Received: 19 March 2023 | Revised: 5 November 2023 | Accepted: 8 November 2023
DOI: 10.1002/sd.2835

RESEARCH ARTICLE

Sustainable Development WILEY

Measuring regions' vulnerability and adaptation to climate change in China: An application of hybrid assessment approach

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Funding information
National Natural Science Foundation of China, Grant/Award Numbers: 72122002, 72174056; National Social Science Fund of China (NSSFC) Major project, Grant/Award Number: 20&ZD110

Abstract
A timely and systematic assessment can provide valuable insights for decision-making aimed at reducing vulnerability and enhancing adaptive capacity. This study assesses the vulnerability and adaptation of China's provinces to climate change by employing a combination of the criteria importance intercriteria correlation method and Grey relational analysis. We establish a comprehensive three-level index system for evaluation, allowing us to prioritize various factors. Our findings reveal significant disparities in the levels of adaptation and vulnerability to climate change across various regions, Generally, regions with well-developed economies exhibit greater resilience to the impacts of climate change. the ecological system emerges as a key determinant influencing provincial vulnerability to climate change. Moreover, our study underscores the pivotal role of energy system transition in facilitating adaptation to climate change. The findings suggest policy recommendations in areas of ecosystem protection, energy intensity, roadmap, and funding allocation.

KEYWORDS
adaptation, assessment, China, climate change, vulnerability

1 | INTRODUCTION

Climate change has brought a substantial negative impact on both natural ecosystems and human beings (Esperon-Rodriguez et al., 2022). Its consequences are recognized as one of the most pressing challenges facing humanity (Barnes et al., 2020; Harrington et al., 2021). This has garnered significant attention from various nations, countries have invested a lot of money in climate change research (Sovacool et al., 2022). Climate vulnerability and adaptation are critical information for decision-makers to take action to improve their resilience. According to the "Summary for Policymakers" of the Sixth Assessment Report (AR6) released by the Second Working Group (WGII) of the Intergovernmental Panel on Climate Change (IPCC). Vulnerability is defined as the propensity or predisposition to be adversely affected, and encompasses a variety of concepts and elements. Adaptation is defined, in human systems, as the process of adjustment to actual or expected climate and its effects to moderate harm or take advantage of beneficial opportunities. In natural systems, adaptation is the process of adjustment to the actual climate and its effects; human intervention may facilitate this.

As one of the most climate-vulnerable countries in the world (He, 2017), the government has implemented a range of measures to mitigate climate change, including Emission Trading Scheme (Shan, Guan, Hubacek, et al., 2018), the expansion of forested areas, wetlands, and grasslands as carbon sinks (Chen et al., 2019; Lian et al., 2023). These actions have played a substantial role in reducing greenhouse gas emissions. In addition, the "National Climate Change Adaptation Strategy 2035" has outlined a variety of measures aimed at enhancing climate change adaptation, including strengthening climate change monitoring, early warning systems, and risk management; enhancing the adaptive capacity of natural and socio-economic ecosystems; and discussing specific measures to enhance climate change adaptation, such as increasing the utilization of renewable energy (Suman, 2021), raising public awareness and stakeholder engagement (Pietrapertosa et al., 2018; Ray Biswas & Rahman, 2023), and adopting energy conservation technologies (Huang et al., 2022).

Measuring vulnerability and adaptation to climate change is challenging due to the complexity of research. This complexity arises not only from the great uncertainty surrounding the future development and structure of society and the economy (Sun et al., 2021), but also from the complex interactions between biophysical and social dimensions at multiple scales (Crandon et al., 2022; IPCC, 2022) Therefore, identifying which factor plays a more important role in measuring the vulnerability and adaptation to climate change has perplexed policymakers. At present, The existing research about climate change in China primarily focuses on specific fields such as urban water infrastructures (Dong et al., 2020), urban ecosystems (Zhao et al., 2019), or regions vulnerable to climate change, such as the coast of Bohai Economic Rim (Zhang et al., 2021). In addition, a minority of scholars have conducted research on the climate change adaptation of Chinese cities (Zhao et al., 2019). In short, there is a lack of research evaluating the vulnerability and adaptation of provinces to climate change. Moreover, limited research has conducted cross-regional and cross-temporal assessments of regional adaptive capacity (Zhao et al., 2019). To fill this gap, this study examines how can we systematically assess the vulnerability and adaptation strategies of different Chinese provinces to climate change, including cross-regional and cross-temporal comparisons, in order to enhance our understanding of regional adaptive capacity and inform more effective climate change mitigation and adaptation policies in China. This study endeavors to address three central questions:(1) What factors should be considered when assessing the vulnerability and adaptation of different regions to climate change? (2) How can the impact factors be objectively weighted to ensure the validity and reliability of the analysis? (3) What has been the climate change vulnerability and adaptation profile of Chinese provinces in recent years?

In response to the growing threat of climate change, numerous vulnerability assessment approaches have been developed rapidly. Over the last decade, there has been a notable upsurge in research efforts focused on climate change vulnerability and adaptation. First, some studies rely on questionnaires (Hasan & Kumar, 2019; Londono Pineda et al., 2019). this method can directly capture the subjective experiences of individuals affected by climate change but data collection requires a lot of human resources and financial support. Second, researchers employ various approaches, including scenario modeling (Debortoli et al., 2019; Lutz & Muttarak, 2017; Ravestein et al., 2018) and coupling models (Behrens et al., 2017; Miara et al., 2017), to assess the impacts of climate change in specific contexts but they are not suitable for regional multi-index evaluation Third, index-based approaches are widely favored for evaluating climate change vulnerability and adaptation. These methods amalgamate multiple indicators into a single composite index using specific aggregation techniques. The index-based approach not only captures diverse aspects of human and natural systems affected by climate change but also bridges the gap between academic research and policy-making by providing an easily understandable measure of vulnerability and adaptation (Dasgupta et al., 2022). However, it's worth noting that there is no consensus on the best method for evaluating climate change vulnerability and adaptation.

For index-based approaches, weighting and aggregation methods have always been a problem worthy of further investigation. Averaging weight is the simplest way to aggregate indicators (Dong et al., 2020; Rana et al., 2022), but it cannot distinguish the importance of each indicator (Li et al., 2016). Principal component analysis (PCA) and analytic hierarchy process (AHP) methods have emerged as the most popular solutions (Watson et al., 2013). The PCA method assigns weights to factors based on the factor loading, but this method may lack some information, which can still be important when assessing vulnerability and lack of variation. The AHP method allows for different weights to be assigned to each indicator based on expert advice, but the results may be subjective and fail to capture the degree of uncertainty (Londono Pineda et al., 2019). Therefore, the selection of suitable weighting and aggregation methods should be guided by the specific objectives of the analysis, while considering the strengths and limitations inherent to each approach. The study presents a new hybrid model is proposed to objectively assign weights to multiple indicators, which has three key contributions.

1. We introduce the Criteria Importance Through Intercriteria Correlation (CRITIC) method, which improves the determination of the objective weight of each factor by considering the volatility of data and the correlation between factors. This method fully utilizes the information contained within and between indicators.
2. Using the Grey relational coefficient instead of the Spearman rank correlation coefficient is more suitable and accurate for analyzing samples with poor information (Deepanraj et al., 2017).
3. Identifying the most urgent priorities among the factors that affect the region's vulnerability and its adaptation to climate change.

The rest of this article is organized as follows. Section 2 introduces the multi-level index system and discusses data collection. Section 3 lays down the foundations of the novel model. In Section 4, we empirically analyze the vulnerability and adaptation of various provinces. Section 5 concludes the article and proposes policy implications.

2 | THE INDEX SYSTEM FOR ASSESSING VULNERABILITY AND ADAPTATION TO CLIMATE CHANGE IN CHINA

The incorporation of diverse factors within an evaluative framework predominantly hinges upon the accessibility of pertinent data and the contextual intricacies inherent to distinct scholarly investigations. In this study, the criteria for indicator selection primarily consist of three aspects. First, the framework provided by the Working Group II (WGII) of the AR6 of IPCC concerning vulnerability and adaptation. Second, we reviewed the existing literature and selected the indicators related to this article, such as treatment rate of consumption wastes, CO2 emissions per unit of GDP (Shen et al., 2023). Finally, the availability of indicator data during the period from 2010 to 2020. Specifically, the selection of primary and secondary indicators is based on the IPCC's vulnerability and adaptation framework. The tertiary indicators are derived from the secondary indicators, incorporating relevant metrics obtained from the National Bureau of Statistics. These indicators are chosen based on their data integrity within the period from 2010 to 2020.

2.1 | Definition of vulnerability

According to the AR6 of IPCC, the analysis framework for vulnerability now places greater emphasis on the impact of climate change on ecosystems and human systems. Based on this framework, we categorize the first-level factors as humans and ecological systems. In the ecological system, there is evidence within the ecological system that degradation and destruction of ecosystems result from non-climatic human-induced factors. Unsustainable land use and land cover change, the unsustainable use of natural resources, deforestation, and loss of biodiversity are some of the key contributors to ecosystem degradation (Watson et al., 2013). In addition, environmental pollution was identified as one of the five main drivers of biodiversity loss. Climate change has major impacts on and complex interactions with forest health and productivity (Gauthier et al., 2015). It may directly or indirectly affect the roles of certain substances, originating from either natural or anthropogenic sources, as they flow from the atmosphere into forest ecosystems through wet or dry deposition (Mitchell & Likens, 2011), resulting in the reduction of biodiversity. For example, acidification from industrial pollutants, photochemical formation of ozone, and excess N deposition have appeared in sequence as the main causes of tree and forest decline in Northeast Asia, affecting forest growth and carbon sequestration (Qiao et al., 2016; Tian et al., 2018). Based on the above, the second-level factors within the ecological system are non-climatic human-induced and environmental destruction.

In the human system, environmental changes pose a significant threat to the most vulnerable segments of humanity, including the elderly, children, and those living in poverty, who lack the necessary resilience to withstand environmental risks (O'Lenick et al., 2019). The most significant environmental hazard to human health is air pollution, which includes SO_2 and particulate matter and leads to a higher incidence rate of health issues (Makri & Stilianakis, 2008). Additionally, factors such as gender, ethnicity, low income, and demographic pressure exacerbate vulnerability in various regions, contributing to inequities and marginalization (IPCC, 2014). Therefore, we choose inequity, demographics, and environmental risk as the second-level factors in the human system. It is worth noting that, in selecting data related to income inequality, due to the unavailability of Gini coefficient data, and considering that previous scholars have conducted research related to income inequality based on the level of income (Pulok et al., 2020), this article assesses regional income inequality using the ratio of urban and rural consumer expenditure to disposable income. In this article, we choose the third-level factors are highly correlated with the second-level factors and are publicly available, comparable, and easy to interpret and understand. The detailed information is given in Table 1.

2.2 | Definition of adaptation

In line with the AR6 of IPCC, this study employs a range of indicators pertaining to adaptation from four key perspectives. First, concerning cross-cutting options, it is widely recognized that adaptation options are highly applicable across various sectors, and can offer significant socio-economic benefits. Various determinants such as technology (Hallegatte et al., 2011), economics (Davenport et al., 2017), education (Sietsma et al., 2021), human resources, and health systems have been identified as influential factors. It is worth that we exclusively focus on the regional economic capacity, excluding intricate processes of economic transformation. Economic transformation pertains to numerous systemic changes associated with the economy, necessitating a more intricate and comprehensive modeling approach for in-depth study (Stern, 2022). Financial constraints are pivotal determinants of soft adaptation limits across sectors and regions (IPCC, 2022), countries with high income levels can effectively manage the environment and adapt to climate change through macroeconomic governance (Akan et al., 2023). Therefore, this article selects indicators of industrialization level, consumption level, economic capacity, and government budget as representatives of the economic strength of regions.

Second, concerning urban, rural, and infrastructure transitions, it is worth noting that individuals residing in rural areas with limited social protection are especially vulnerable to the impacts of climate change, in addition to challenges related to infrastructure (Mauree et al., 2019). Third, concerning land, ocean, and ecosystems transitions, a range of actions, including conservation, protection, and restoration of terrestrial, freshwater, and forest ecosystems, as well as targeted management approaches to adapt to the inevitable impacts of climate change, can effectively enhance biodiversity's adaptation to climate change (Mauree et al., 2019). Moreover, effective adaptation actions related to water and food can improve the availability and stability of food systems while reducing climate risks (Mauree et al., 2019). Fourth, addressing the transition of the energy system is widely acknowledged as one of the most crucial methods for mitigating climate change. This is due to the fact that climate change is primarily triggered by the accumulation of greenhouse gases, primarily CO_2, in the atmosphere, largely resulting from human activities such as the burning of fossil fuels for energy. In this regard, addressing the transition of the energy system is widely acknowledged as one of the most crucial methods for mitigating climate change (Akan, 2023) and enhancing energy efficiency, have been undertaken as part of efforts to mitigate climate change. Consequently, this article has established a three-level framework index system for assessing adaptation to climate change, as depicted in Table 2.

TABLE 1 Factors affecting regions' vulnerability to climate change.

First-level factor	Second-level factor	Third-level factor	Formula	Unit	Properties
Ecological systems	Environmental destruction	CO_2 per billion yuan	CO_2 emissions/GDP	Ton/10^8 yuan	+
		Wastewater per billion yuan	Wastewater emissions/GDP	Ton/10^8 yuan	+
		Proportion of investment completed in the treatment of industrial pollution in GDP	Proportion of investment completed in the treatment of industrial pollution/GDP × 100%	%	−
	Non-climatic human-induced factors	Forest coverage rate	Forest area/gross area × 100%	%	−
		Proportion of wetlands in total area of territory	Area of the wetlands/gross area × 100%	%	−
		Proportion of nature reserve in total area of territory	Nature reserve area/gross area × 100%	%	−
		Proportion of soil erosion area in total area of territory	Soil erosion area/gross area × 100%	%	+
		Proportion of natural disaster affected area in total area of territory	The area affected by hailstorms, droughts, floods, geological disasters, freeze/gross area × 100%	%	+
		Proportion of affected agriculture area in total area of territory	Affected agriculture area/gross area × 100%	%	+
Human systems	Demographic pressures	Children dependency ratio	Children/working-age population × 100%	%	+
		Old dependency ratio	Elderly population/working-age population × 100%	%	+
		The proportion of urban population	Urban population/total population × 100%	%	+
		Natural growth rate	Birth rate-death rate	%	+
	Inequity	Urban–rural comparison of minimum living security (rural = 1)	Minimum living security population/ total population	−	+
		Urban–rural comparison of residents' consumption expenditure (rural = 1)	Consumption expenditure of urban residents/consumption expenditure of rural residents	−	+
		Urban–rural comparison of disposable income (rural = 1)	Disposable income of urban residents/disposable income of rural residents	−	+
		Male–female comparison of illiteracy (female = 1)	Proportion of illiterate males aged 6 years and over/Proportion of illiterate females aged 6 years and over	−	+
	Environmental risk	SO_2 emissions per billion yuan	SO_2 emissions/GDP	Ton/10^8 yuan	+
		Particulate matter per billion yuan	Particulate matter emissions/GDP	Ton/10^8yuan	+
		Proportion of affected population	Affected population/total population × 100%	%	+

3 | METHODOLOGY AND DATA

3.1 | The improved CRITIC method based on GRA

As previously mentioned, weighting and aggregation methods have gained prominence as critical areas of research (Dong et al., 2020), especially concerning the assessment of regions' vulnerability and adaptation to climate change. Climate change vulnerability and adaptation depend on numerous factors spanning various domains, including human, financial, social, and natural capital. These factors play pivotal roles in both human and ecological systems, making them indispensable (Ahmadalipour & Moradkhani, 2018; Amegavi et al., 2021; Barnes et al., 2020; Dasgupta et al., 2022; Sarkodie & Strezov, 2019; Tapia et al., 2017). For instance, factors like forest

TABLE 2 Factors affecting regions' adaptation to climate change.

First-level factor	Second-level factor	Third-level factor	Formula	Unit	Property
Urban, rural and infrastructure transition	Social protection programs	Maternity insurance ratio	Maternity insurance contributors at year-end/total population × 100%	%	+
		Unemployment insurance ratio	Unemployment insurance contributors at year-end/total population × 100%	%	+
		Industrial injury insurance ratio	Industrial injury insurance contributors at year-end/total population × 100%	%	+
		Endowment insurance ratio	Endowment insurance contributors at year-end/total population × 100%	%	+
	Infrastructure	Daily sewage treatment capacity	Daily municipal wastewater treatment/total population	m^3/person	+
		Passenger capacity	Passenger traffic/total population	–	+
		Treatment rate of consumption wastes	Treatment of consumption wastes/all of consumption wastes × 100%	%	+
Cross-cutting options	Health systems	Beds of medical institutions per 1000 population	Number of beds in medical institutions/1000 population	Beds	+
		Medical technical personnel in health care institutions per 1000 persons	Number of medical technical personnel in health care institutions/10^4 population	Person	+
	Technology	Number of patents per billion yuan	Number of patent granted/GDP	Unit/10^8 yuan	+
		Proportion of R&D expenditure of industrial enterprises above designated size in GDP	R&D expenditure of industrial enterprises above designated size/GDP × 100%	%	+
		Proportion of R&D personnel of industrial enterprises above designated size in the population	R&D personnel of industrial enterprises above designated size/total population × 100%	%	+
		Proportion of sales revenue of new products of industrial enterprises above designated size in GDP	Sales revenue of new products of industrial enterprises above designated size/GDP × 100%	%	+
		Technological achievements marketization	Technology market turnover/GDP × 100%	%	+
	Human resources	Proportion of population aged 15–65	Population aged 15–65/total population × 100%	%	+
		Registered urban unemployment rate	Unemployment/(employee + unemployment) × 100%	%	–
		Overall labor productivity in terms of total output value	Total output value of construction industry/Number of construction workers	Yuan	+
	Education	Ratio of education expenditure to GDP	Educational fund/GDP × 100%	%	+
		Student-teacher ratio in universities (teacher = 1)	Number of students in university/teachers	–	-
		Ratio of expected graduates of universities	Expected graduates of universities/total population × 100%	%	+

(Continues)

TABLE 2 (Continued)

First-level factor	Second-level factor	Third-level factor	Formula	Unit	Property
		Percentage of illiterate population to total aged 15 and over	Number of illiterate population aged 15 and over/total population × 100%	%	–
	Economics	Advanced stage of industry structure	Value added of tertiary industry/Value added of secondary industry	–	+
		Marketization of total retail sales of consumer goods	Total retail sales of consumer goods/GDP × 100%	%	+
		GDP per capita	GDP/total population	Yuan	+
		General public budget revenue and expenditure comparison	General public budget revenue/General public budget expenditure	–	+
Land, ocean and ecosystems transition	Ecosystem	Green coverage rate of built district	Green coverage/gross area × 100%	%	
		The proportion of afforestation area in total area of territory	Afforestation area/gross area × 100%	%	–
		Proportion of forestry investment in GDP	Forestry investment/GDP × 100%	%	+
	Food and water security	Food per capita	Grain/total population (FW1)	kg/person	–
		Water resources security	Per capita available water resources/water consumption per capita	–	+
		Water-saving irrigation ratio	Water-saving irrigation area/total irrigation area × 100%	%	+
Energy system transition	Power systems	Hydropower ratio	Hydropower generating capacity/power generation × 100%	%	+
		electricity consumption per unit output	Electricity consumption/GDP	kwh/yuan	+
		Thermal power generation ratio	Thermal power generation/power generation × 100%	%	–
		Power resources security	Power generation per capita/electricity consumption per capita	–	+

coverage rate and wetlands coverage rate, categorized under natural capital, are interconnected. Their rates of increase or decrease are interdependent, and both contribute significantly to mitigating a region's vulnerability to climate change. While PCA is a widely used method for aggregating multiple indicators into a composite index, it tends to emphasize variable classification over the determination of each indicator's weight. During the aggregation process, PCA extracts partial information from all variables based on their variance contribution rates, potentially leading to the loss of valuable information. This article introduces a novel approach by combining the CRITIC method and Grey relational analysis (GRA) to assign weights to each factor. This method prioritizes more important factors in addressing climate change without sacrificing any factor's information (Chang & Zhu, 2020; Paramanik et al., 2022; Zhu & Chang, 2020).

The CRITIC method, proposed by Diakoulaki in 1995, is an objective weighting technique employed in multi-criteria decision-making (Diakoulaki et al., 1995). It involves thorough analytical examination of the evaluation matrix to extract all relevant information from the evaluation criteria. This method uses contrast intensity and assesses the conflicting nature of factors using standard deviation and the Spearman rank correlation coefficient, respectively, to ascertain the weight of each factor.

Assuming there are i alternative evaluation objects (regions) and j evaluation factors, which can be expressed as:

$$X = x_{i\times j}\ (i=1,2,\ldots,m;\ j=1,2,\ldots,n)$$

$x_{i\times j}$ is the j factor used to evaluate the vulnerability and adaptability to climate change in region i. In many instances, datasets under analysis may consist of variables with significantly different orders of magnitude. To achieve data normalization when dealing with both positive and negative factors, a combination of scaling and standardization techniques can be employed. When the index is positive, Formula (1) can be used for conversion, as it helps to achieve the following:

$$x_{ij}' = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} (i=1,2,\ldots,m;\ j=1,2,\ldots,n) \tag{1}$$

When the index is negative, it can be converted by Formula (2):

$$x_{ij}' = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} (i=1,2,\ldots,m;\ j=1,2,\ldots,n) \tag{2}$$

The CRITIC method primarily emphasizes the assessment of contrast intensity and factor conflict to determine the weights of indicators. These aspects are quantified through the use of standard deviation and the correlation between factors. Standard deviation, denoted as σ_j, signifies the contrast intensity of the j_{th} factor, which, in turn, reflects the variations in the same factor across different evaluation schemes. Larger standard deviation values indicate greater disparities. Consequently, this article investigates the disparities in adaptation among regions using the coefficient of variation. The formula for calculating σ_j is as follows:

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}\left(x_{ij}' - \overline{x_j'}\right)}{m-1}} (i=1,2,\ldots,m;\ j=1,2,\ldots,n) \tag{3}$$

Conflict analysis measures the degree of correlation among various factors. The traditional CRITIC method uses the Spearman rank correlation coefficient to quantify the conflict among a indicators. The calculation formula is:

$$r = \frac{\sum_{i=1}^{m}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\sum_{i=1}^{m}(x_i-\overline{x})^2}\sqrt{\sum_{i=1}^{m}(y_i-\overline{y})^2}} \tag{4}$$

The application of the Spearman rank correlation coefficient, although valuable, is not without limitations. (1) It is most appropriate for use with large sample sizes that follow a normal distribution. When dealing with small sample sizes, the coefficient may exhibit significant fluctuations. (2) The Spearman rank correlation coefficient requires significance testing, but the traditional CRITIC method does not account for this requirement. (3) it's important to note that correlation coefficients may be either positive or negative, while the traditional CRITIC method treats them as absolute values without considering their inherent positive or negative relationship. When considered together, these factors may lead to inaccurate assessments. In response to these challenges, this article proposes an improved CRITIC method that incorporates the gray correlation coefficient as an alternative to the Spearman rank correlation coefficient.

The GRA method, proposed by Deng (1989), is employed to identify the overall trend of an information system, particularly suitable for small sample. At its core, GRA aims to assess the proximity of the relationships between different factors by examining the similarity of the geometric shape within sequence curve. Gray correlation degrees provide a direct measure of the degree of association between different factors. Unlike traditional multi-factor analysis methods, GRA doesn't necessitate a large sample size or data with a specific distribution. As a result, it is well-suited to determine the influence of each factor within the system in which it is operates. The detailed calculation process is presented below.

Supposing the reference sequences X_0 are:

$$X_0 = \{x_0(i) | i=1,2,\ldots,m\} = (x_0(1), x_0(2), \ldots, x_0(m))$$

where, i is the number of individuals. Then, assuming the comparative sequences $X_1, X_2 \cdots, X_n$, which are expressed as:

$$X_j = x_j\{x_i(i) | i=1,2,\ldots,m\} = \left(x_j(1), x_j(2), \ldots, x_j(m)\right) \quad j=1,2,\ldots,n$$

The relational coefficient between reference sequence x_0 and comparative sequence x_j is:

$$\gamma\left(x_0(i), x_j(i)\right) = \frac{\min_j \min_i \left|x_0(i) - x_j(i)\right| + \rho \max_j \max_i \left|x_0(i) - x_j(i)\right|}{\left|x_0(i) - x_j(i)\right| + \rho \max_j \max_i \left|x_0(i) - x_j(i)\right|} \tag{5}$$

where $\rho \in (0,1)$ is resolution coefficient, and usually $\rho = 0.5$. $\min_j \min_i |x_0(i) - x_j(i)|$ and $\max_j \max_i |x_0(i) - x_j(i)|$ are the two-level minimum difference and maximum difference. The relational coefficient defined by Equation (5) is a measure that describes the degree of association between a comparative sequence and a reference sequence in a given region. As each region has its own correlation coefficient, the information appears dispersed, making it challenging to compare. Therefore, it is necessary to aggregate and average the correlation coefficients from all regions to obtain the degree of association between the two variables. The formula of correlation degree between X_j and X_0 is:

$$\gamma(X_0, X_j) = \frac{1}{m}\sum_i^m \gamma(x_0(i), x_j(i)) \quad i = 1,2,\ldots,m,\ j = 1,2,\ldots,n \tag{6}$$

In order to calculate the correlation between two variables, we sequentially set each index as the reference sequence, while the other variables within the same evaluation system serve as comparative indexes. Through this process, we can obtain the gray correlation degree between each variable and the other variables. Therefore, we get the correlation degree matrix of all of the indexes.

$$\Gamma = \begin{bmatrix} 1 & \gamma_{12} & \cdots & \gamma_{1n} \\ \gamma_{21} & 1 & & \gamma_{2n} \\ \cdots & \cdots & 1 & \cdots \\ \gamma_{n1} & \gamma_{n2} & \cdots & 1 \end{bmatrix}$$

In this article, our objective is to quantify the correlation between various variable. The variables under consideration serve dual roles as both reference sequences and comparison sequences. Instead of utilizing the traditional Spearman rank correlation coefficient employed in the CRITIC method, we employ the gray correlation degree to assess the conflict between the variables. Denoting that conflict between factorjand the other factors as f_j, we express this relationship using Equation (7)

$$f_j = \sum_{i=1}^m (1 - \gamma(X_i, X_j)) \tag{7}$$

As previously mentioned, the quantity of information within weight-determine is related to both contrast intensity and conflict among decision criteria. Therefore, the information contained c_j in each factor can be obtained using formula (8):

$$c_j = \sigma_j f_j \tag{8}$$

According to the previous analysis, it becomes evident that the quantity of information plays a pivotal role in influencing its relative significance within the decision-making process, the weight of j_{th} factor can be calculated by using Equation (9)

$$w_j = \frac{c_j}{\sum_{j=1}^n c_j} \tag{9}$$

The sets of weights and x'_{ij} are used to construct a multicriteria score s_i by using Equation (10):

$$s_i = \sum_{j=1}^n w_j x'_{ij} \tag{10}$$

where, s_i is a comprehensive index for assessing the vulnerability and adaptation of regions to climate change.

3.2 | Data collection

We collected data of 26 provinces and 4 municipalities in China spanning the years 2010–2020, Tibet, Hong Kong, Macau, and Taiwan were excluded from this study due to data limitations. All of the data were sourced from the National Bureau of Statistics[1] and Carbon Emission Accounts & Datasets[2] (CEADs) (Guan et al., 2021; Shan et al., 2016; Shan et al., 2020; Shan, Guan, Zheng, et al., 2018). To address missing data on CO_2 emissions and wastewater, we employed the gray model (GM (1,1)). For certain indicators, including coal consumption, old dependency ratio, children dependency ratio, natural growth rate, urban population, forestry investment, particulate matter emissions, area of wetlands, educational fund, R&D expenditure of industrial enterprises above designated size, and R&D personnel of industrial enterprises above designated size, we used the nearest neighbor algorithm to estimate the missing values.

4 | RESULTS AND DISCUSSION

The hybrid model, as presented in Section 3, has been utilized to monitor the evolution of vulnerability and adaptation statuses for each province from 2010 to 2020. It is essential to acknowledge that the scoring system primarily serves to facilitate comparisons between provinces in terms of their vulnerability and adaptation to the impacts of climate change. Consequently, it does not provide an absolute assessment of the provinces' overall preparedness. our emphasis has consistently been on the intercomparison of provincial statuses rather than the assessment of individual indicators.

4.1 | Vulnerability to climate change in different province

The vulnerability of provinces to climate change varies significantly (Figure 1). Generally, provinces situated in the southeast coastal region (Shanghai, Zhejiang, Jiangsu, Fujian, Guangdong, and Hainan) and North China (Beijing and Tianjin) exhibit relatively lower vulnerability. In contrast, provinces located in the southwest region (Guizhou) and northwest region of China (Gansu and Ningxia) display higher vulnerability. Furthermore, the vulnerability of each province to climate change changes over time (Figure 2), Notably, Ningxia, Gansu, and

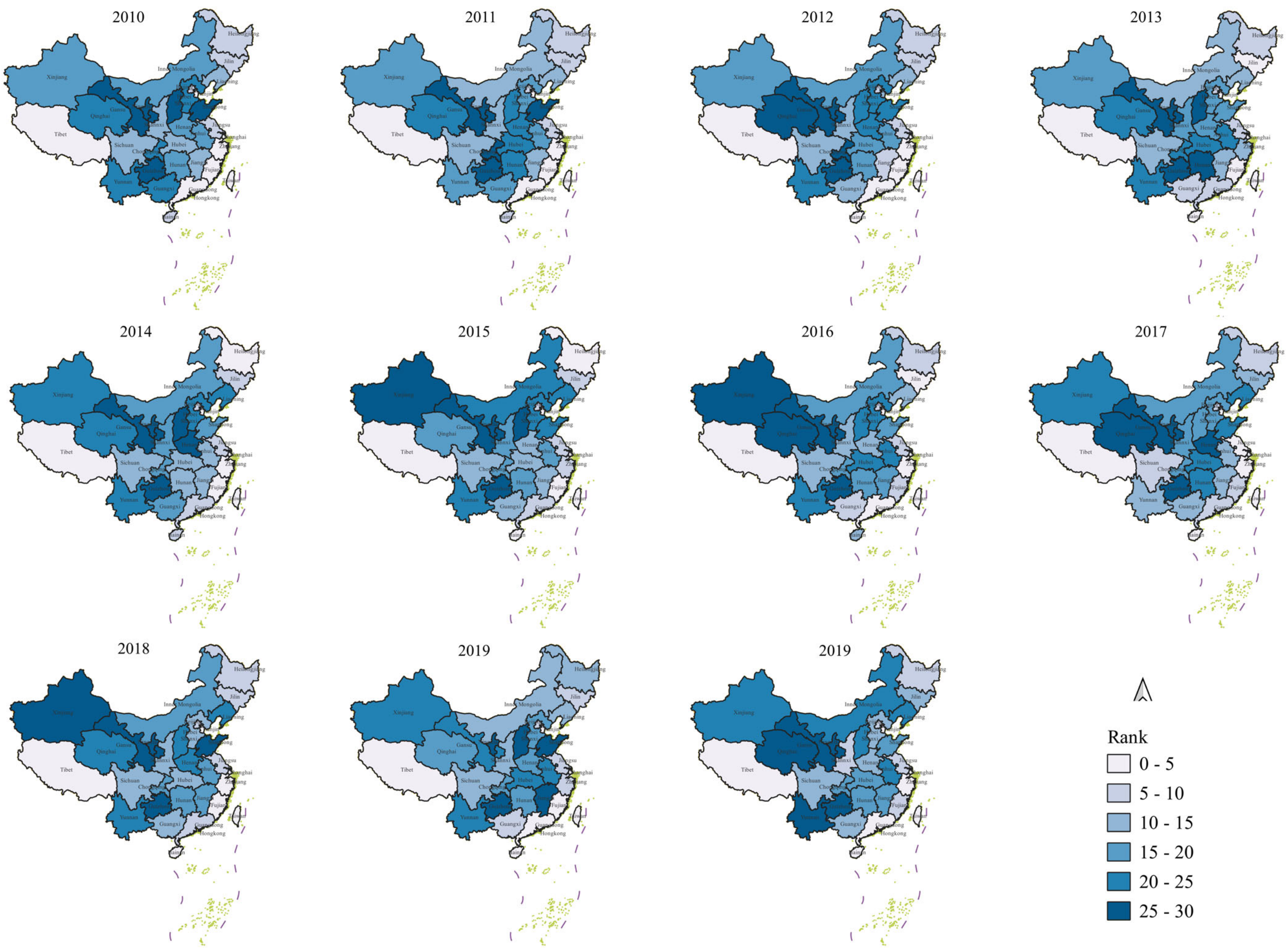

FIGURE 1 The rank of vulnerability to climate change in different regions during 2010–2020. The darker the color of a region, the higher its vulnerability to climate change.

Year	Beijing	Tianjin	Hebei	Shanxi	Inner Mongo	Liaoning	Jilin	Heilongjiang	Shanghai	Jiangsu	Zhejiang	Anhui	Fujian	Jiangxi	Shandong
2010	8	3	22	26	16	14	10	6	1	9	2	18	4	15	27
2011	8	3	19	25	11	14	7	6	2	10	4	18	1	12	26
2012	7	11	24	22	18	15	6	10	2	8	5	20	3	9	25
2013	7	2	19	28	13	12	5	9	1	6	11	25	3	14	17
2014	9	3	21	27	17	24	7	5	1	8	2	15	4	13	18
2015	8	1	25	27	22	24	10	5	2	9	6	18	4	13	23
2016	9	2	24	22	17	13	5	10	1	6	3	21	8	16	18
2017	9	3	18	19	16	21	12	8	2	5	4	13	6	15	23
2018	10	1	12	23	16	25	9	7	2	6	4	20	5	17	26
2019	8	1	16	30	14	11	7	13	3	6	9	23	5	26	28
2020	8	1	13	25	22	23	12	9	2	7	4	21	6	18	16

Year	Henan	Hubei	Hunan	Guangdong	Guangxi	Hainan	Chongqing	Sichuan	Guizhou	Yunnan	Shaanxi	Gansu	Qinghai	Ningxia	Xinjiang
2010	19	12	20	5	21	7	24	13	30	23	11	29	25	28	17
2011	24	22	21	5	16	9	27	13	30	20	15	28	23	29	17
2012	23	17	16	4	14	1	27	13	30	21	12	28	26	29	19
2013	20	21	26	8	10	4	24	15	30	23	16	29	22	27	18
2014	26	11	14	6	16	10	20	12	30	22	19	29	23	28	25
2015	14	15	17	7	12	3	16	11	29	21	19	28	20	30	26
2016	14	23	20	4	7	12	19	11	29	25	15	30	26	28	27
2017	26	22	24	7	11	1	20	10	29	14	17	30	27	28	25
2018	22	15	18	8	11	3	19	13	30	21	14	29	24	28	27
2019	19	21	18	4	10	2	17	12	27	25	15	24	20	29	22
2020	14	19	17	5	11	3	20	15	28	26	10	30	27	29	24

FIGURE 2 The rank change of vulnerability of each region to climate change during 2010–2020. Each bar chart represents a region's climate change vulnerability ranking for a specific year. The taller the bar, the higher the ranking, indicating a higher level of climate change vulnerability for that year.

Guizhou consistently demonstrate higher vulnerability, underscoring the imperative for these provinces to implement substantial reforms aimed at reducing their susceptibility to climate change. Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Fujian, and Guangdong consistently maintain lower vulnerability to climate change. The vulnerability rank of Hainan, Hunan, Hubei, Henan, Anhui, and Liaoning fluctuates considerably, indicating that these provinces lack effective measures to reduce their vulnerability to climate change. In summary, provinces with a high vulnerability to climate change are concentrated in the Southwest Region, Northwest Region, and central China, while provinces with low vulnerability are concentrated in East China and South China.

The present study aims to provide an in-depth analysis of the factors influencing the vulnerability to climate change in different regions of China. While the vulnerability rank analysis has highlighted the disparity in vulnerability among provinces, this study adopts a comprehensive approach to measure the objective weight of indicators that contribute to the vulnerability gap. The weight of the indicators is determined by assessing the contrast intensity between them and the conflicts that may arise. A higher weight for an indicator signifies a larger range of fluctuations and a lower correlation with other indicators. Consequently, indicators with higher weights are inferred to be more significant and easier to modify, potentially reducing the region's climate vulnerability. Previous research in this field has predominantly concentrated on evaluating climate vulnerability in specific regions or sectors without emphasizing the critical determinants of priority. Our study aims to pinpoint the most significant factor influencing vulnerability to climate change using indicator weights. Table 3 presents the weights of the first and second-level factors, while a radar graph illustrates the weights of the third-level factors (Figure 3).

The study finds that ecological systems held greater weight during the period 2010–2013, with the exception of 2012, 2015, 2016, and 2020. Meanwhile, the human system had a higher weight only in 2020. This suggests that, in recent years, greater priority should be given to mitigating vulnerability to climate change within ecological systems than within human systems. As we know, biodiversity and human life on earth are interrelated, intertwined, and inseparable, the healthier ecosystems, the less damage to people (Duffield et al., 2021). Of the third-level factors, the protection and treatment of soil erosion control infrastructure in disaster-affected areas and forests held the highest weight, except in 2012 and 2019. It has been established that climate change significantly impacts soil erosion (Eekhout & de Vente, 2019), and sustainable land management can be increasingly promoted to contribute to climate change mitigation (Griscom et al., 2017). Regarding the human system, demographic pressure factors play a significant role in decreasing vulnerability to climate change among second-level factors. Among third-level factors, the children dependency ratio had the highest weight since 2012. Previous research demonstrated that climate change adversely affects both the physical and psychological health of children (Vergunst & Berry, 2022). Warmer temperatures pose a risk to their food, water, and nutrient security, and also increase the transmission risk of infectious diseases and climate-sensitive infections, particularly in vulnerable regions (Council on Environmental, 2015). What's more, A large number of children around the world report climate anxiety and a wide range of painful, complex emotions because of climate change (Crandon et al., 2022). Therefore, addressing demographic pressure factors, especially the well-being of children, should be central to our strategies for reducing vulnerability to climate change.

4.2 | Adaptation capability to climate change in different province

The study reveals the agglomeration characteristics of climate change adaptation, where certain provinces in China have shown high-level adaptation to climate change compared to others (Figure 4). Provinces

TABLE 3 The weight of first and second level vulnerability factors during 2010–2020.

	First-level factors		Second-level factors				
Year	Ecosystem	Human	Environmental destruction	Non-climatic	Demographic	Inequity	Environmental impact
2010	0.053	0.048	0.050	0.054	0.051	0.046	0.046
2011	0.052	0.048	0.045	0.055	0.050	0.048	0.047
2012	0.050	0.050	0.045	0.053	0.052	0.047	0.050
2013	0.051	0.049	0.043	0.055	0.051	0.045	0.052
2014	0.051	0.049	0.043	0.054	0.055	0.047	0.046
2015	0.050	0.050	0.043	0.054	0.055	0.048	0.045
2016	0.050	0.050	0.043	0.053	0.057	0.049	0.044
2017	0.051	0.049	0.046	0.053	0.060	0.045	0.041
2018	0.051	0.049	0.045	0.054	0.057	0.045	0.044
2019	0.051	0.049	0.043	0.055	0.058	0.046	0.042
2020	0.049	0.051	0.044	0.051	0.058	0.045	0.050

Note: The variables and numbers in orange and blue shades belong to ecological systems and human system, respectively.

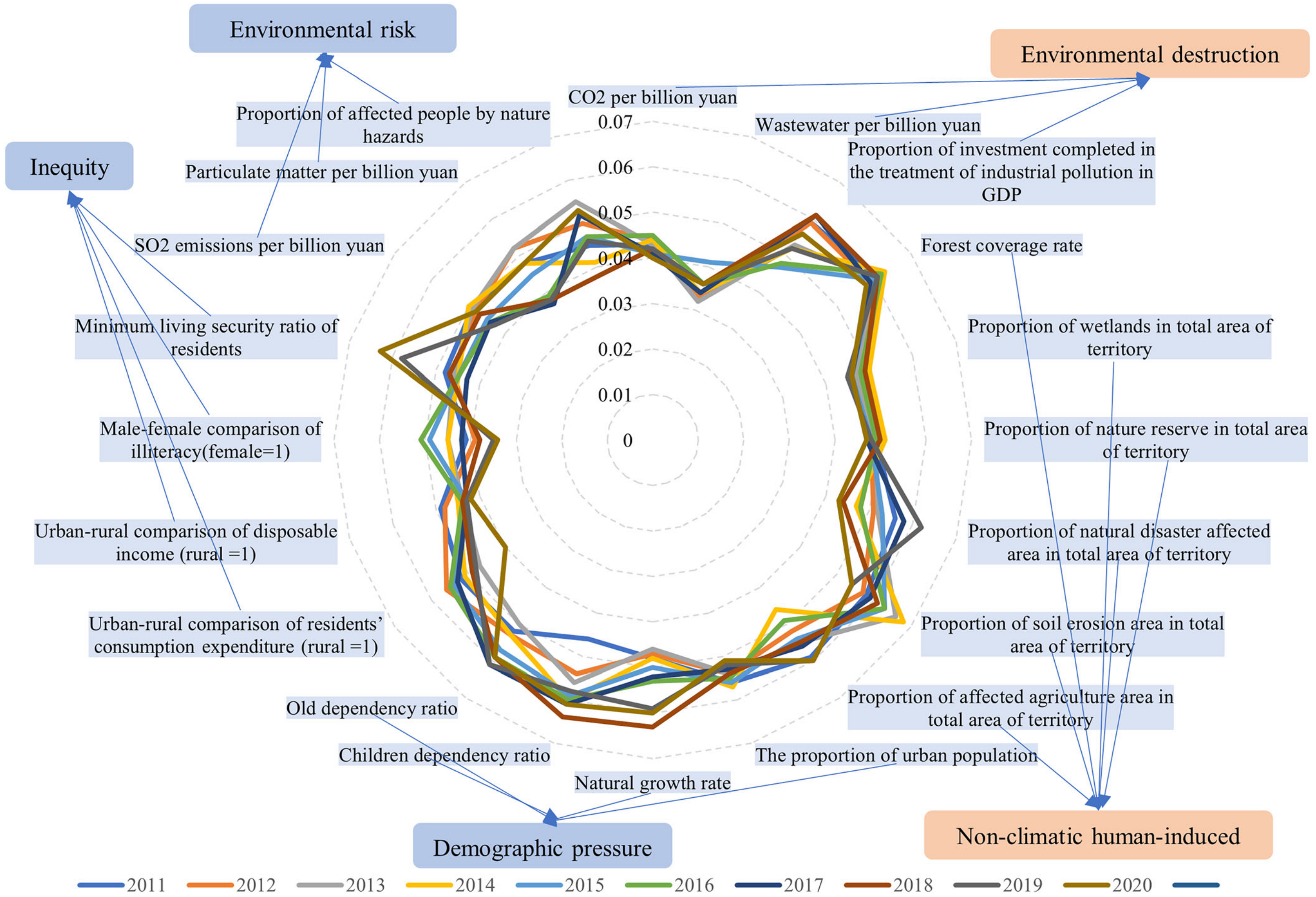

FIGURE 3 The weight of third level vulnerability factors during 2010–2020. In the radar map, the larger radius of concentric circles closest to the variable, the greater the weight of the variable.

on the southeast coast of China, such as Shanghai, Zhejiang, and Jiangsu, have demonstrated high-level adaptation. Conversely, regions in the southwest of China, including Xinjiang, Gansu, Ningxia, and Qinghai, have shown low levels of adaptation. Economic development has emerged as a critical factor in determining the level of adaptation to climate change (Kalafatis, 2017), where provinces with better economic development have shown higher-level adaptation. For instance, Beijing, Tianjin, Shanghai, Zhejiang, and Jiangsu have demonstrated high-level adaptation, while the regions with underdeveloped economies, such as Gansu, Qinghai, Ningxia, and Xinjiang, have exhibited low-level adaptation to climate change. Moreover, the study reveals that the adaptation ranks of each province have changed over time (Figure 5), with some provinces exhibiting a downward trend in their adaptation ranks, including Tianjin, Shanxi, Inner Mongolia, Heilongjiang, Fujian, Hunan, Guangxi, Hainan, Chongqing, Yunnan, and Xinjiang. However, the adaptation of other provinces, including Hebei, Anhui, Jiangxi, Hubei, Shaanxi, Gansu, and Qinghai, has shown an upward trend, while other provinces' adaptation fluctuates within a narrow range. The analysis of adaptation trends over time demonstrates that each province's adaptation to climate change is not static, and local governments have adopted a series of policies to improve adaptation, with varying results. It is plausible to infer that the provinces whose adaptation is constantly improving have more effective policies to deal with climate change, while the provinces with reduced adaptation or greater fluctuations have fewer effective policies to deal with climate change.

This study affirms that the energy system transition is a critical component of climate adaptation, as it has the highest weight in the period between 2010 and 2020 (Table 4). Consequently, it is not surprising that the power system is the factor with the greatest significance among the second-level factors. Specifically, except for 2015, electricity consumption per unit output exhibits the highest weight among the third-level factors related to power systems (Figure 6). It is widely acknowledged that climate adaptation actions can be energy-intensive (Colelli et al., 2022), Despite a growing body of research on the relationship between climate change and the power system, scholars have primarily focused on power generation and electricity service systems (Chen et al., 2021), with less attention paid to power consumption. Clearly, power generation plays an indispensable role in electric power systems such as hydropower generation systems (Miara et al., 2017).This study underscores the significance of electricity consumption per unit output, highlighting that energy efficiency is one of the pillars upon which the government can build its climate and energy strategy.

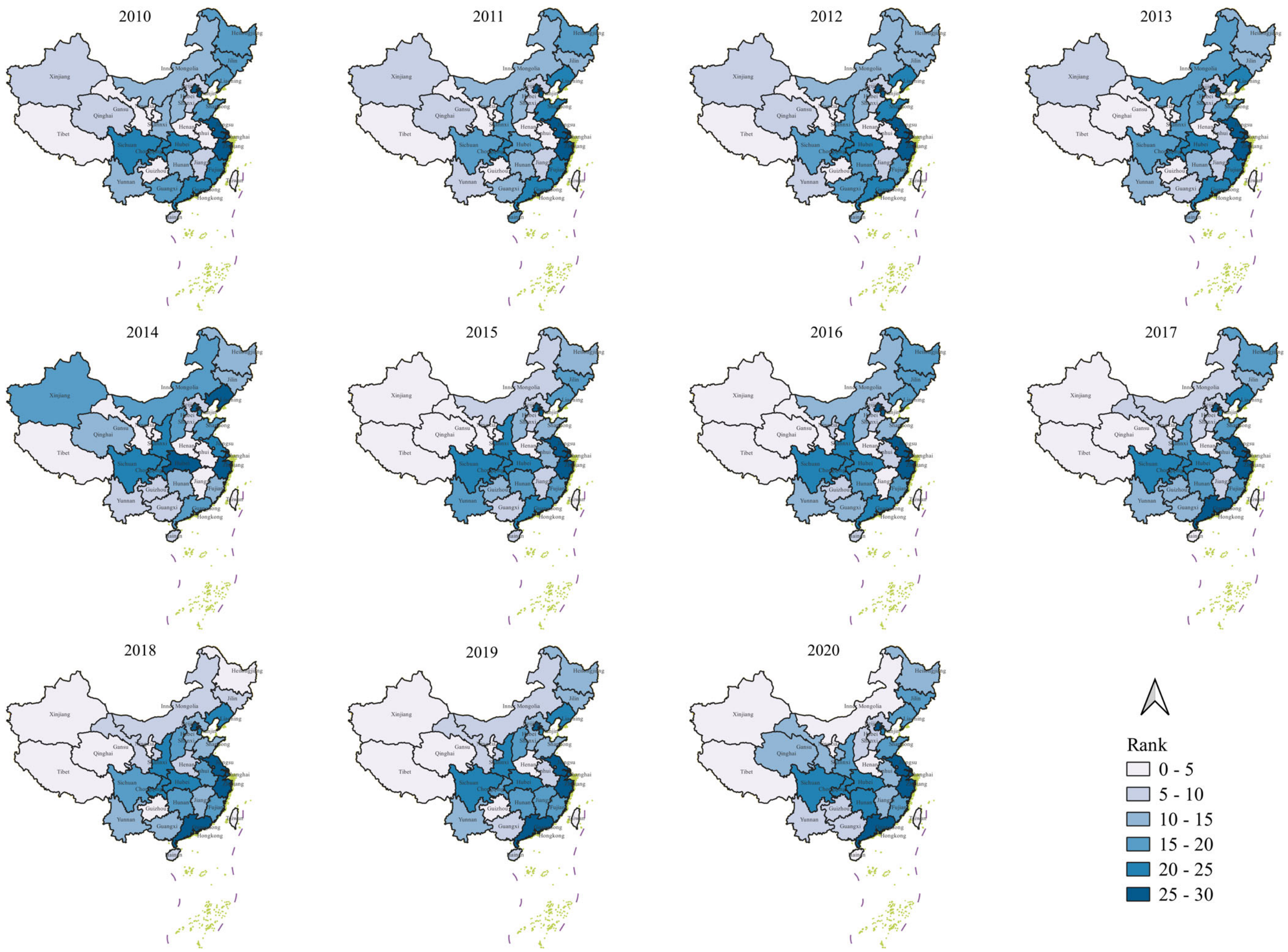

FIGURE 4 The adaptation rank of each region to climate change during 2010–2020. The darker the color of a region, the higher its adaptation to climate change.

4.3 | The categories of each province

Growing evidence suggests a connection between adaptation and vulnerability (Thomas & Warner, 2019). Based on the levels of adaptation and vulnerability exhibited by each province in response to climate change impacts, we can categorize them into four distinct groups: climate-vulnerable, climate-stable, climate-developing, and climate-sustainable. Table 5 provides a detailed overview of these categories and their corresponding classifications.

In this study, we investigate regional variations in climate adaptation and vulnerability within China. Our findings reveal substantial disparities among the country's regions. Specifically, provinces such as Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Guangdong, and Sichuan provinces consistently exhibit a climate-sustainable profile (Table 6). These areas, primarily situated in North and East China, collectively account for a population of 422 million and contribute 40.3% of the country's GDP in 2020. They boast well-developed economies, experience fewer natural disasters, possess robust social, economic, and governance capabilities, and are better equipped to respond to climate-related events (Barnes et al., 2020; Conway et al., 2019). In contrast, provinces like Guizhou, Gansu, Qinghai, and Ningxia consistently exhibit climate vulnerability, primarily in the Northwest Region. These regions, with a combined population of 77 million, contributed only 2.7% to the national GDP in 2020. They face economic development challenges and a higher susceptibility to natural disasters, emphasizing the urgent need for tailored climate adaptation policies. Furthermore, Inner Mongolia, Liaoning, Heilongjiang, Jiangxi, and Hubei have seen a gradual decline in their climate resilience, particularly in the Northeast Region and central China. These areas, home to 201 million people, contributed 14.3% to the national GDP. This indicates that recent climate adaptation efforts have fallen short in reducing vulnerability and improving resilience, necessitating further adjustments. The classification of Shanxi, Anhui, Hebei, Jilin, Fujian, Shandong, Hunan, Guangxi, Hainan, Chongqing, Yunnan, Shaanxi, and Xinjiang displays fluctuations but shows an overall improvement trend. These provinces are mainly located in the Northeast Region, encompass a population of 708 million and contribute 42.7% to the national GDP. Our findings suggest that recent climate adaptation measures have effectively enhanced their adaptive capacity. However, continued efforts are essential to further strengthen their climate resilience. In conclusion, this study provides valuable insights into the disparities in climate adaptation and vulnerability across

Year	Beijing	Tianjin	Hebei	Shanxi	ıner Mongoli	Liaoning	Jilin	Heilongjiang	Shanghai	Jiangsu	Zhejiang	Anhui	Fujian	Jiangxi	Shandong
2010	30	28	6	14	11	20	16	17	29	26	27	1	23	7	19
2011	30	28	7	12	13	24	15	17	29	26	27	5	21	6	23
2012	30	28	6	13	12	24	15	11	29	26	27	4	20	8	22
2013	30	27	7	17	16	25	14	13	28	26	29	8	22	6	20
2014	30	21	7	20	19	28	14	15	29	25	27	2	12	1	18
2015	30	27	8	15	10	19	17	12	28	26	29	11	20	6	13
2016	30	27	8	12	14	20	17	16	29	26	28	10	19	5	11
2017	30	25	7	10	9	22	14	17	29	26	28	13	20	6	16
2018	30	23	12	17	8	22	9	3	29	26	28	16	19	13	11
2019	30	24	15	17	6	23	13	14	28	26	29	7	18	16	11
2020	30	23	8	9	2	17	16	11	28	27	29	13	18	15	19

Year	Henan	Hubei	Hunan	Guangdong	Guangxi	Hainan	Chongqing	Sichuan	Guizhou	Yunnan	Shaanxi	Gansu	Qinghai	Ningxia	Xinjiang
2010	3	22	29	25	18	10	24	21	5	12	13	2	8	4	9
2011	4	20	11	25	14	18	22	19	3	8	16	1	10	2	9
2012	5	21	16	25	17	14	23	19	3	10	18	1	7	2	9
2013	4	21	15	24	10	12	23	19	3	11	18	5	1	2	9
2014	5	26	13	17	9	6	22	23	8	10	24	3	11	4	16
2015	2	25	18	24	9	7	23	22	14	16	21	1	4	5	3
2016	1	24	18	25	13	7	23	22	9	15	21	2	4	6	3
2017	3	24	18	27	11	5	23	21	12	15	19	8	2	4	1
2018	6	24	18	27	14	10	25	20	5	15	21	7	4	2	1
2019	4	25	20	27	10	8	19	22	3	12	21	9	5	2	1
2020	5	25	22	26	10	4	21	24	6	7	20	12	14	3	1

FIGURE 5 The rank change of adaptation of each region to climate change during 2010–2020. Each bar chart represents a region's climate change adaptation ranking for a particular year. The taller the bar, the higher the ranking, indicating a higher level of climate change adaptation for that year.

TABLE 4 The weight of first and second level adaptation factors during 2010–2020.

		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
First-level factor	Cross-cutting options	0.027	0.027	0.027	0.027	0.027	0.028	0.029	0.029	0.029	0.029	0.029
	Energy system transition	0.038	0.037	0.039	0.037	0.038	0.037	0.034	0.034	0.034	0.036	0.034
	Land, ocean and ecosystems transition	0.027	0.028	0.025	0.027	0.028	0.027	0.026	0.025	0.026	0.025	0.026
	Urban, rural and infrastructure transition	0.028	0.028	0.028	0.028	0.028	0.027	0.027	0.026	0.027	0.027	0.027
Second-level factor	Economics	0.027	0.027	0.027	0.026	0.027	0.028	0.027	0.027	0.027	0.026	0.027
	Education	0.03	0.027	0.031	0.031	0.03	0.031	0.03	0.03	0.031	0.031	0.029
	Human resources	0.027	0.027	0.027	0.026	0.028	0.028	0.031	0.03	0.029	0.028	0.031
	Technology	0.027	0.029	0.027	0.026	0.025	0.026	0.027	0.03	0.028	0.029	0.029
	Health systems	0.023	0.023	0.023	0.025	0.025	0.027	0.029	0.031	0.029	0.029	0.027
	Power systems	0.038	0.037	0.039	0.037	0.038	0.037	0.034	0.034	0.034	0.034	0.036
	Food and water security	0.027	0.029	0.023	0.026	0.027	0.027	0.026	0.026	0.026	0.025	0.026
	Ecosystem	0.028	0.028	0.029	0.029	0.028	0.026	0.026	0.025	0.026	0.026	0.024
	Infrastructure	0.031	0.031	0.031	0.033	0.033	0.03	0.031	0.03	0.032	0.033	0.031
	Social protection programs	0.026	0.025	0.025	0.024	0.025	0.024	0.024	0.023	0.023	0.023	0.023

Note: The variables and numbers in orange, green, blue, and black shades belong to cross-cutting options, energy system transition, land, ocean, and ecosystems transition, urban, and rural and infrastructure transition, respectively.

China's regions. It underscores the imperative for region-specific policies to address the challenges posed by climate change effectively.

5 | CONCLUSIONS AND POLICY IMPLICATIONS

This article constructs a three-level framework index system for evaluating regional responses to climate change, focusing on vulnerability and adaptation. our approach not only consolidates multiple indicators into a comprehensive and comparable metric, but also prioritizes key factors, eliminating the need for arbitrary weight allocation while retaining all relevant information. We validate the methodology through empirical analysis using data from Chinese provinces. This approach is adaptable to any economy seeking to assess its climate change adaptation and vulnerability. By emphasizing data-driven adjustments, policymakers can make informed decisions based on a comprehensive indicator.

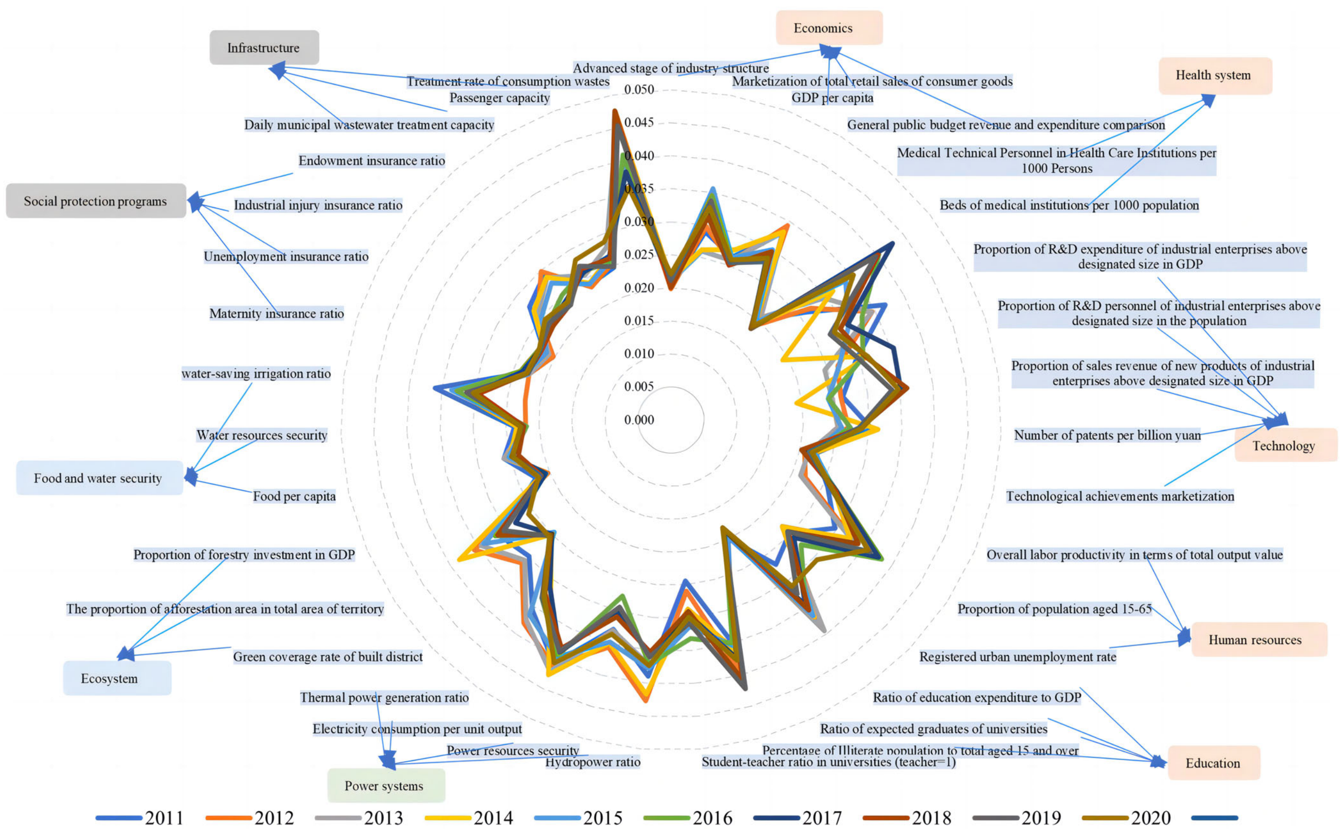

FIGURE 6 The weight of each third level adaptation factor during 2010–2020. In the radar map, the larger radius of concentric circles closest to the variable, the greater the weight of the variable.

TABLE 5 The definition of four categories.

Categories	Feature	Definition
Climate-vulnerable	High vulnerability, low adaptation	The socioeconomic system is the most vulnerable area because of their high exposure to climate change and low capacity to adapt.
Climate-stable	High vulnerability, high adaptation	The socioeconomic system is highly affected by climate change and have high adaptive capacity, so it is important to maintain high adaptive capacity to reduce vulnerability.
Climate-developing	Low vulnerability, low adaptation	The socioeconomic system is less affected by climate change, but also less adaptative, so it needs to improve adaptative capacity to reduce vulnerability.
Climate-sustainable	Low vulnerability, high adaptation	The socioeconomic system is the least affected by climate change, it has a high capacity to adapt, so they are in a state of sustainable development.

Furthermore, this method is transferable to other evaluations involving multiple variables.

The analysis of vulnerability and adaptation assessment to climate change could be invaluable to national and regional agencies for climate change response planning. Our study reveals significant gaps in both vulnerability and adaptation across different regions. These disparities are influenced not only by ecological factors but also by socio-economic development. Furthermore, we delve into the key factors impacting provincial vulnerability and adaptation to climate change. Regarding vulnerability, the ecological system consistently holds the highest weight from 2010 to 2019. Notably, the protection and treatment of soil erosion control infrastructure in disaster-affected areas and forests has the highest weights among third-level ecological factors, except in 2012 and 2019. Concerning adaptation, the energy system transition as the most critical factor at the first level. Notably, electricity consumption per unit output consistently carries the highest weight among third-level factors within the energy system, except in 2012. Based on our analysis, we propose the following mitigation strategies for provinces:

1. *Prioritizing the preservation of ecological systems*. The foremost objective is to prevent the deterioration and destruction of ecological systems. To achieve this, it is essential to implement tailored water erosion control policies based on the specific conditions of affected areas. These policies may include measures such as reducing runoff, promoting afforestation, adopting grain-for-green

TABLE 6 The category of each region during 2010–2020.

Regions	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Beijing	4	4	4	4	4	4	4	4	4	4	4
Tianjin	4	4	4	4	4	4	4	4	4	4	4
Hebei	1	1	1	1	1	1	1	1	3	4	3
Shanxi	1	1	1	2	2	1	1	1	2	2	1
Inner Mongolia	4	3	1	4	2	1	1	4	4	3	1
Liaoning	4	4	4	4	2	2	4	2	2	4	2
Jilin	4	3	3	3	3	4	4	3	3	3	4
Heilongjiang	4	4	3	3	3	3	4	4	3	3	3
Shanghai	4	4	4	4	4	4	4	4	4	4	4
Jiangsu	4	4	4	4	4	4	4	4	4	4	4
Zhejiang	4	4	4	4	4	4	4	4	4	4	4
Anhui	1	1	1	1	3	1	1	3	4	1	1
Fujian	4	4	4	4	3	4	4	4	4	4	4
Jiangxi	3	3	3	3	3	3	4	3	1	4	1
Shandong	2	2	2	2	2	1	1	4	1	1	4
Henan	1	1	1	1	1	3	3	1	1	1	3
Hubei	4	2	2	2	4	4	2	2	4	2	2
Hunan	1	1	4	1	3	2	2	2	2	2	2
Guangdong	4	4	4	4	4	4	4	4	4	4	4
Guangxi	2	1	4	3	4	3	3	3	3	3	3
Hainan	3	4	3	3	3	3	3	3	3	3	3
Chongqing	2	2	2	2	2	4	2	2	2	2	2
Sichuan	4	4	4	4	4	4	4	4	4	4	4
Guizhou	1	1	1	1	1	1	1	1	1	1	1
Yunnan	1	1	1	1	1	4	1	3	1	1	1
Shaanxi	3	4	4	4	2	2	4	2	4	4	4
Gansu	1	1	1	1	1	1	1	1	1	1	1
Qinghai	1	1	1	1	1	1	1	1	1	1	1
Ningxia	1	1	1	1	1	1	1	1	1	1	1
Xinjiang	1	1	1	1	4	1	1	1	1	1	1

Note: 1 represents the climate-vulnerable; 2 represents the climate-stable; 3 represents the climate-developing; 4 represents the climate-sustainable.

initiatives to enhance vegetation cover, implementing soil management techniques like no-tillage and soil amendment, and utilizing engineering techniques like terraces and contour bunds.

2. *Focusing increased attention on promoting energy efficiency is crucial.* Technological advancements, particularly in energy-saving technologies and enhanced output, have played a significant role in reducing energy intensity. Local governments can facilitate the financing of energy efficiency projects and the adoption of cleaner energy technologies. Additionally, improving labor productivity can contribute to a decrease in energy intensity. Governments have the power to influence labor wages and energy prices, which can affect the balance of labor and energy in energy-intensive industries. Furthermore, restructuring both the economic and energy sectors can effectively reduce energy intensity and support sustainable economic development. Encouraging energy-intensive firms to adopt sustainable practices and replace energy-intensive assets is essential for achieving sustainable economic growth. Therefore, it is crucial to incentivize energy-intensive enterprises to transition towards more efficient and sustainable practices to promote overall economic sustainability.

3. *Emphasizing key technologies for energy transition.* In the realm of energy production, the government can prioritize key technologies such as renewable energy generation and integrated utilization techniques, low-carbon emission and carbon resource utilization technologies for coal-fired power generation, and hydrogen production, storage, conversion, and application technologies. Concerning system security, technologies such as novel energy storage, superconducting power transmission, and advanced integrated energy transmission technologies hold significant importance in sustaining the energy sector's efficiency and

stability. In the domain of system planning, emerging technologies such as novel electric power system simulation techniques, digital system technologies, and energy IoT (Internet of Things) technologies can be employed in a scientifically effective manner to plan the energy system.

4. *Developing dynamic and adaptive roadmaps for regions to address vulnerability and enhance adaptation*. Researchers and policymakers alike may need to consider adaptation actions as experiments with uncertain outcomes that need to be dynamically revisited on an ongoing basis. Developing dynamic roadmaps for regions can systematically evaluate their vulnerabilities and adaptation to climate change, and determine the main factors affecting the vulnerability and adaptation of each region to climate change over time, priority adaptation measures can provide a fruitful avenue to improve the effect of regional adaptation.
5. *Establish a dedicated fund to provide financial resources and support to regions assist vulnerable regions highly vulnerable to diverse climate change challenges*. This fund can be initiated by governments, international organizations, or private entities, highlighting the importance of a collaborative approach. To create such a fund successfully, it is imperative to first identify the most pressing needs and challenges faced by these vulnerable regions. Subsequently, a transparent process for fund allocation should be developed, alongside clearly defined eligibility criteria, to ensure equitable distribution. Moreover, effective and efficient fund management is paramount for the fund's long-term viability and impact.

It is worth highlighting again that our approach should be seen as a first step in addressing the issue at hand. We contend that the complexity of local assessments renders it unlikely for a single assessment tool or indicator model to suffice. The approach we propose underscores the inherent volatility and relevance of data within this research domain, underscoring the need for a broader methodological framework. Furthermore, obtaining the necessary data poses a significant challenge for many local governments, as they often lack the requisite financial, technical, and human resources. Although we have preliminarily established a three-level framework index system for an evaluation system, the selection of appropriate factors invariably hinges on the specific conditions of each locality. This particularly holds true for the identification of indicators requiring measurement and the methodologies employed for aggregating indicators across diverse criteria to generate composite indicators. These composite indicators should also be periodically updated and subjected to further study. In addition, given the dynamic and long-term nature of climate change, more precise, comprehensive, and in-depth comparative studies are imperative. Much work remains to be undertaken in this regard.

ACKNOWLEDGMENTS

This work was supported by the National Natural Science Foundation of China (grant number: 72122002, 72174056; and National Social Science Fund of China Major Project: 20&ZD110).

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ENDNOTES

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How to cite this article: Li, Q., Zhu, L., & Shi, X. (2024). Measuring regions' vulnerability and adaptation to climate change in China: An application of hybrid assessment approach. *Sustainable Development*, *32*(4), 3115–3132. https://doi.org/10.1002/sd.2835