimensions) and measures of components can be identified.

employed qualitative methods, such as questionnaires, interviews, and focus group discussions. While qualitative research offers in-depth, context-rich insights and is well-suited to capturing diverse experiences and uncertainties, quantitative approaches are equally essential for systematically identifying patterns of transition vulnerability, tracking changes across regions and over time, and supporting evidence-based policy decisions. Carley et al.[11] pioneered the application of the vulnerability scoping diagram (VSD) framework from climate change adaptation literature to energy transition analysis, devising a measure of energy transition vulnerability across US counties due to the implementation of the renewable portfolio standard. This framework has since been expanded in studies examining the energy sector across nations,[12] subnational regions,[13] and communities.[14]

Despite sustained efforts to delineate and measure energy transition vulnerability, there is a notable lack of estimates for China, which is the world's largest carbon emitter and also exhibits considerable heterogeneity at the sub-national level. China's socio-economic development, characterized by a moderate level, poses the dual challenge of meeting ambitious climate targets while sustaining growth. Energy transition is central to China's climate change mitigation strategy, with implementation largely reliant on subnational governments, particularly at the city level.[15] The vast disparities among Chinese regions—across socio-economic, geographic, and other dimensions—necessitate a gradual, region-specific approach to energy transition to mitigate impacts on vulnerable groups.[3] However, differentiated actions aimed at achieving a just and equitable energy transition must be underpinned by detailed and reliable data on the associated vulnerability heterogeneity. Therefore, this study seeks to profile energy transition vulnerability at the subnational level in China and then explore regional disparities from temporal and spatial perspectives.

Specifically, the study quantifies the energy transition vulnerability index (ETVI) scores for 281 Chinese cities from 2010 to 2019, providing a baseline and quantitative evidence for spatiotemporal patterns and trends. Our conceptual framework for assessing energy transition vulnerability (see Figure 1 and methods) builds upon the VSD proposed by Carley et al.[11] The analysis focuses on coal phase-out, as it represents the most critical component of China's low-carbon energy transition. Building on this, the study examines regional disparities by assessing the extent of regional inequality and spatial clustering across cities. Furthermore, by linking city-level ETVI scores with per capita CO_2 emissions, we identify differentiated decarbonization pathways that align mitigation priorities with local transition capacities, offering actionable insights for a just transition. Sovacool et al.[16] noted that current literature predominantly addresses equity from demographic, regional distribution, and intergenerational perspectives. While there has been a surge in studies focusing on regional equity in the low-carbon transition process—such as Snyder[17] on decarbonization in US hydrocarbon-intensive counties, Raimi et al.[13] on energy transition in US fossil fuel communities, and McDowall et al.[14] on European energy transition—most existing research relies on data from a single time point, limiting its ability to capture historical dynamics and long-term trends. Moreover, while spatial agglomeration significantly influences the energy transition process due to geographic, economic, and resource (including energy) endowment structures, there is a noticeable lack of studies exploring energy justice among regions from a spatial agglomeration perspective.[18,19]

This study attempts to make three major contributions to the existing literature. First, it provides the first quantitative assessment of varied energy transition vulnerability across China using an extended version of a classic conceptual framework, enabling both historical trend analysis and cross-city comparison. The

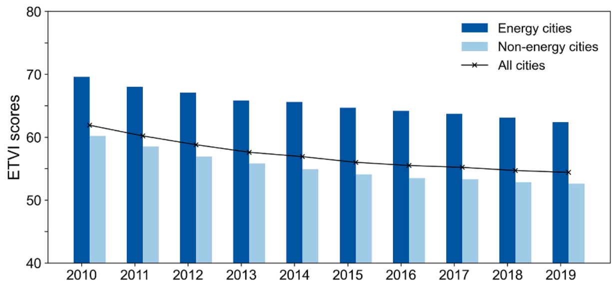

Figure 2. Time trend of ETVI scores in the 2010s
Averaged energy transition vulnerability index (ETVI) scores across the city groups from 2010 to 2019.

time-series ETVI scores for 281 Chinese cities from 2010 to 2019, if properly applied and updated, could empirically assist policymakers in protecting vulnerable cities while striving toward the country's net zero commitments by 2060. In addition, the dataset offers new opportunities for future research, such as exploring the determinants of energy transition vulnerability or its impacts on other economic and social outcomes. Second, beyond visualizing regional disparities on the map, the study formally investigates regional inequality in the low-carbon energy transition using inequality indices and explores regional agglomeration through spatial clustering analysis. In particular, identifying these clusters enables the central government to design regionally differentiated strategies, ensuring that mitigation policies and transition support are effectively directed toward the most at-risk areas. The uneven findings could also assist local decision-makers in identifying weaknesses and barriers in their energy transitions. Finally, the proposed analytical framework can be readily adapted to other geographic contexts, promoting a more equitable and inclusive global energy transition. In particular, the study demonstrates how, in China's context, the proposed measure of energy transition vulnerability can inform the design of national decarbonization pathways and highlight the importance of tailoring the pace of transition across cities to minimize socio-economic hardships.

RESULTS

The ETVI offers a comprehensive evaluation of a city's socio-economic vulnerability to the low-carbon energy transition, assessing performance across three key dimensions: exposure, sensitivity, and adaptive capacity. The ETVI score ranges from 0 to 100, where 0 represents the least vulnerable and 100 represents the most vulnerable to potential adverse impacts of the low-carbon energy transition. Thus, a lower score indicates lower vulnerability, while a higher score reflects greater vulnerability. We calculated the ETVI scores for 281 Chinese cities from 2010 to 2019 and analyzed regional disparities from both temporal and spatial perspectives. The 2019 ETVI scores are discussed in detail as the baseline results for each city's energy transition vulnerability.

Overview of energy transition vulnerability

Figure 2 illustrates the national average ETVI scores from 2010 to 2019, highlighting an overall improvement in transition vulnerability over the past decade. This positive trend is primarily driven by enhanced adaptive capacity, a result of rapid socio-economic development during the 2010s, alongside reductions in sensitivity, largely due to decreased poverty, and a slight decline in exposure. While energy cities—defined as those with energy production sectors designated as pillar industries by the Chinese government[20]—have consistently exhibited higher levels of energy transition vulnerability, they have also experienced a gradual decrease in vulnerability over time. However, the long-term sustainability of this trend remains uncertain, particularly given the significant impacts of COVID-19 and China's economic slowdown.

Despite the general improvements, certain trends are cause for concern. As shown in Figure 3, 30 cities, accounting for 10.7% of those assessed, experienced an increase in vulnerability between 2010 and 2019. Specifically, 69 cities (24.6%) saw increased exposure, 75 cities (26.7%) had heightened sensitivity, while 9 cities (3.2%) showed a reduction in adaptive capacity. These findings indicate that reductions in transition vulnerability are unevenly distributed across regions, reflecting substantial variations in China's ongoing economic, social, and environmental development process.

Figure 4 and Table S1 present the 2019 ETVI scores for 281 Chinese cities, revealing significant regional disparities in energy transition vulnerability. Cities in Eastern China generally exhibit lower ETVI scores compared with those in Western China, and Southern China fares better than Northern China, indicating persistent east-west and north-south divides in energy transition vulnerability. The southeast coastal area, in particular, demonstrates strong performance with higher adaptive capacity and reduced exposure. Cities with the lowest ETVI scores are concentrated in the Yangtze River Delta, Pearl River Delta, and Jiaodong Peninsula on the east coast. These clusters outshine other cities mainly due to higher adaptive capacity, primarily driven by more advanced economic development and technology, and lower sensitivity to energy transition, mainly characterized by fewer coal miners and lower poverty rates. However, even economically and technologically advanced cities, despite having low overall vulnerability, remain quite exposed to the challenges of low-carbon energy transition. For instance, major cities like Beijing, Shanghai, Guangzhou, and Shenzhen still rely heavily on coal in their energy mix. In 2021, power rationing and restrictions in China, including in the southeastern coastal regions, underscored the underlying vulnerabilities associated with aggressive and sometimes unrealistic energy-saving and emission reduction targets, leading to significant socio-economic tensions.[21]

Energy cities, primarily located in Northeast and Western China, particularly in Shanxi and Inner Mongolia, are the most vulnerable to energy transition. Cities such as Jincheng and Hegang exhibit the highest levels of vulnerability nationwide due to their high exposure to coal and limited adaptive capacity. However, vulnerability levels vary among these cities. For example, despite Ordos's significant exposure to fossil fuels, its lower sensitivity and better adaptive capacity make it less vulnerable to the energy transition. This is consistent with Ordos's more diversified economy, including a significant expansion in the service sector and investments in renewable energy.[22]

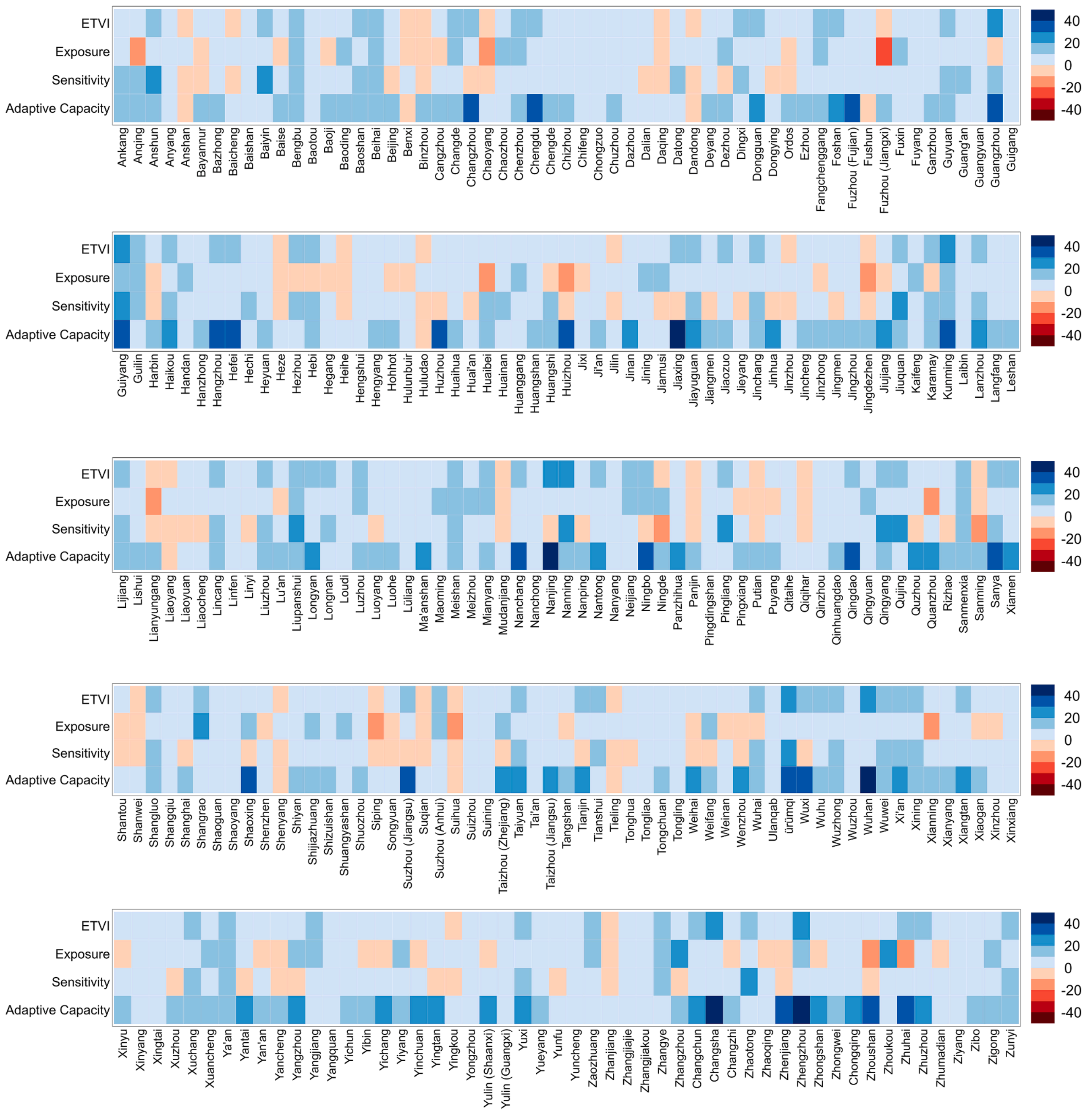

Figure 3. Changes in ETVI scores for each city from 2010 to 2019

The color scale depicts changes in ETVI and its dimensional index scores. A positive value (blue) indicates improvement, whereas a negative value (red) signifies a deterioration.

Nonetheless, energy cities like Ordos are still more vulnerable than most non-energy cities, which are mainly located in China's middle and western regions and exhibit moderate transition vulnerability. These cities typically have lower exposure to energy transition but face higher sensitivity and lack adequate economic, fiscal, and technological capacity to adapt to the socio-economic challenges posed by energy transition.

Intertemporal inequality of transition vulnerability

Table 1 presents the regional inequality in transition vulnerability from 2010 to 2019. Notably, the Gini coefficient, Theil index, and Atkinson index all show a consistent increase over time, from 0.073, 0.010, and 0.005 in 2010 to 0.095, 0.019, and 0.010 in 2019, respectively. Two key conclusions can be drawn from these results. Firstly, the non-zero estimates confirm the

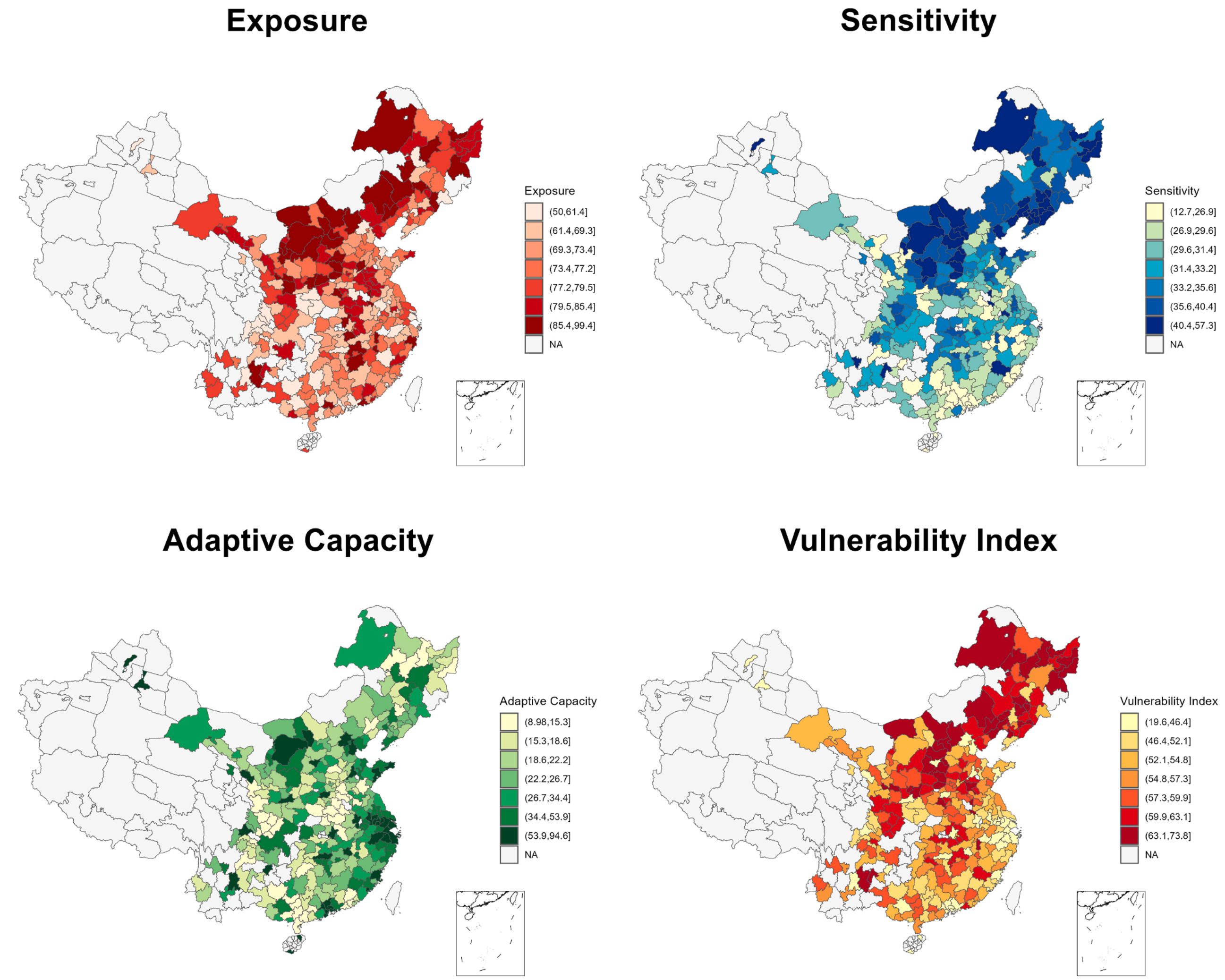

Figure 4. ETVI and its dimensional index scores in 2019

Maps display exposure, sensitivity, adaptive capacity, and aggregate vulnerability scores for low-carbon energy transition, using a quantile classification scheme with equal observations per category. Lower scores indicate less exposure, lower sensitivity, lower adaptive capacity, and reduced vulnerability, respectively.

existence of regional inequality in China's low-carbon energy transition, consistent with the observations in Figure 4. Second, the results indicate that regional disparities have continued to widen throughout the 2010s, signaling a growing underlying threat to social stability during the low-carbon energy transition process. It is important to note that the three inequality indices ceased rising in 2019. However, it remains unclear whether this represents a genuine halt in further deterioration or merely a temporary pause.

Given the rising inequality identified by these three indices, it is crucial to examine the changes in transition vulnerability at the extremes of the ETVI score distribution, particularly at the lower end. Therefore, we conducted a focused analysis on the dynamics of transition vulnerabilities among the top and bottom-ranked cities, with the results displayed in Figure 5. Overall, there was no notable improvement in the energy transition vulnerability of cities with initially high ETVI scores, mainly located in the northeastern and western regions, as shown in Figure 4. Cities like Anshan, Benxi, and Tieling even experienced further deterioration in their energy transition vulnerability, primarily due to their increased reliance on heavy industry and declining economic development. By contrast, cities that started with low ETVI scores in 2010—most of which are located in eastern regions such as the Yangtze River Delta, Pearl River Delta, and Jiaodong Peninsula—especially those in the top 5 and top 10, have continued to reduce their vulnerability. Specifically, Wuhan, Nanjing, and Guangzhou recorded the fastest reduction in energy transition vulnerability, largely due to improvements across all three dimensions.

Spatial clustering of transition vulnerability

Since national economic and industrial policies are often formulated and implemented at the regional level (e.g., the provincial level), examining the regional clustering of cities in the energy

Table 1. Inequality indices of regional transition vulnerability, 2010–2019

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Gini	0.073	0.077	0.080	0.082	0.085	0.089	0.091	0.093	0.095	0.095
Theil	0.010	0.011	0.012	0.013	0.014	0.016	0.017	0.018	0.019	0.019
Atkinson	0.005	0.006	0.006	0.007	0.008	0.008	0.009	0.010	0.010	0.010

transition process is essential for safeguarding the interests of vulnerable groups and formulating effective top-down low-carbon policies. As indicated in Table 2, the global Moran's *I* is robustly positive and significant at the 1% level, demonstrating a pronounced spatial clustering of city-level socio-economic vulnerability to low-carbon energy transition. Over time, the Moran's *I* shows a decreasing trend, suggesting a reduction in spatial autocorrelation, although strong regional clustering persists. Additionally, even though economic indicators such as GDP per capita were incorporated into the vulnerability index, the Moran's *I* based on economic distance did not show stronger spatial autocorrelation compared with the results based on adjacent or geographical distance matrix. These findings underscore the crucial role of geographical connections, rather than purely economic ones, in addressing socio-economic challenges that may arise during the energy transition.

To better understand the local autocorrelation of regional energy transition vulnerability and its spatial distribution, annual Moran scatterplots for 281 Chinese cities have been generated. These scatterplots visualize local spatial associations, such as clusters and outliers, identified by the local indicator of spatial association (LISA) statistics. By tracking the quadrant changes (i.e., changes in local autocorrelation) for each city over the period, we can observe the evolution of regional concentration in energy transition vulnerability. Figure 6 presents the scatterplots for 2010, 2015, and 2019, showing that most cities clustered in the first quadrant (i.e., high-high clustering) and third quadrant (i.e., low-low clustering). Between 2010 and 2019, the number of cities in high-high clusters decreased from 108 to 95, while those in low-low clusters increased from 86 to 98. The remaining cities are outliers in terms of regional clustering, either as vulnerable cities in non-vulnerable neighboring regions (i.e., high-low clustering) or as non-vulnerable cities in vulnerable neighboring regions (i.e., low-high clustering). Despite the encouraging trend of declining spatial clustering of high vulnerability, the number of clustered vulnerable cities remains significantly high. Figure 7 shows the spatial distribution and intertemporal evolution of the four clustering categories, revealing a clear north-south divide and notable shifts in regional clustering. From 2010 to 2019, low-low clusters gradually expanded from the southeastern coastal areas into central provinces such as Anhui, Hunan, and Hubei. In the western region, low-low clusters also emerged, as relatively developed cities like Chengdu, Xi'an, and Chongqing reduced their energy transition vulnerability. However, many less developed cities still lagged behind, leading to widening regional disparities—one of the key drivers behind the decline in global Moran's *I*. By contrast, high-high clusters have spread more widely in the northeastern region, where manufacturing cities dominate. Shanxi and Inner Mongolia have also remained persistent high-high cluster areas throughout the period. The energy transition in these regions warrants particular attention due to the socio-economic vulnerabilities of affected cities. These findings emphasize the importance of regionally tailored policies rather than a one-size-fits-all national approach.

Designing national decarbonization pathways while considering socio-economic vulnerability

The primary motivation behind the energy transition is to reduce CO_2 emissions and combat climate change. The concept of energy transition vulnerability highlights the potential societal challenges that cities may face during this process, representing the cost side of climate change mitigation. In this section, we connect city-level CO_2 emissions in each city—the widely recognized responsibility side of climate change mitigation—with the cost side captured by energy transition vulnerability. This linkage illustrates how quantitative measurement of vulnerability can help inform the design of inclusive and just national decarbonization pathways. Due to data availability at the city level in China, we focus here on scope 1 territorial emissions.

Figure 8 shows the positions of each city in terms of energy transition vulnerability and per capita CO_2 emissions. Following the World Economic Forum (WEF)'s practice,[23] we adapted a bivariate analysis framework and classified all cities into 4 quadrants (transition status): "stressful," "leapfrog," "potential challenges," and "less painful." Each city is also labeled with its pillar industry, using classifications from Shan et al.[24,25] and Shen et al.[26] The results show that the high-tech and most service cities tend to exhibit low vulnerability and high per capita emissions (quadrant II, leapfrog cities), making them better positioned to undertake a faster energy transition in pursuit of national decarbonization targets. By contrast, energy cities need particular attention, as they are mainly located in the least desirable quadrant—high vulnerability and high per capita emissions (quadrant I, stressful cities). Most less developed cities fall into quadrant IV (potential challenges cities), marked by high vulnerability and relatively low per capita emissions. Unfortunately, few cities achieve both low vulnerability and low per capita emissions simultaneously (quadrant III, less painful cities), the most desirable status for simultaneously meeting energy transition and decarbonization goals.

Our results suggest that the socio-economic hardships in the national decarbonization process could be mitigated if the pace of energy transition is appropriately tailored to the transition status of each city.[3] For example, leapfrog cities such as Shanghai, Beijing, and Suzhou (in Jiangsu province) should be incentivized to accelerate their energy transition, as they have the capacity to do so and currently exhibit relatively high per capita emissions (on average 15.3 tonnes). However, for stressful cities such as Jincheng and Yulin (Shaanxi), the energy transition is urgently

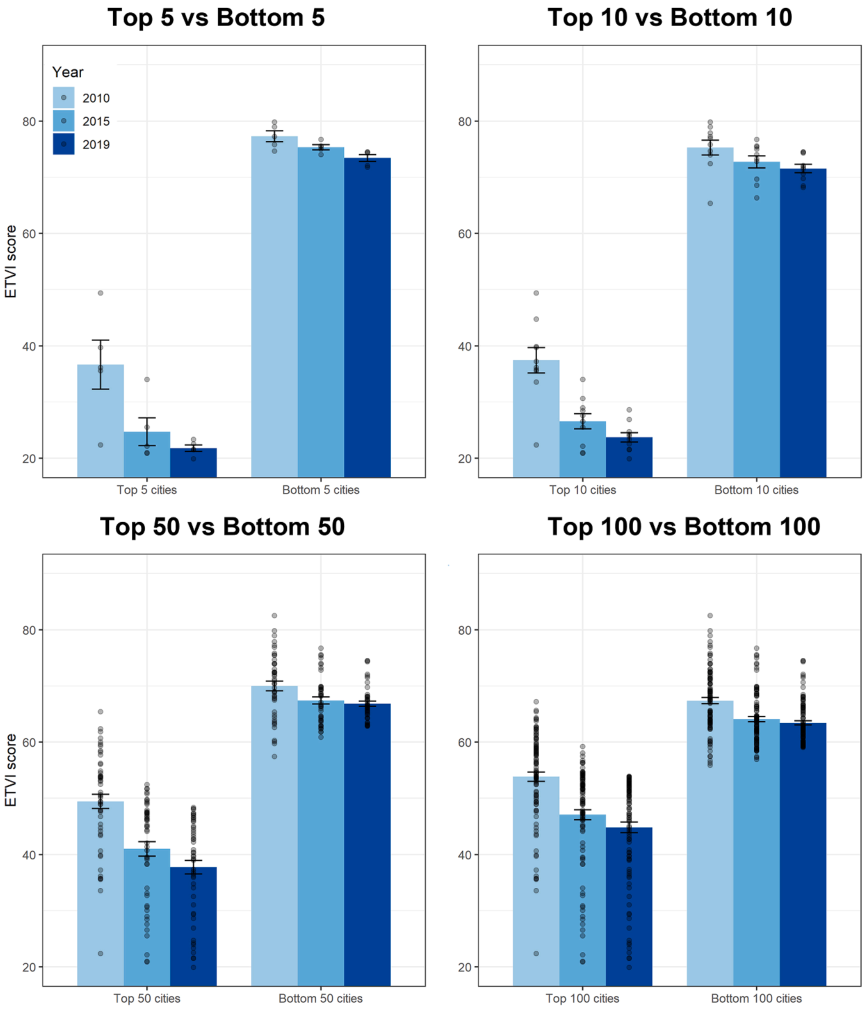

Figure 5. Dynamics of gaps between top and bottom cities

The cities are selected according to their ETVI scores in 2010. The dots represent the ETVI scores of selected cities in each group, and the vertical lines within the bars indicate the standard error of the mean value.

needed but should be carefully managed.[3] It should not be too radical and must be aligned with their socio-economic development, given their heightened vulnerability to the transition process. Furthermore, both national and cross-regional support will be essential to facilitate a just transition in these cities. For potential challenge cities, stringent decarbonization measures are less urgent, as they have the lowest per capita emissions but high transition vulnerability. However, since most of these cities are less developed, a green development path is crucial to ensure that future economic growth does not become increasingly coupled with emissions.[27,28]

Building on these insights, we designed three scenarios that incorporate city-level energy transition vulnerabilities into the national decarbonization pathway. In each scenario, carbon reduction priorities are determined based on each city's transition status: leapfrog cities—characterized by high per capita emissions but low vulnerability—are targeted first, followed by stressful cities, which exhibit both high per capita emissions and high vulnerability. Less painful and potential challenge cities, with relatively low per capita emissions, are excluded from stringent carbon reduction efforts. We further assume that cities can only emulate better-performing peers within their respective industry group (i.e., energy, manufacturing, high-tech, services, and others). Based on these assumptions, we define three levels of carbon reduction efforts: (1) the moderate scenario, in which leapfrog cities reduce emissions by converging to the average per capita emissions within their respective industry groups; (2) the progressive scenario, in which leapfrog cities aim for the 20th percentile of per capita emissions among their industry peers; and (3) the ambitious scenario, which builds on the progressive scenario by additionally requiring stressful cities to reduce their per capita emissions to the average levels within their respective industry groups.

These scenarios demonstrate significant reductions in national aggregate carbon emissions compared with the current baseline. In the moderate scenario, carbon emissions decline by 1,012.93 million tonnes (Mt), or −7.94%, underscoring the substantial mitigation potential of targeting leapfrog cities with relatively modest efforts. The progressive scenario yields a larger reduction of 2,421.94 Mt (−18.97%) through the adoption of leading practices by leapfrog cities. The ambitious scenario results in the greatest reduction—4,452.94 Mt (−34.88%)—but would be more challenging to implement, given the high capital

Table 2. Global Moran's *I*

Years	Adjacent	Geo	Eco	Geo-eco
2010	0.503***	0.172***	0.132***	0.159***
2011	0.472***	0.166***	0.137***	0.144***
2012	0.454***	0.170***	0.147***	0.142***
2013	0.463***	0.171***	0.153***	0.143***
2014	0.452***	0.168***	0.146***	0.146***
2015	0.421***	0.162***	0.148***	0.141***
2016	0.432***	0.161***	0.149***	0.146***
2017	0.436***	0.156***	0.143***	0.146***
2018	0.404***	0.144***	0.140***	0.139***
2019	0.390***	0.142***	0.102***	0.128***

Notes: *** denotes significance at the 1% level. The null hypothesis is no global spatial autocorrelation.

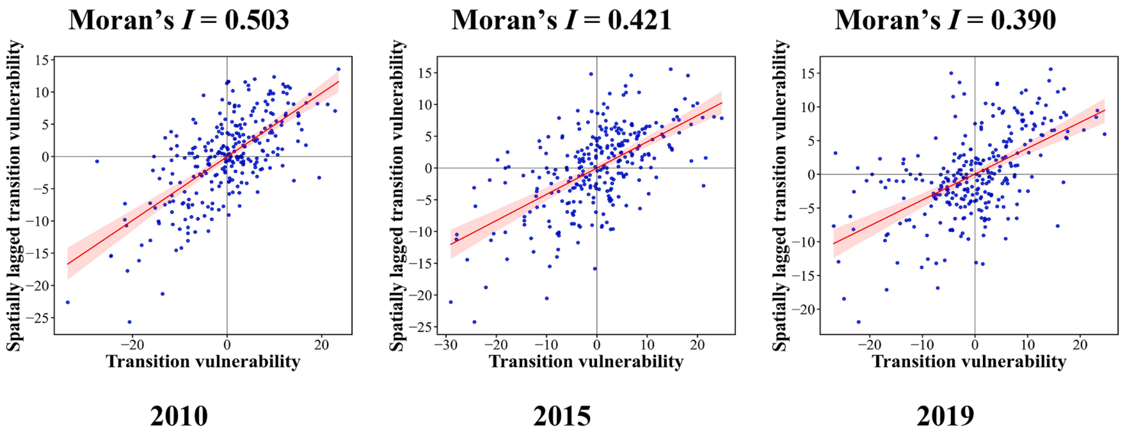

Figure 6. Moran scatterplot of ETVI scores

The results are based on an adjacent distance-weighted matrix and are robust to other spatial weights matrices.

costs of rapid transitions and potential disruptions to energy-intensive industries. Collectively, these scenarios provide a framework for allocating city-level carbon reduction targets and offer insights for designing regionally differentiated decarbonization strategies. Ultimately, the results outline a viable pathway for China to achieve its dual carbon goals while contributing meaningfully to global climate targets.

Sensitivity analysis for transition vulnerability

To assess the robustness of the constructed ETVI scores, a sensitivity analysis is conducted, accounting for uncertainty factors. Specifically, we evaluate the index's sensitivity to variations in upper and lower bounds when normalizing the original data, alternative aggregation methods, and the successive exclusion of indicators. These are standard practices in robustness analysis when constructing an index.[29,30] For the upper and lower bounds, we apply the 1st and 99th percentiles as well as the 5th and 95th percentiles to normalize the data, minimizing the impact of skewed distributions on the standardized values. For the aggregation method, in addition to the arithmetic mean used in the baseline results, we also consider the geometric mean to calculate the values for each dimension. For the successive exclusion of indicators, we remove one dimension at a time and reconstruct the index to ensure that the results are not disproportionately influenced by any single dimension.

The resulting variations in cities' rankings and scores for 2019 are depicted in Figure 9, with cities ordered according to the median ETVI rank/score across different methods. In each box plot, the central rectangle represents the first quartile to the third quartile, with the line segment inside the rectangle indicating the median. The baseline ETVI rank/score is marked in red, and the results based on alternative upper and lower bounds are highlighted in blue (1st and 99th percentile) and green (5th and 95th percentile), respectively. Generally, city rankings are stable for those in the top and bottom quintiles. Although cities listed between these extremes show a wider interquartile range, the baseline ETVI ranking remains close to the median-based ranking. More than half of the cities shifted by only one position from their median rank. For the ETVI score, variations are more pronounced for cities in the bottom quintiles. Major differences in rank and score are observed when an indicator representing a city's comparative advantage or disadvantage in transition vulnerability is excluded. However, testing alternative results by excluding indicators revealed that neither the ETVI rankings nor the scores are likely to be driven by outliers in any single dimension.

DISCUSSION

By developing a VSD framework, our study quantitatively assesses the energy transition vulnerability of 281 cities from 2010 to 2019, enabling both historical trend analysis and cross-city comparison. The derived ETVI scores indicate a general decline in transition vulnerability over the decade, driven primarily by enhanced adaptive capacity, along with reductions in sensitivity and a modest decrease in exposure. Specifically, nearly 90% of cities became less vulnerable; however, at the sub-index level, 69 cities (24.6%) faced increased exposure, 75 cities (26.7%) became more sensitive, and 9 cities (3.2%) experienced a decline in adaptive capacity. The derived inequality indices and follow-up focused analysis reveal that the absence of a significant catch-up effect has led to widening regional inequalities over the decade. Spatially, these disparities manifest as pronounced east-west and north-south divides. In particular, the southeast coastal region exhibits the lowest ETVI scores due to higher adaptive capacity and reduced exposure. Spatial cluster analysis also demonstrates a clear north-south divide, with high-high clusters mainly concentrated in the north. Despite the expansion of high-high clusters in the north-eastern region, an encouraging trend is that low-low clusters have proliferated from the southeast coastal region into central and western regions.

The identified regional disparities, especially the spatial clustering, underscore the importance of both central government's intervention and regionally tailored strategies to enhance the resilience of more vulnerable cities in the coal phase-out process. At the exposure dimension, beyond tapping local renewable resources, the central government should further develop the

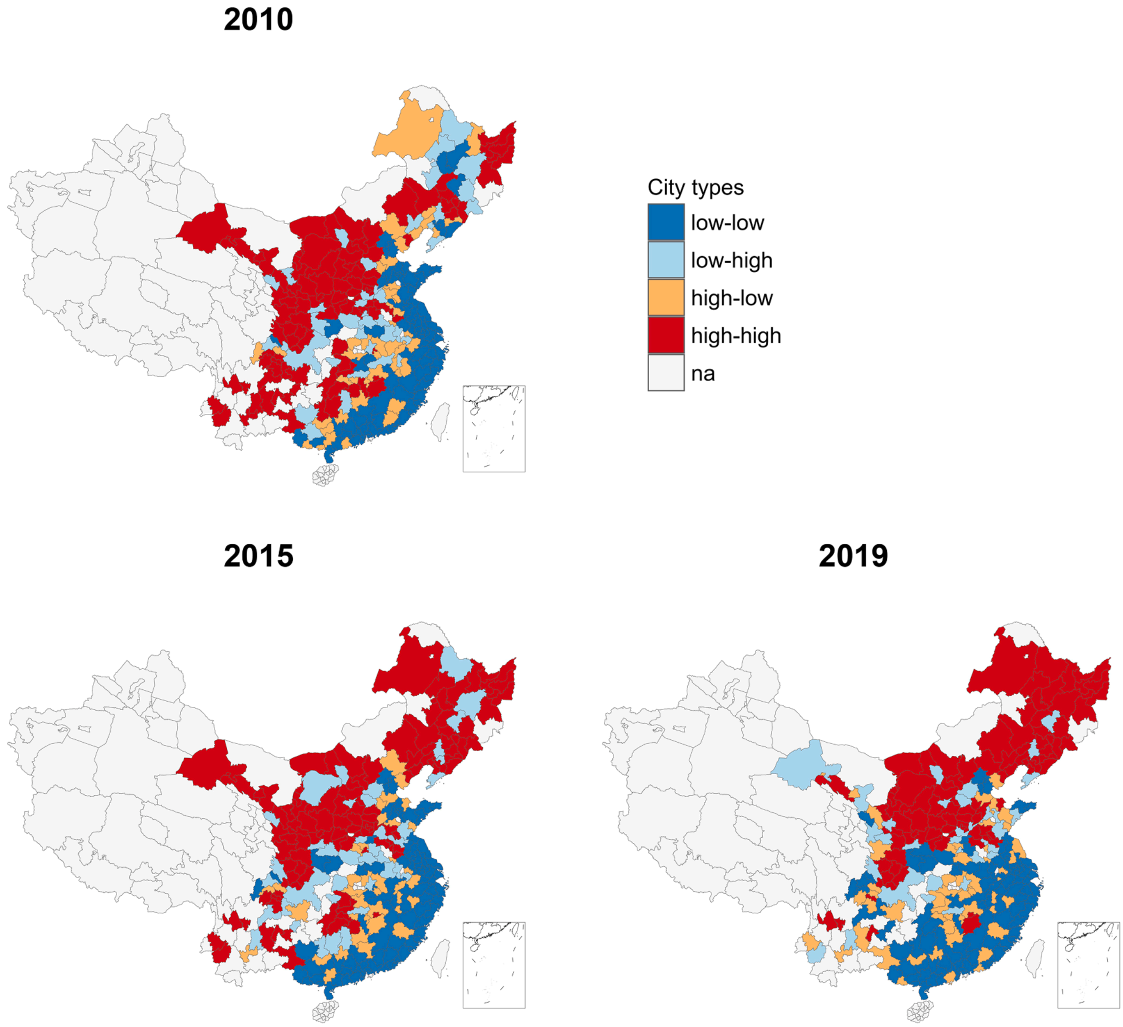

Figure 7. Spatial distribution of cluster categories
The results are based on an adjacent distance-weighted matrix and are robust to other spatial weights matrices.

green electricity certificate market and green electricity trading mechanisms to help bridge regional disparities in renewable energy endowments. Currently, the certificate market faces challenges such as low trading volumes and limited participation, while green electricity trading is hindered by regional trade barriers that restrict the transmission of renewables from resource-rich areas to demand centers. At the sensitivity dimension, it is essential to implement support measures for those displaced by the coal phase-out, such as short-term income assistance and reskilling programs. More fundamentally, governments must focus on job creation and on stemming the outflow of young workers. This requires national-level economic planning targeting less developed areas, drawing on initiatives such as the Western Development Strategy,[31] the Northeast Revitalization Strategy,[32] and the successful "Pairing Assistance for Poverty Alleviation."[33] At the adaptive dimension, persistent regional disparities point to the need for external support, including targeted funding or transfer payments from the central government, as well as knowledge sharing, technology transfers, and capacity-building programs from more advanced regions to less capable cities. Moreover, the low-carbon transition creates substantial opportunities, particularly through new investments and employment in renewable energy industries and their supply chains. To ensure that disadvantaged cities share in these opportunities, it is essential to establish coordinated governance frameworks and facilitate stakeholder dialogues that promote their participation.

By linking energy transition vulnerability and CO_2 emissions—the responsibility and cost sides of climate change mitigation, respectively—our findings also highlight the need to differentiate the pace of energy transition across cities to ensure an inclusive and just national decarbonization. For potential challenge cities (low emissions and high vulnerability), which comprise the majority of less developed areas, and the few less painful cities (low emissions and low vulnerability), stringent decarbonization measures are less urgent given their limited abatement potential.

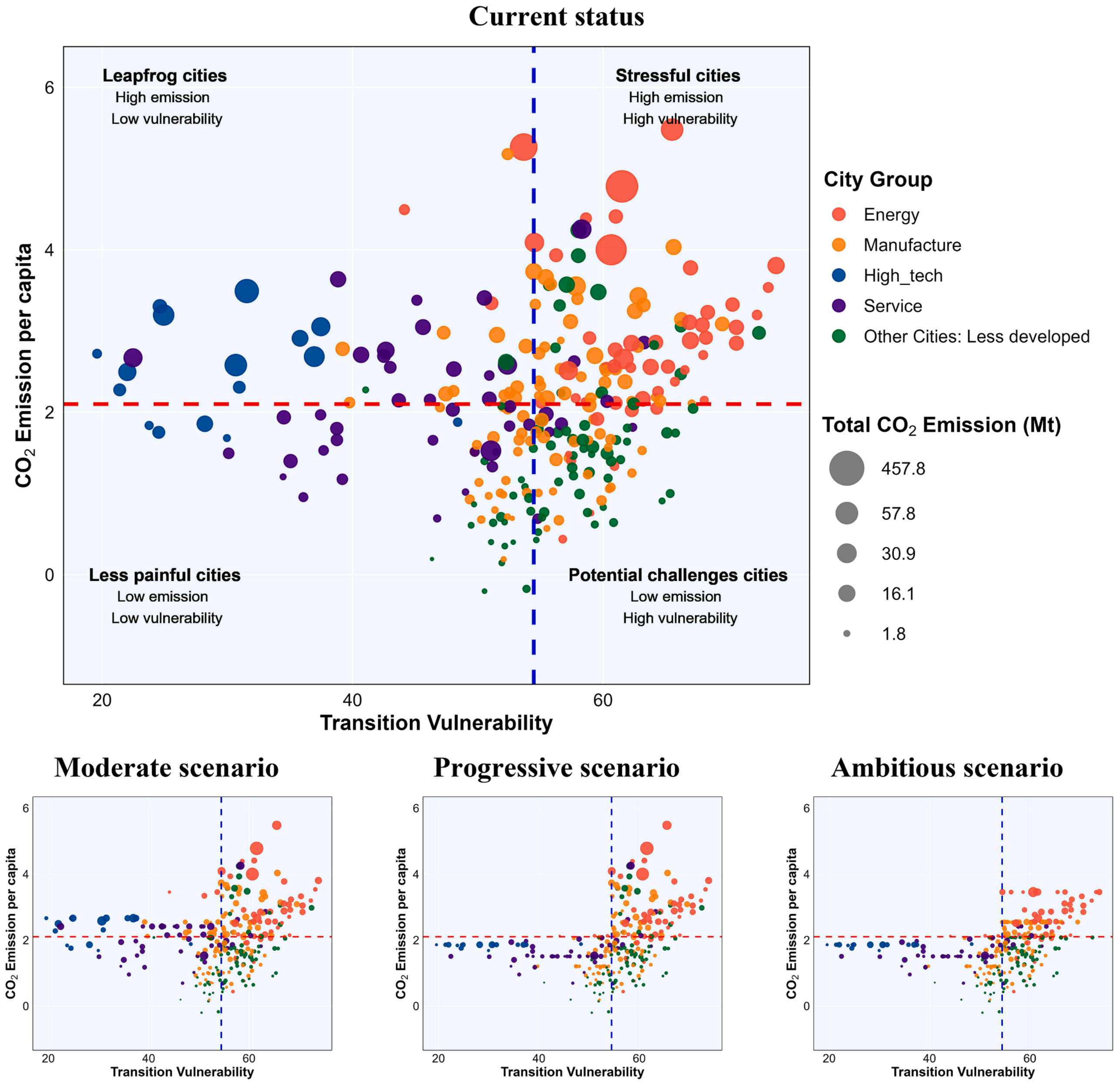

Figure 8. Transition vulnerability and CO_2 emission across cities

This figure shows the relationship between transition vulnerability and per capita CO_2 emissions across 281 cities. We present results for 2019 to reflect the current status of each city, alongside three scenarios that simulate potential decarbonization pathways. The vertical and horizontal lines are the mean values of the x and y axes variables in the current status, respectively. A logarithmic transformation has been applied to the per capita CO_2 data (in tonnes) to reduce the impact of extreme values. In the moderate scenario, *leapfrog* cities aim to match the average per capita emissions within their respective industry groups (e.g., energy or service cities). The progressive scenario sets a more ambitious benchmark, with *leapfrog* cities targeting the 20th percentile of per capita emissions among their industry peers. The ambitious scenario builds on the progressive one by additionally requiring *stressful* cities to target the average per capita emissions within their respective industry groups.

Since many of these cities are relatively less developed, pursuing socio-economic development remains a primary priority. Such development can also help reduce energy transition vulnerability by lowering sensitivity and enhancing adaptive capacity. However, it is crucial that this development follow a green trajectory to prevent future economic growth from becoming increasingly carbon intensive.[27,28] Leapfrog cities (high emissions and low vulnerability) include most high-tech and service-oriented cities and are thus well-positioned to accelerate their energy transition from the perspectives of substantial abatement potential and stronger adaptive capacity. For stressful cities (high emissions and high vulnerability), the energy transition remains an urgent

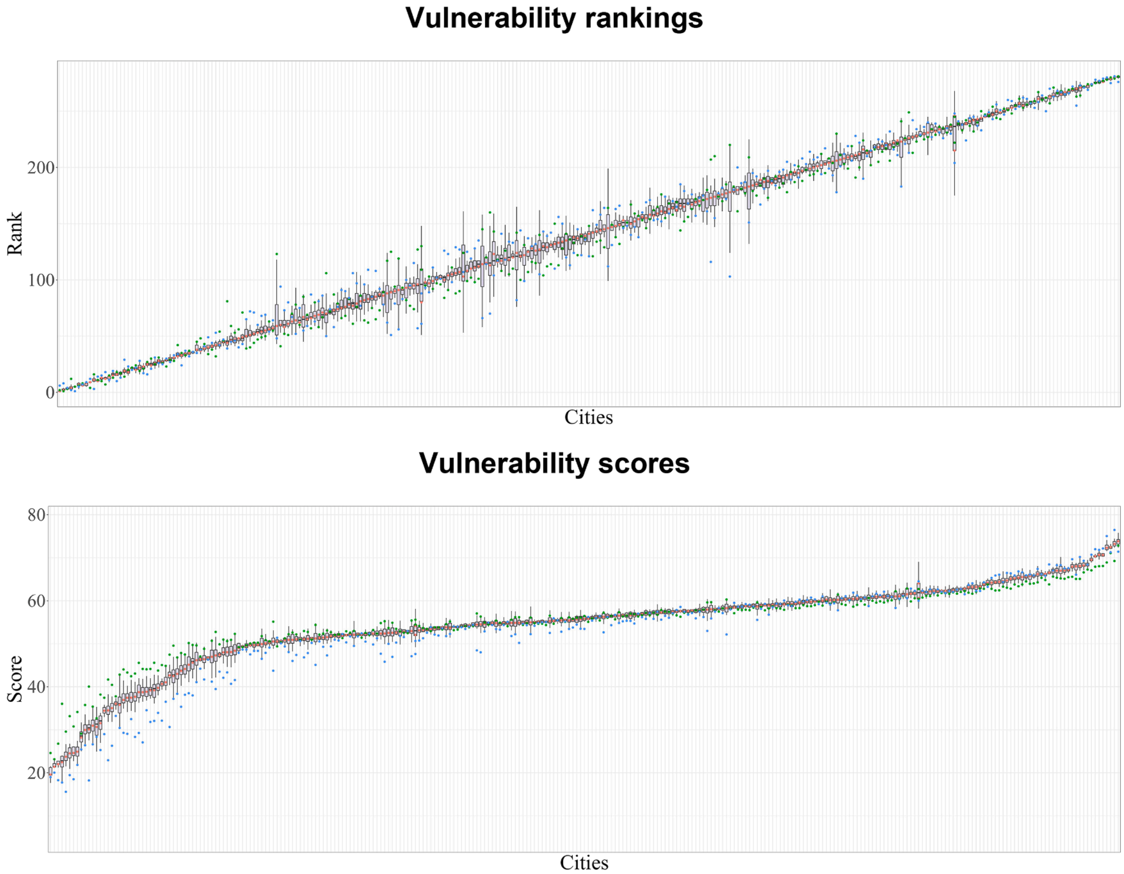

Figure 9. Sensitivity analysis for 2019 EVTI scores

The robustness is tested by varying upper and lower bounds when normalizing the original data, alternative aggregation methods, and successive exclusion of indicators. The cities are arranged according to their median ETVI rank/score. The baseline ETVI rank/score is indicated in red, while results based on alternative upper and lower bounds are shown in blue (0.01 and 0.99) and green (0.05 and 0.95), respectively. In each box plot, the central rectangle represents the first quartile to the third quartile, with the line segment inside the rectangle indicating the median.

priority but must be accompanied by policy measures that address potential socio-economic challenges. These include large-scale layouts and labor outflows, the slow development of alternative and emerging sectors, and constrained technical and financial resources. Such efforts are essential to mitigate sensitivity and strengthen adaptive capacity. Scenario analysis shows that moderate and progressive decarbonization efforts by leapfrog cities—primarily through advancing the energy transition—could reduce national carbon emissions by 7.94% and 18.97%, respectively. When combined with moderate efforts by stressful cities, the projected national reduction nearly doubles, presenting a viable pathway for China to contribute meaningfully to the global 1.5°C target.

This study focuses exclusively on energy transition vulnerability associated with coal phase-out. The exclusion of other major structural shifts—such as the phase-out of other fossil fuels, the rapid adoption of electric vehicles, and the transformation of related industries—constitutes a key limitation. These dynamics represent important directions for further research, particularly as more comprehensive and disaggregated data become available. A second limitation lies in the lack of exploration of alternative decarbonization scenarios, including technological advancements (e.g., in hydrogen, nuclear, and carbon capture and storage), demand-side behavioral shifts, and the expansion of carbon sinks. In addition, when assessing the impacts of coal phase-out under the sensitivity dimension, this study does not account for multiplier and spillover effects transmitted through input–output linkages within the production system. This omission may lead to an underestimation of the broader socio-economic consequences of the transition.

METHODS

Analytical framework for energy transition vulnerability

Our conceptual framework for assessing the energy transition vulnerability builds upon the VSD initially developed by Carley et al.[11] and the original IPCC definition.[34] In this framework, energy transition vulnerability is conceptualized as a function of three dimensions: the magnitude of changes required in each city's energy system to support a low-carbon transition (exposure), with a focus on the energy supply side; the city's susceptibility to the impacts of such changes (sensitivity), primarily in relation to households; and its capability to attenuate, cope with, or mitigate adverse effects (adaptive capacity), with an emphasis on the socio-economic resources available for adaptation. This framework is grounded in an extensive review of the literature, with supporting studies for each element detailed below and illustrated in Figure 1.

In the exposure dimension, we focus on coal phase-out—one of the most critical aspects of the low-carbon energy transition in China—as the key exposure. Coal remains the dominant energy source in China, accounting for over 60% of the country's total energy consumption.[35] As the transition away from coal is central to China's climate change mitigation strategy, reducing coal dependence has been enforced as a nationwide policy across all cities, akin to the renewable portfolio standard policy applied to US counties in Carley et al.[11] In line with the literature, the exposure dimension is evaluated using two components: the share of coal in the energy mix and the contribution of coal to regional revenue.[36] Cities with a higher share of coal in their energy and electric power generation mix are considered more exposed—and therefore more vulnerable—because they must undergo substantial transformations in their energy systems to achieve a low-carbon transition. Consequently, these cities are likely to experience more severe direct socio-economic impacts during the coal phase-out process. Similarly, cities that derive a larger share of income from the coal sector are more exposed than those with smaller shares,[37,38] as their economies are more susceptible to the income loss and structural challenges associated with the coal phase-out.

Cities may demonstrate varying levels of vulnerability even if they are exposed to the same degree of impacts from the energy transition, as the vulnerability also depends on a city's sensitivity to exposure and its adaptive capacity to mitigate such exposure. The sensitivity dimension measures a city's susceptibility to impacts on its energy and economic structure due to the energy transition and is positively correlated with the vulnerability. According to existing literature, at a given level of exposure, cities with higher energy use,[39,40] a larger share of the population employed by fossil fuel sectors,[41] a higher poverty ratio,[42–45] and a greater share of susceptible demographics,[44,46–48] are more sensitive—and thus more vulnerable—to the challenges posed by the energy transition. Our broad measurements of the sensitivity dimension are comparable to those used in Carley et al.[11] and align with commonly used measures of social vulnerability, such as those in Cutter and Finch[49] and Flanagan et al.[50]

The adaptive capacity dimension measures a city's ability to attenuate, cope with, or mitigate the negative impacts and is negatively related to the vulnerability. This dimension is evaluated based on critical components related to the energy transition as identified in the literature. Specifically, cities with lower levels of economic development,[2,11,51,52] lower scientific and technological capability,[53–56] lower educational attainment,[37,57–59] and fewer fiscal and financial resources[60–62] will face greater challenges in adapting to these negative impacts compared with cities with higher levels of these attributes when faced with the same level of exposure.

Quantification of energy transition vulnerability

To operationalize the VSD and derive an ETVI score for each city, we propose using the geometric mean of three normalized and arithmetically averaged dimensional indices—exposure, sensitivity, and adaptive capacity—following the equation below:

$$V = \sqrt[3]{\left(\frac{1}{I}\sum_{i=1}^{I} \mathrm{E}_i\right) * \left(\frac{1}{J}\sum_{j=1}^{J} \mathrm{S}_j\right) * \left(100 - \frac{1}{K}\sum_{k=1}^{K} \mathrm{A}_k\right)}, \qquad \text{(Equation 1)}$$

where V is the ETVI score, E represents the exposure dimension with i components related to energy transition, S represents the sensitivity dimension with j components, and A represents the adaptive capacity dimension with k components. The geometric mean is a commonly used method for aggregating multi-dimensional indices into a composite index, such as in the Human Development Index (HDI) and Sustainable Development Goals (SDG) index published by the United Nations.[29,63] In line with the SDG index construction, we arithmetically average each component of exposure, sensitivity, and adaptive capacity to obtain the corresponding dimensional index. Within each component, measures are equally weighted since there is no a priori reason to give one measure greater weight than another.[11,29]

Beyond being a standard aggregation method, the geometric mean of the three dimensions has a clear economic interpretation in this study. Sensitivity and adaptive capacity are multiplied by exposure, as their measures are tailored to specific exposure contexts. That is, sensitivity and adaptive capacity only matter if a city is exposed to a certain type of change required by the low-carbon energy transition, such as the coal phase-out considered. Moreover, the same level of exposure will have different negative impacts on cities with varying levels of sensitivity: more fragile cities will experience greater adversity when facing the same level of exposure. The product of exposure and sensitivity measures the magnitude of direct vulnerability given the energy transition, which can be mitigated or offset by the adaptive capacity of each city, yielding an overall assessment of energy transition vulnerability.

Intertemporal inequality analysis

To investigate regional inequality of energy transition vulnerability, we primarily utilize the Gini coefficient, the most widely used inequality index in economics. The Gini coefficient measures inequality among the values of a frequency distribution, where a coefficient of 0 reflects perfect equality, and a coefficient of 1 reflects maximal inequality among values. The formula for the Gini coefficient (G) is as follows:

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left|V_i - V_j\right|}{2\sum_{i=1}^{n}\sum_{j=1}^{n} V_j} \qquad \text{(Equation 2)}$$

where V_i and V_j are the ETVI scores of city i and city j ($i \neq j$), respectively, and n is the total number of cities. To assess the robustness of the Gini index, we also apply the Theil index (T) and Atkinson index (A) to quantify the inequality trends:

$$T = \frac{1}{n}\sum\nolimits_{i=1}^{n} \frac{V_i}{\overline{V}} ln\left(\frac{V_i}{\overline{V}}\right) \qquad \text{(Equation 3)}$$

$$A = 1 - \frac{1}{\overline{V}}\left(\prod\nolimits_{i=1}^{n} V_i\right)^{1/n} \qquad \text{(Equation 4)}$$

where $\overline{V} = \left(\sum_{i=1}^{n} V_i\right)/n$ is the mean value of ETVI scores. Both the Theil and the Atkinson indices are widely used alternatives for measuring economic inequality, offering sensitivity to changes in different parts of the distribution, particularly in the tails. In the context of this study, the tails refer to the most and least vulnerable cities.

Spatial clustering analysis

The well-established Moran Index, introduced by Moran,[64] is adopted to examine the spatial autocorrelation of socio-economic vulnerability in energy transition. The global Moran index (Moron's I) is used to verify whether the attribute values of spatial units have an overall spatial autocorrelation:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(V_i - \overline{V})(V_j - \overline{V})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(V_i - \overline{V})^2}, \qquad \text{(Equation 5)}$$

where n is the number of cities, and w_{ij} is the spatial weight matrix. The values of Moran's I range from -1 and 1, where a positive/negative value implies positive/negative spatial autocorrelation and 0 indicates no spatial autocorrelation. The higher the absolute value of Moran's I, the stronger the autocorrelation. The spatial weight matrix expresses the degree of interdependence between different spatial regions and is an essential part of spatial analysis. In this study, we consider four widely used types of spatial weights matrices:

(1) Adjacent distance-weighted matrix

$$w_{ij} = \begin{cases} 1, & \text{if region } i \text{ shares a boundary with region } j \\ 0, & \end{cases} \qquad \text{(Equation 6)}$$

(2) Geographic distance-weighted matrix

$$w_{ij}^{d} = \begin{cases} \frac{1}{d_{ij}}, & i \neq j \\ 0\ , & i = j \end{cases} \qquad \text{(Equation 7)}$$

where d_{ij} represents the minimum geographical distance between region i and j.

(3) Economic distance-weighted matrix

$$w_{ij}^{e} = \begin{cases} \frac{1}{|GDP_i - GDP_j|}, & i \neq j \\ 0\ , & i = j \end{cases} \qquad \text{(Equation 8)}$$

where GDP_i and GDP_j represent the per capita GDP of spatial observation units i and j, respectively. The smaller the difference in economic development between the two regions, the larger the spatial weight and the greater the spatial spillover effect.

(4) Geo-economic distance-weighted matrix

$$w_{ij}^{de} = \begin{cases} \frac{1}{|GDP_i - GDP_j| \cdot d_{ij}}, & i \neq j \\ 0\ , & i = j \end{cases} \qquad \text{(Equation 9)}$$

which accounts for both geographical distance and the level of economic development between regions. The closer the geographical distance between two regions and the smaller the difference in economic development, the greater the spatial spillover effect.

The local Moran's I (LISA) is used to test spatial autocorrelation at the regional level:

$$I_i = \frac{(V_i - \overline{V})}{S^2}\sum_{j=1}^{n} w_{ij}(V_j - \overline{V}) \qquad \text{(Equation 10)}$$

where $S^2 = \sum_{i=1}^{n}(V_i - \overline{V})^2/n$, and other parameters are defined as in Equation 5. A high positive I_i implies that the city has similar vulnerability with its neighbors, forming a high–high spatial cluster (i.e., a vulnerable neighboring region) or a low–low spatial cluster (i.e., a non-vulnerable neighboring region). A high negative I_i means that the city is a spatial outlier, with significantly different vulnerability compared with its surrounding cities.[65] Spatial outliers could be a vulnerable city in a non-vulnerable neighboring region (noted as a high-low cluster) or a non-vulnerable city in a vulnerable neighboring region (noted as a low-high cluster).

Data

Following the developed conceptual framework, we collected indicators for each ETVI component from authoritative energy, environmental, and socio-economic data sources. Each component is represented by one or more indicators, weighted equally. Indicator selection was based on their relevance to our conceptual framework and the availability of data across cities and time. Our final dataset includes a total of 20 indicators from 2010 to 2019 for 281 Chinese cities (see Table 3 for more details). These cities cover 98% of the population, and their GDP and CO_2 emissions account for 99% and 97% of the national values, respectively. Most of the studied cities are located to the east of the

Table 3. Indicators and data sources

Dimensions	Components	Measurements (units)	Data sources
Exposure	coal in energy mix	coal in energy supply mix (%)	Shan et al.[67–70], Shen et al.[26]
		coal in power generation mix (%)	Shan et al.[67–70]; Shen et al.[26]
	coal in regional income	coal sector income, share of regional GDP (%)	China city statistical yearbook, Zheng et al.[71]
Sensitivity	energy use	energy consumption per capita (kJ)	Shan et al.[67–70]; Shen et al.[26]
		electricity consumption per capita (kW)	Shan et al.[67–70]; Shen et al.[26]
	occupational sectors	proportion of population employed by mining sector (%)	China city statistical yearbook
	wealth	proportion of population in poverty (%)	China city statistical yearbook, poverty monitoring report of China
	susceptible demographics	proportion of population that is unemployed (%)	China city statistical yearbook
		proportion of population that is elderly (%)	China city statistical yearbook, population census of China
Adaptive capacity	economic capability	GDP per capita (yuan)	China city statistical yearbook
	science and technology	R&D expenditure (yuan per capita)	China city statistical yearbook
		researchers in R&D (per 10^4 capita)	China city statistical yearbook
		number of green invention and utility model patents applied for (per 10^4 capita)	Chinese research data services (CNRDS) platform (https://www.cnrds.com/home/index#/)
	education and training	education expenditure (yuan per capita)	China city statistical yearbook
		employees in the education industry (per 10^4 capita)	China city statistical yearbook
		number of students enrolled in regular institutions of higher education (per 10^4 capita)	China city statistical yearbook
	fiscal and governability	public expenditure (yuan per capita)	China city statistical yearbook
		social security expenditure (yuan per capita)	China city statistical yearbook
		total investment in fixed assets (yuan per capita)	China city statistical yearbook
		amount of foreign capital per capita (US dollars per capita)	China city statistical yearbook

Notes: city-level data from 2010 to 2019, covering 281 cities. These cities covered 98% of the population, and their GDP and CO_2 emissions accounted for 99% and 97% of the national values in 2019, respectively.

Heihe-Tengchong line, where 96% of the Chinese population resides.[66] The standard min-max method was adopted to normalize the original data, with the top and bottom 2.5th percentile performers as upper and lower bounds for the baseline results. The 2.5th percentile has been widely used in previous studies (e.g., Sachs et al.[29,30] and Xu et al.[29,30]) to minimize the potential effects of skewed data distributions on the standardized values during normalization. The robustness of the ETVI scores under alternative choices of upper and lower bounds is evaluated in the robustness analysis section.

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to, and will be fulfilled by, the lead contact, Yingzhu Li (li_yingzhu@zju.edu.cn).

Materials availability

This study did not generate new, unique materials.

Data and code availability

The data used in this study are sourced from official government statistics, public databases, and existing literature, all of which are cited in the paper. The study data and code have been deposited on GitHub and are available at https://doi.org/10.5281/zenodo.15462129.

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AUTHOR CONTRIBUTIONS

Y.S.: conceptualization, formal analysis, writing – original draft, and funding acquisition; Y.L.: conceptualization, writing – review and editing, and funding acquisition; X.S.: conceptualization and writing – original draft; Y.W., J.H., and Y.C.: formal analysis and data curation.

DECLARATION OF INTERESTS

The authors declare no competing interests.

SUPPLEMENTAL INFORMATION

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