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Assessing climate vulnerability in China's industrial supply chains: A multi-region network analysis approach

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ABSTRACT

The extreme weather caused by climate change can easily impact the supply chain network (SCN) of industrial sectors, and its direct effects can spread along the SCN to other regions, thereby indirectly affecting the normal production and transactions of industrial products. This study integrates multi-region input-output analysis (MRIO), complex network analysis, and the technique for order preference by similarity to an ideal solution based on entropy weight method (TOPSIS-Entropy) to systematically assess the climate vulnerability of industrial sectors in 31 provinces of China from the perspective of SCN. The results reveal that, in resource-intensive industrial sectors, provinces exerting significant influence on SCN are mainly those rich in natural resources or those achieving economic development despite a lack of resources. These provinces exhibit relatively high climate change vulnerability index (CCVI). In contrast, for manufacturing sectors, the influential provinces on the SCN are primarily those with robust economic growth and substantial trade flows. These provinces display relatively high CCVI. Based on these findings, provinces should develop climate change management plans for industrial supply chains, implement demand-driven inventory strategies in resource-scarce areas, create collaborative platforms to enhance supply chain reliability, and establish mitigation measures for key manufacturing and resource-exporting provinces to manage risks and minimize the impacts of climate change effectively.

Abbreviations

Nomenclature	
T_l^{rs}	The trade flow of products of industrial sector l from province r to province s
X_l^{ro}	The total products from industrial sector l flowing out from province r to all other provinces
X_l^{os}	The total products of industrial sector l from other provinces flowing into province s
$f(d_l^{rs})$	The trade barriers between provinces
d_l^{rs}	The economic distance
α_l^s	The distance decay coefficient
$\overline{d^s}$	The average transportation distance
C_l^{rs}	Total products from industrial sector l sent from province r to province s
K^s	Proportional coefficient
G	A directed weighted network
V	The nodes of a network
E	The edges of a network
W	The weight of edges in a network
TD_r	Trade dependence
Abbreviations	
CCVI	Climate change vulnerability index
SCN	Supply chain network
MRIO	Multi-region input-output analysis
X_r	The total consumption of province r
γ_s	Response coefficient
δ_r	Influence coefficient
In(r)	All nodes pointing to node r
Out(r)	All nodes pointed to by node r
y_{ij}	The j_{th} indicator in the i_{th} province
p_{ij}	The proportion of i_{th} province relative to all provinces under j_{th} indicator
en_j	The entropy value for the j_{th} indicator
wei_j	The weight of indicators
dis_i^+	The positive ideal solution
dis_i^-	The negative ideal solution
$y_j^{\prime max}$	The maximum values of indicators

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$y_j^{\prime min}$	The minimum values of indicators
I_i	The relative closeness of each research object to the ideal solution
TOPSIS-Entropy	An ideal solution based on entropy weight method
HITS	Hyperlink-Induced Topic Search
IPCC	Intergovernmental Panel on Climate Change

1. Introduction

Over the past few years, the unprecedented increase in extreme weather events, such as floods, droughts, storms, and hurricanes, caused by climate change has multiplied fivefold over the past 50 years (Ghadge et al., 2019). Against a backdrop of climate change, these extreme weather events significantly impact the efficiency and quality of industrial products, including industries sectors such as energy, construction, mining, and transportation (Miao et al., 2018). The energy sector, in particular, has been frequently affected by extreme weather events such as blizzards and floods in recent years. Large-scale damage to power supply facilities has resulted in interruptions to electricity supply, substantially affecting industrial production (Matko et al., 2017). Ali and Gölgeci emphasized that climate change events have resulted in unprecedented annual global economic losses amounting to $215 billion(Ali and Gölgeci, 2020). Climate change has become one of the most critical factors affecting societal and business operations (Ghadge et al., 2019). Many developing countries face the challenge of climate change in the context of industrial restructuring, unbalanced development among different regions within their borders and resource shortage under rapidly developing economies. For developing countries currently undergoing industrialization and urbanization, addressing climate change becomes critically important at this historical stage. Spatial analysis of industrial sector vulnerability to climate change can help countries understand the differences in vulnerability to climate change between industries and regions and help them respond to climate change in their regions.

With the continuous advancement of economic globalization, production in industrial sectors is exhibiting an increasingly networked trend(Habibi et al., 2023).The production and trade processes of industrial products can be conceptualized as an aggregation of network nodes (regions) and edges (trade flows)(Borgatti and Li, 2009). Against the backdrop of climate change, it is widely acknowledged that unforeseen extreme events and disruptions are inherently integral to the supply chain network (SCN) (Zavala et al., 2019). The global community has observed an unparalleled surge in extreme events linked to climate change, leading to diverse magnitudes of disruption within supply chains (Ali et al., 2023). Due to the complexity of the networked structure and the interconnected nature of nodes(Roque Júnior et al., 2023), the adverse effects on one node can rapidly diffuse throughout the network(Belhadi et al., 2021), they can lead to the paralysis of the entire sector's supply network(Kim et al., 2015; Lim-Camacho et al., 2017). In this context, some scholars have increasingly focused on supply chain issues within the energy sector, recognizing the interdependencies among energy production, transmission, and distribution. For instance, Wang et al. analyzed the transmission sector supply chain using a betweenness-based approach to provide a supplementary perspective, evaluating provincial-level CO_2 emissions and CO_2 emission intensity in China in 2017(Wang et al., 2023). Feng et al. identified critical transmission sectors within energy supply chains, proposing sustainable energy development strategies for specific energy types at a regional level in China(Feng et al., 2023). Additionally, some scholars have explored sectoral emissions from a supply chain perspective, such as CH_4 emissions across the supply chain from production to distribution of biomethane and biogas(Bakkaloglu et al., 2022), and carbon emissions associated with remanufacturing(Ullah, 2023).

For policymakers, it is challenging to identify the structural characteristics of SCN in various sectors and their climate change vulnerability index (CCVI)(Park et al., 2021; Zhao et al., 2019). CCVI is a composite measure used to assess the susceptibility of regions, countries, sectors, or specific areas to the impacts of climate change. It evaluates vulnerability by combining factors such as exposure, sensitivity, and adaptive capacity. Currently, there is a greater abundance of research on supply chains in developed countries compared to the limited research conducted on developing nations. Despite facing more significant impacts from supply chain risks due to deficiencies in social, political, or human resource structures, research in developing countries remains scarce (Tukamuhabwa et al., 2015). It is undeniable that more and more research has been done on the vulnerability of supply chains to climate change. Vafadarnikjoo et al. identified and assess the climate risks associated with the electric power supply chain in the United Kingdom (Vafadarnikjoo et al., 2022). Pizarro et al. assessed the climate change vulnerability of Australia's two largest uranium mine supply chains (Pizarro et al., 2018).In addition, discussions on climate change vulnerability in supply chain have increasingly encompassed a broader range of sectors.(IPCC, 2014), such as fisheries, agriculture, and mining (Fleming et al., 2014; Loechel et al., 2013; Malek et al., 2022; Ridoutt et al., 2016). However, despite concerns about the potential widespread impact of climate change on industrial SCN (Hofmann et al., 2013; Linnenluecke et al., 2011), research on industrial SCN has received limited attention (Fleming et al., 2014; Lim-Camacho et al., 2014; Meinel and Abegg, 2017). Furthermore, a notable research limitation in existing studies on SCN is the concentration on individual components, particularly at the primary production stage, rather than considering the entire SCN (Lim-Camacho et al., 2017).Climate change not only affects industrial production but also has direct and indirect impacts on many other stages within SCN (van Putten et al., 2015). Currently, there is a lack of research on the interdependence within the entire SCN and its implications for climate-induced shocks(Ridoutt et al., 2016), as well as for studying climate change vulnerability and adaptation within SCN (Fleming et al., 2014; Lim-Camacho et al., 2014; Ridoutt et al., 2016).

This study focuses on 25 industrial sectors in 31 provinces of China and combines the multi-region input-output analysis (MRIO) with a complex network method to develop an assessment system for the vulnerability of the industrial sector to climate change from the perspective of SCN. Our contribution is twofold.

(1) Utilize MRIO analysis for quantifying the interdependence between industrial sectors. This paper integrated economic interdependencies by capturing inter-industry linkages and quantify the indirect impacts of climate risks across entire supply chains, providing a comprehensive evaluation of sectoral vulnerability that accounts for both direct and cascading effects of climate change.
(2) Introduce directed weighted network to evaluate industrial sector significance in SCN. We first establish a directed weighted network based on inter-provincial trade flows of industrial products to explore the importance of the industrial sector in the SCN. Based on this, we build a CCVI assessment system including supply chain characteristics, and use the technique for order preference by similarity to an ideal solution based on the entropy weight method (TOPSIS-Entropy) to estimate it.

The rest of this study is organized as follows. Section 2 introduces the methodology. Section 3 describes the selection and attributes of indicators of CCVI. In section 4, we empirically analyze the vulnerability of 25 industrial sectors in 31 provinces. Section 5 concludes the paper and proposes policy implications.

2. Methodology

2.1. Multi-region input-output analysis

MRIO is a model developed on the basis of input-output tables for multiple regions, utilizing inter-regional trade data to connect and adjust the inflows and outflows of goods and services across various areas. The MRIO model allows for a detailed tracking of the flow of resources and products within the industrial sector's supply chain, systematically and comprehensively reflecting the output and distribution relationships among provinces. This helps identify critical supply chain links and potential risks within the industrial sector, revealing the vulnerabilities of these supply chains under the impacts of climate change.

Based on the interregional input-output analysis proposed by Anderson in 1955 and the spatial distribution model derived by Wilson in 1967 based on the gravity model (Anderson, 1955; Wilson, 1967). This study can estimate trade flows among multiple provinces for industrial sectors. The trade flow matrix T_l^{rs} can be represented by the following formula:

$$T_l^{rs} = \begin{bmatrix} t_l^{11} & \cdots & t_l^{1s} \\ \vdots & \ddots & \vdots \\ t_l^{r1} & \cdots & t_l^{rs} \end{bmatrix} = A_l^r B_l^s X_l^{ro} X_l^{os} f\left(d_l^{rs}\right) \quad (1)$$

A_l^r and B_l^s are the Gravity model coefficient, which are:

$$A_l^r = \left[\sum_r B_l^s X_l^{os} f\left(d_l^{rs}\right)\right]^{-1} \quad (2)$$

$$B_l^s = \left[\sum_r A_l^r X_l^{ro} f\left(d_l^{rs}\right)\right]^{-1} \quad (3)$$

Where, l is the industrial sector, $l = 1, 2, \cdots, 25$, r is the province from which products flow out, $r = 1, 2, \cdots, 31$, and s is the province from which products flow in, $s = 1, 2, \cdots, 31$. t_l^{rs} is the trade flow of products of industrial sector l from province r to province s. Additionally, X_l^{ro} is the total products from industrial sector l flowing out from province r to all other provinces, while X_l^{os} is the total products of industrial sector l from other provinces flowing into province s. $f\left(d_l^{rs}\right)$ is the "trade barriers" between provinces and is associated with distance between provinces. The calculation equation is expressed as follows:

$$f\left(d_l^{rs}\right) = \left(d_l^{rs}\right)^{-\alpha_l^s} \quad (4)$$

Where, d_l^{rs} is the economic distance for the products of industrial sector l transported from province r to province s. α_l^s is the distance decay coefficient, reflecting the strength of spatial distance in hindering trade spatial activities between provinces. α_l^s is determined through the utilization of linear programming. The average transportation distance $\overline{d^s}$ for products from various provinces to province s can be computed using the following formula:

$$\overline{d^s} = \frac{\sum_{l,r} C_l^{rs} d_l^{rs}}{\sum_{l,r} C_l^{rs}} \quad (5)$$

C_l^{rs} are total products from industrial sector l sent from province r to province s. $C_l^{rs} \geq 0$, C_l^{rs} can be expressed using the following gravity model:

$$C_l^{rs} = K^s \bullet X_l^{ro} \bullet X_l^{os} \bullet \left(d_l^{rs}\right)^{-\alpha_l^s} \quad (6)$$

K^s is a proportional coefficient. In this model. Substituting Eq (6) into Eq (5) can obtain the following formula:

$$\overline{d_l^s} = \frac{\sum_r X_l^{ro} \bullet X_l^{os} \bullet \left(d_l^{rs}\right)^{\left(1-\alpha_l^s\right)}}{\sum_r X_l^{ro} \bullet X_l^{os} \bullet \left(d_l^{rs}\right)^{\left(-\alpha_l^s\right)}} \quad (7)$$

α_l^s can be calculated through Eq (7), and subsequently, the computed result is inserted into Eq (4) to obtain $f\left(d_l^{rs}\right)$. Then, by substituting $f\left(d_l^{rs}\right)$ into Eq (1), T_l^{rs} can be estimated.

2.2. The complex network model based on input-output analysis

This study establishes a directed weighted network $G = (\mathrm{V}, \mathrm{E}, \mathrm{W})$ composed of sets of nodes V, edges E, and weights W. V comprises 31 provinces in China. E is constituted by the connections between nodes, and W is the trade flow between multiple provinces. Subsequently, this study describes the network characteristics of SCN through the following parameters.

(1) Trade dependence

Trade dependence usually refers to the dependence degree of a country or region on trade. In this study, trade dependence is defined as the proportion of the sum of imports and exports of an industrial sector to the total local consumption. The calculation formula is expressed as follows:

$$TD_l^r = \frac{\left(X_l^{ro} + X_l^{os}\right)}{X_l^r} \quad (8)$$

Where, X_l^r is the total consumption of industrial sector l in province r.

(2) Response and influence coefficients

To unveil the degree of inter-sectoral linkages, this study draw upon the research by Chenery and Watanabe(Chenery and Watanabe, 1958), establishes response coefficient γ_s and influence coefficient δ_r. A higher response coefficient indicates a greater extent to which a node is influenced by other nodes, thereby exerting a stronger economic support. Nodes with higher influence coefficients play a more prominent role in driving economic growth in other nodes. The calculation formulas are as follows:

$$\gamma_s = \frac{\sum_{r=1}^{n} t^{rs}}{\frac{1}{n}\sum_{r=1}^{n}\sum_{s=1}^{n} t^{rs}} \quad (9)$$

$$\delta_r = \frac{\sum_{s=1}^{n} t^{rs}}{\frac{1}{n}\sum_{r=1}^{n}\sum_{s=1}^{n} t^{rs}} \quad (10)$$

(3) Network centrality

This study draws upon the concepts of Hubs and Authorities centrality from the Hyperlink-Induced Topic Search (HITS) algorithm to construct centrality indicators, Authorities denote the significance of nodes connected by other nodes, while Hubs represent the importance of nodes connecting to other nodes. The formula for calculating the values of Authorities and Hubs is expressed as follows:

$$\text{Authorities}_r = \sum_{r \in In(r)} Hub_r \quad (11)$$

$$Hub_r = \sum_{r \in Out(r)} \text{Authorities}_r \quad (12)$$

Where, $In(r)$ is all nodes pointing to node r, $Out(r)$ is all nodes pointed to by node r.

2.3. TOPSIS-entropy method

The TOPSIS is a commonly used multi-criteria decision-making method (Tzeng and Huang, 2011). Based on the raw data information of

Table 1
The Attribute of indicators.

Categories	Indicators	Definition	Attribute
Exposure	Labors	Workforce in the province	–
	Gross capital formation	Provincial gross fixed capital formation and inventory changes	–
Sensitivity	Direct economic loss from natural disasters	Provincial economic losses due to natural disasters	+
Adaptation	Hubs	The importance of provinces connecting to other nodes	+
	Authorities	The importance of provinces being connected by other nodes	+
	Response coefficient	The degree to which a province is affected by other provinces	+
	Influence coefficient	The degree to which a province affects other provinces	+
	Trade dependency	The province's dependence on trade	+
	Turnover in the technology market	Technical turnover of each industrial sector in the market	–

Table 2
Industrial sectors and their codes.

Categories	Code	Industrial sectors
Mining industries	2	Mining and washing of coal industry
	3	Oil and gas extraction products
	4	Metal ore mining products
	5	Non-metallic ore and other mining products
Manufacturing industries	6	Food and tobacco
	7	Textile
	8	Textiles, clothing, shoes, hats, leather, down and their products
	9	Wood products and furniture
	10	The goods of papermaking, printing, culture, education, and sport
	11	Petroleum, coking, nuclear fuel processing products
	12	Chemical products
	13	Nonmetal mineral products
	14	Metal smelting and rolling products
	15	Metal product
	16	General equipment
	17	Special equipment
	18	Transport equipment
	19	Electrical machinery and equipment
	20	Communications equipment, computers and other electronic equipment
	21	Instruments and apparatus
	22	Other manufacturing products and waste materials
	23	Metal products, machinery and equipment repair services
Production and supply of electricity, gas and water industries	24	Production and supply of electric power and heat power
	25	Production and supply of gas
	26	Production and supply of water

multiple criteria, TOPSIS standardizes the data and identifies the optimal and worst solutions, then calculates the distance between each research object and the optimal and worst solutions to assess the superiority or inferiority of each research object (Ertuğrul and Karakaşoğlu, 2009). In the calculation process, the entropy weight method is introduced to determine the weights of each indicator. The steps of the TOPSIS-Entropy Method can be outlined as follows.

Step 1: Construct normalized evaluation matrix

Assuming there are n research subjects and m evaluation indicators, where y_{ij} is the j_{th} indicator in the i_{th} province $(i = 1,2,\cdots,n, j = 1,2,\cdots m)$, the original evaluation matrix is defined as follows:

$$Y = \begin{bmatrix} y_{11} & \cdots & y_{1m} \\ \vdots & \ddots & \vdots \\ y_{n1} & \cdots & y_{nm} \end{bmatrix} \tag{13}$$

To ensure accurate comparison and analysis of these indicators, we performed data standardization, resulting in the transformation of the data into Y'.

Step 2: Determine the entropy weight of the indicator.

In the context of computing the proportion of i_{th} province relative to all provinces under j_{th} indicator, the calculation formula of p_{ij} is expressed as follows:

$$p_{ij} = \frac{y'_{ij}}{\sum_{i=1}^{n} y'_{ij}} \tag{14}$$

The entropy value for the j_{th} indicator is calculated as follow:

$$en_j = -\frac{1}{ln(n)} \sum_{i=1}^{n} p_{ij}\, ln\left(p_{ij}\right) \tag{15}$$

Where $en_j \geq 0$. If $p_{ij} = 0$,then $en_j = 0$.

Step 3:Determine the weight of the indicator.

A larger weight wei_j assigned to j_{th} indicator indicates a higher informational significance of that particular indicator. This implies that the indicator holds greater importance in the assessment process. The formula of wei_j is expressed as follows:

$$wei_j = \frac{1 - en_j}{\sum_{j=1}^{m} (1 - en_j)} \tag{16}$$

Step 4:Calculate the relative closeness of each research object to the ideal solution.

The distance between i_{th} province and the positive ideal solution is:

$$dis_i^+ = \sqrt{\sum_{j=1}^{m} wei_j^2 \left(y_j'^{max} - y'_{ij}\right)^2} \tag{17}$$

The distance between i_{th} province and the negative ideal solution is:

$$dis_i^- = \sqrt{\sum_{j=1}^{m} wei_j^2 \left(y'_{ij} - y_j'^{min}\right)^2} \tag{18}$$

Where, the positive ideal solution $y_j'^{max}$ is composed of the maximum values from each indicator, the negative ideal solution $y_j'^{min}$ is composed of the minimum values from each indicator. I_i is the relative closeness of each research object to the ideal solution, the formula is expressed as follows:

$$I_i = \frac{dis_i^-}{dis_i^- + dis_i^+} \tag{19}$$

3. Establishment of the indicator systems

3.1. Selection of the indicator

According to the 4th Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC), vulnerability refers to the degree to which a system is susceptible to adverse impacts of climate

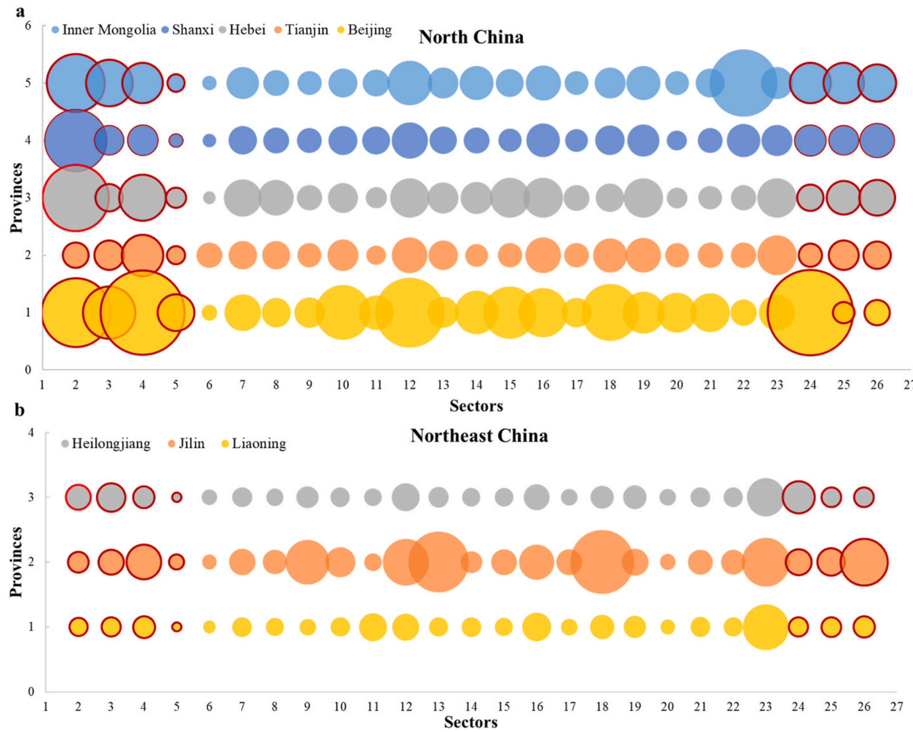

Fig. 1. The industrial sectors' CCVI of provinces in North and Northeast China.
Note: The circle with a red border is the CCVI of the resource-intensive industrial sectors, and the circle without a border are the CCVI for manufacturing sectors. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

change, including the extent to which it is unable to cope with the effects of climate variability and extreme events. The critical parameters for assessing vulnerability include the system's exposure, sensitivity, and adaptive capacity (IPCC, 2007; Kc et al., 2015). This study aims to assess the climate change vulnerability of industrial supply chains, with a particular focus on key indicators specific to different industrial sectors. The selection of exposure and sensitivity indicators follows the principle of prioritizing the most essential factors, ensuring a targeted and relevant analysis.

Exposure refers to the presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings are susceptible to adverse impacts(de Sherbinin et al., 2019; Filho et al., 2019). For industrial sectors, labor and capital constitute primary inputs and are highly vulnerable to the effects of climate change. For example, from July 17 to 23, 2021, Henan experienced historically unprecedented heavy rainfall, leading to multiple disasters such as river floods and mountain torrents, resulting in significant loss of life and property damage. In total, 14.78 million people suffering, 398 deaths or disappearances, and a direct economic loss of 120.06 billion. Therefore, this study selects the total population of labor and gross capital formation at various provinces in SCN of the industrial sector as the exposure indicators of climate change, aiming to measure the CCVI of the industrial sector.

Sensitivity refers to the extent to which a system is affected by climate change, including both adverse and beneficial impacts. The industrial sector faces both direct and indirect impacts from climate change. Direct impacts involve resource or production losses directly attributable to climate change. Indirect impacts stem from damages caused by various natural disasters intensified by climate change. Although some studies have attempted to quantify climate change's effects on industrial output, differences in measurement methods and approaches add complexity and result in varied outcomes. This study primarily focuses on indirect losses, using the direct economic loss from natural disasters in each province as a sensitivity indicator to represent climate change's adverse indirect effects on the industrial sector. This approach captures a range of negative impacts, including transmission disruptions in the power industry and production interruptions in the mining industry.

Adaptive capacity refers to the self-regulation of a system in response to climate change, mitigating potential losses, and the capacity to capitalize on favorable opportunities to cope with the consequences of climate change. For industrial sectors' SCN, the self-regulation capability in the face of interruptions caused by extreme events is crucial for addressing climate change. This study selects Hubs, Authorities, response coefficient, influence coefficient, and trade dependence, all of which are representative features of the industrial sector's SCN. Provinces occupies significant positions in the industrial sector's supply hierarchy, have more inputs or outputs in terms of provinces. Consequently, when the SCN in such a province is disrupted, it must contend with numerous upstream or downstream interruptions, necessitating urgent adjustments. In addition, technological progress can enhance the potential and capability of industrial sectors in addressing climate change. For instance, technological progress can optimize production processes, making industrial production more efficient and energy-saving, thereby mitigating climate change intensification. This study selects the turnover in the technology market for various industrial sectors in each province as an indicator of adaptive capacity.

3.2. Attribute of indicator

When the SCN of the industrial sector needs to cover a broader regional scope, long and complex SCN often exhibit a slow response to changes(Tang and Tomlin, 2008). They are more susceptible to the impacts of natural and man-made disasters (Manuj and Mentzer, 2008; Singh Srai and Gregory, 2008), as well as vulnerable to the effects of climate change. Therefore, the indicator reflecting the characteristics of SCN, which are Hubs, Authorities, response coefficient, influence coefficient, and trade dependence, reflecting the characteristics of SCN, are established as positive indicators of climate change vulnerability. In

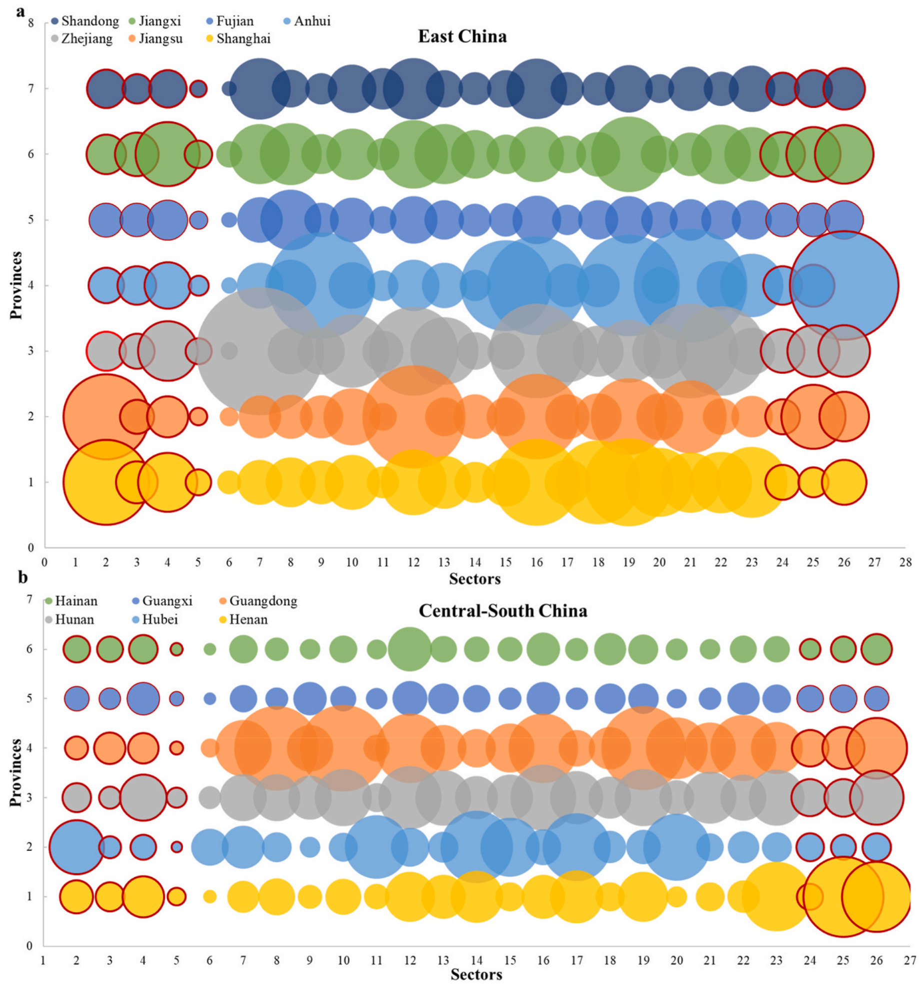

Fig. 2. The industrial sectors' CCVI of provinces in East and Central-South China.

addition, direct economic loss from natural disasters is considered as a positive indicator. Because a greater magnitude of economic loss signifies a more severe impact of natural disasters on the industrial sector, indicating a higher level of climate change vulnerability.

Technological progress can enhance the industrial sector's capacity to address climate change. As technology advances, the industrial sector becomes less vulnerable to the effects of climate change. Therefore, turnover in the technology market serves as a negative indicator. In addition, increased capital and labor resources facilitate the industrial sector in allocating and responding to the losses incurred due to climate change. Consequently, this study sets labor and gross capital formation as negative indicators, with the attributes of each indicator outlined in Table 1.

3.3. Data collection

(1) Selection of industrial sectors

The industrial sector, classified as a secondary sector in the economy, comprises businesses that provide support to other enterprises engaged in manufacturing, shipping, or production activities. This classification aligns with the industry categorization outlined in the Classification of National Economic Industries (GB/T4754-2017). For the purpose of our study, we have selected industrial sectors with codes 02–26 from the I-level classification of the 2017 ′Input-Output Table of China' Specifically, industrial sectors 02–05 pertain to mining industries, 06–23 to manufacturing industries, and 24–26 to the production and supply of electricity, gas, and water industries. Details can be found in Table 2.

(2) Selection of trade flow indicators for industrial sectors

We collected empirical data on domestic inflow and outflow, spatial economic distances between provinces, and average transportation distances for 25 industrial sectors across 31 provinces. The aggregate data for domestic inflow and outflow were derived from the 2017 ″China Input-Output Table", encompassing interprovincial movements. The actual distances between provinces were used as approximate proxies for the spatial economic distances between provinces. Additionally, the data on average transportation distances were sourced from the National Bureau of Statistics, with the average distance recorded as 410.78 km in the year 2017. The data on direct economic losses from natural disasters, turnover in the technology market, and the labor are all sourced from the National Bureau of Statistics.

4. Results and discussion

4.1. The CCVI of industrial sectors in 31 provinces

This study categorizes 31 provinces based on geographical locations into North China (Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia), Northeast China (Liaoning, Jilin, Heilongjiang), East China (Shandong, Jiangsu, Anhui, Zhejiang, Fujian, Shanghai, Jiangxi), Central-South China (Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan), Southwest China (Chongqing, Sichuan, Guizhou, Yunnan, Tibet), and

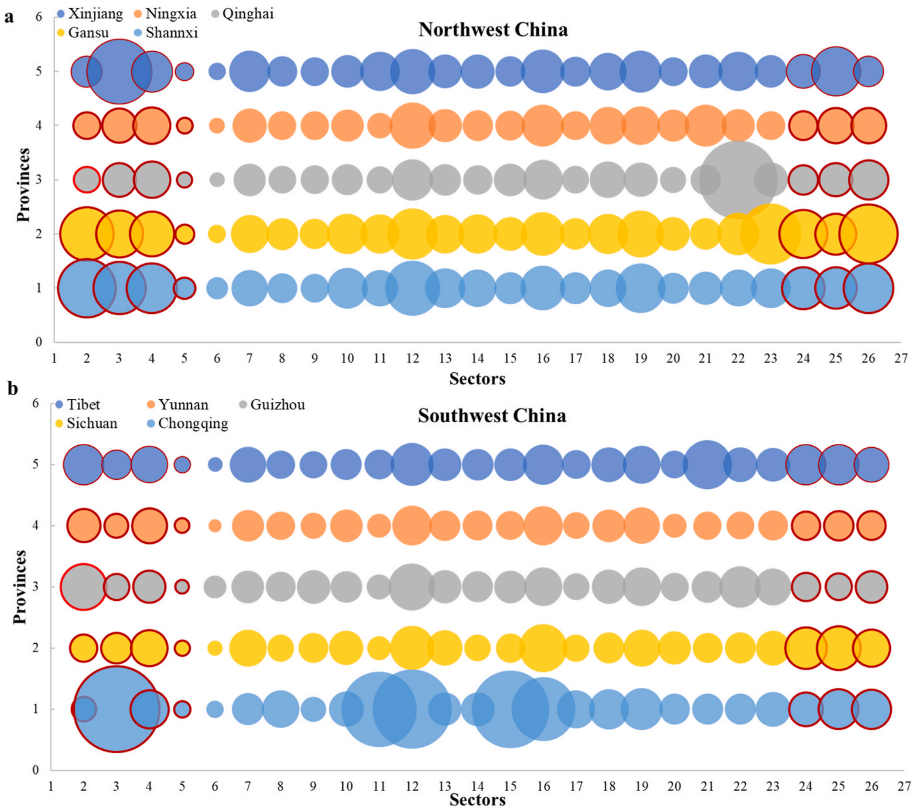

Fig. 3. The industrial sectors' CCVI of provinces in Northwest and Southwest China.

Northwest China (Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang). In addition, this study divides all industrial sectors into two categories according to their dependence on resources: resource-intensive industrial sectors (Sectors 2–5 and 24–26) and manufacturing sectors (Sectors 6–23).

In North China, Beijing exhibits the highest CCVI across multiple resource-intensive industrial sectors, which are Sectors 2, 4, 5, and 24 (Fig. 1). Hebei and Shanxi ranked in the top three for CCVI in Sector 2 and are lower in all other industrial sectors. Inner Mongolia has the second highest CCVI in Sector 22. In the Northeast, Jilin has the highest CCVI in Sectors 13 and 18, and the CCVI in Sectors 9, 23 and 26 ranks in the top three among all provinces. Liaoning' CCVI ranks third in Sector 23, with lower vulnerability observed in other industrial sectors. Heilongjiang ranks second in climate change vulnerability in Sector 24, with lower vulnerability in other industrial sectors.

In the East China, Fujian, Jiangxi, and Shandong demonstrate vulnerability to climate change that falls below the provincial average across 25 industrial sectors (Fig. 2). Shanghai exhibits climate change vulnerability ranking within the top three provinces in Sectors 2 and 18. Jiangsu consistently ranks among the top three for climate change vulnerability in Sectors 2, 12, and 25. Similarly, the vulnerability of Zhejiang to climate change consistently ranks among the top three provinces in Sectors 7, 16, and 21. Anhui displays the highest climate change vulnerability among all provinces in Sectors 9 and 21, and consistently ranks among the top three provinces in Sectors 16, 19, and 26. In the Central-South, Guangxi and Hainan show low CCVI that falls below the provincial average across 25 industrial sectors. Henan exhibits the highest climate change vulnerability in Sectors 23, 25, and 26, ranks in the top three in Sectors 13, 14, and 17. Hubei exhibits the highest climate change vulnerability in Sectors 11, 14, 17, and 20. Hunan ranks in the top three for climate change vulnerability in Sectors 4, 7, 8, 10, 13, 16, 17, 19, and 21. Guangdong exhibits the highest climate change vulnerability in Sectors 8, 10, 12, 16, 19, and 22, ranks in the top three in Sectors 7, 9, and 20.

In the Northwest, Qinghai and Xinjiang respectively rank second in climate change vulnerability in Sectors 22 and 3 (Fig. 3), while Shaanxi, Gansu, and Ningxia exhibit low climate change vulnerability across 25 industrial sectors. In the Southwest, Sichuan, Guizhou, Yunnan, and Tibet demonstrate low climate change vulnerability across 25 industrial sectors. Chongqing exhibits the highest climate change vulnerability in Sectors 3 and 15.

It can be observed that the CCVI of resource-intensive industrial sectors in multiple provinces of North China are higher compared to other provinces, whereas manufacturing sectors in several areas of East China and Central-South China exhibit higher CCVI than other provinces. For northern provinces, where resource-intensive industries are prominent, a shift toward green transformation and energy-saving technologies, and encourage resource-dependent provinces to diversify into service industries and high-value-added manufacturing can help lower vulnerability. For the eastern and central-southern provinces, where manufacturing is concentrated, efforts should prioritize innovation-driven growth and the adoption of environmentally friendly and energy-efficient technologies. Furthermore, collaboration between manufacturing-intensive provinces and those with lower climate vulnerability can facilitate resource sharing and supply chain coordination, reduce the impacts of extreme climate events on production and supply chains. For the southwestern and northwestern provinces, low-vulnerability provinces can play a crucial role in supporting more vulnerable regions by sharing expertise and technology to bolster adaptive capacity.

4.2. *The CCVI of resource-intensive industrial sectors*

The trade flows affect the CCVI of industrial sectors in each province. In addition, the local population density, industrial structure, natural resource endowment and industrial scale have a significant impact on CCVI. The trade flows of resource-intensive industrial sectors are in big ways and small in 31 provinces, their outward trade flow is primarily

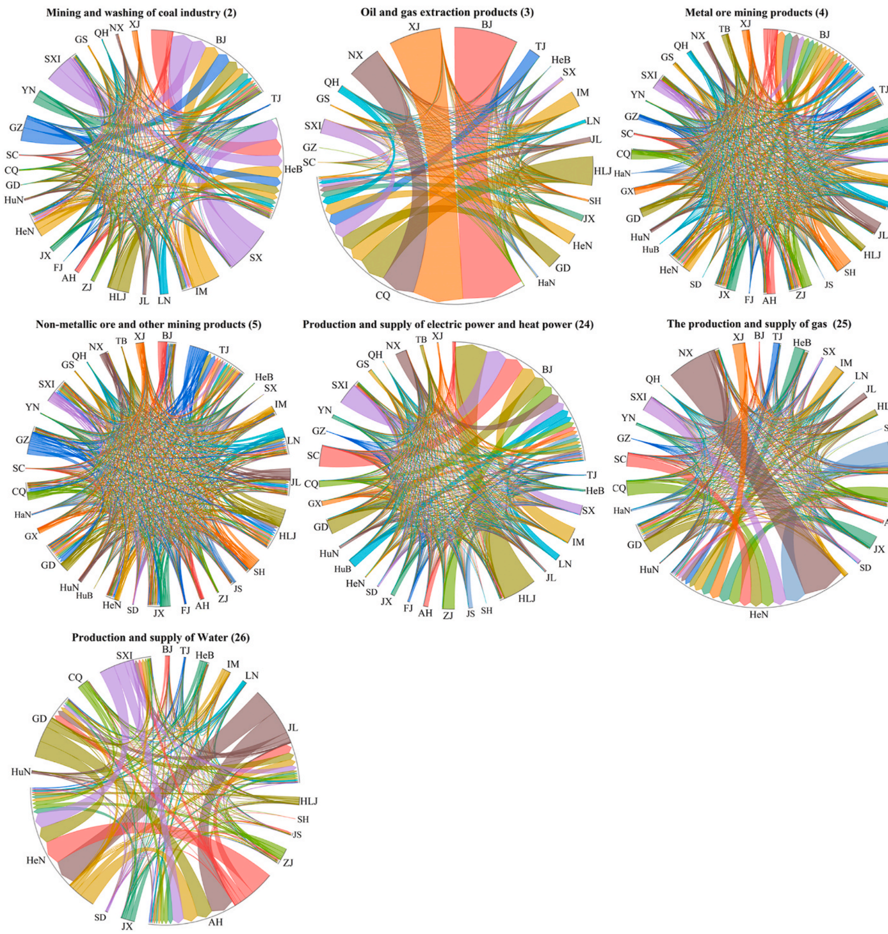

Fig. 4. The trade flows of resource-intensive industrial sectors in 31 provinces.
Note: BJ-Beijing, TJ-Tianjin, HeB-Hebei, SX-Shanxi, IM-Inner Mongolia, LN-Liaoning, JL-Jilin, HLJ-Heilongjiang, SH-Shanghai, JS-Jiangsu, ZJ-Zhejiang, AH-Anhui, FJ-Fujian, JX-Jiangsi, SD-Shandong, HeN-Henan, HuB-Hubei, HuN-Hunan, GD-Guangdong, GX-Guangxi, HaN-Hainan, CQ-Chongqing, SC-Sichuan, GZ-Guangzhou, YN-Yunnan, SXI-Shaanxi, GS-Gansu, QH-Qinghai, NX-Ningxia, TB-Tibet, XJ-Xinjiang.

determined by the natural resource endowment of the province, while the inflow provinces are also closely related to local population density and industrial structure.

Apart from Sector 5 (Non-metallic ore and other mining products), products from other resource-intensive industrial sectors exhibit a concentration of trade flows, both inflow and outflow, clustering predominantly in a few provinces (Fig. 4). For example, products from Sector 2 (Mining and washing of coal industry) mainly flow from Shanxi, Shaanxi, and Inner Mongolia to Beijing and Hebei. This is due to the distribution of coal resources in China, which shows a "rich in the north, poor in the south, more in the west and less in the east" pattern. Northern provinces like Shanxi and Inner Mongolia, as well as western province Shaanxi, are major coal-producing provinces in China, with their coal output consistently ranking top three nationwide. Consequently, there is a higher coal outflow from Shanxi, Inner Mongolia, and Shaanxi. Products from Sector 2 primarily flow into Beijing and Hebei, owing to Beijing's large population (ranking 2nd nationally in population density in 2017) and high energy demand, Beijing's power and heating supply have primarily relied on four major coal-fired thermal power plants for a long time, resulting in high energy dependency. In recent years, Beijing has continuously promoted the development of high-tech and advanced industries, which can significantly reduce the city's CCVI. Hebei's pillar industry is steel (with crude steel production consistently ranking first nationwide since 2002), leading to substantial coal consumption, hence the large inflow of coal into these two provinces. It is evident that Beijing exhibits the highest CCVI, followed by Hebei, Shanxi, and Inner Mongolia.

The main outflow provinces of Sector 26 (Production and supply of water) are Jilin and Guangdong, while the main inflow provinces are Henan and Anhui. Jilin is the source of rivers, as of the end of 2013, the province had surveyed and identified 396 natural drinking mineral water sources, with a total allowable extraction volume of 470,000 tons per day, ranking first in China.[1] Henan and Anhui are one of the provinces in China lacking in water resources. According to reports from the China Water Resources Network, the spatial and temporal distribution of water resources in Henan is uneven, with the total water resources of the province accounting for only 1.42% of the national total, and per capita water resources less than one-fifth of the national average. The contradiction between supply and demand for water resources is becoming increasingly acute, necessitating the transfer of large amounts of water resources from other provinces to ensure water supply for production, living, and agricultural use in Henan. The per capita water resources in Anhui are only half the national average, and its uneven distribution of precipitation, exacerbation of drought, and increased water pollution have also led to water scarcity in Anhui. It can be observed that Henan has the highest CCVI, followed by Anhui, with Jilin and Guangdong also exhibiting relatively high CCVI.

4.3. The CCVI of manufacturing sectors

The scale of provincial industrial development has a significant

[1] https://xxgk.jl.gov.cn/szf/gkml/201812/W020150513580909938307.pdf.

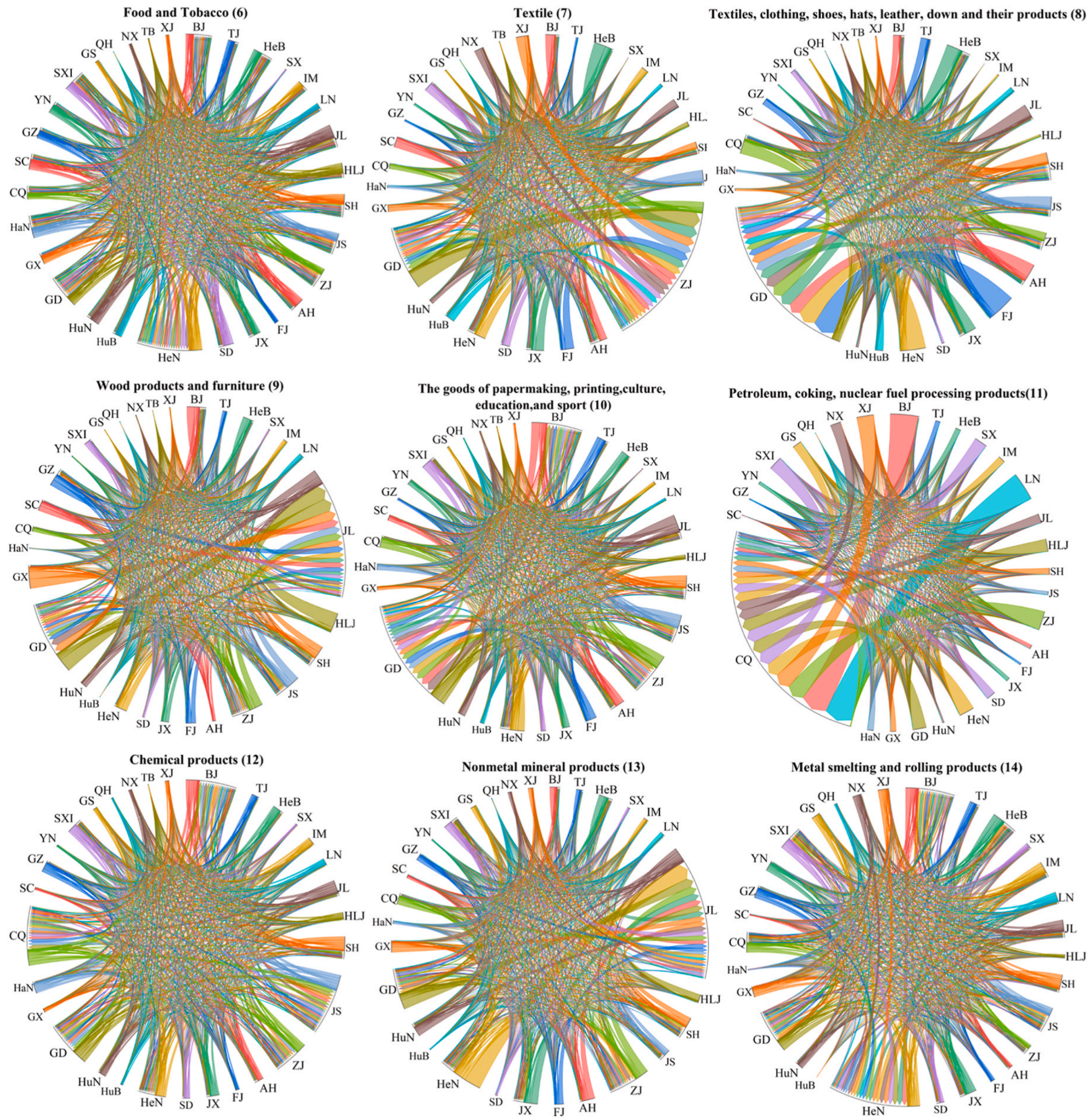

Fig. 5a. The trade flows of Sectors 6–14 in 31 provinces

positive impact on the trade flow of manufacturing sectors, while also influencing the CCVI of industrial sectors in the province. For example, Zhejiang and Guangdong have the highest CCVI in sector 7 and 8, respectively. Products from Sectors 7 and 8 mainly flow to Zhejiang and Guangdong (Fig. 5a). In particular, Zhejiang and Guangdong have the largest trade flows in sectors 7 and 8, respectively. Because the textile and garment industry are a traditional pillar industry and an important consumer industry in Guangdong and Zhejiang, both of which are significant provinces in the textile industry. Fig. 5b According to data from the China Economic Information Network (CEIdata), since 2000, Guangdong has consistently ranked among the top four provinces in China in terms of the number of industrial enterprises above designated size. In contrast, Zhejiang has consistently been among the top two, securing the top position since 2013.[2] In 2017, there were 4573 industrial enterprises above designated size in the textile industry in Zhejiang, accounting for 24.4% of the country, ranking first, and 1464 in Guangdong, ranking third. The number of industrial enterprises above designated size in Guangdong's textile and garment industry is 2,784, accounting for 19.17% of the country, ranking first, and Zhejiang is 2,472, ranking second. Chongqing has the highest CCVI in sectors 11 and 15. As one of China's old industrial bases, Chongqing features a predominantly heavy industrial structure. Its primary industries include automobile manufacturing, military industry, steel production, and aluminum industry, resulting in Chongqing's large demand for the production of metals and petroleum.

Provinces with larger industrial development scales and higher trade flows tend to have higher CCVI. This is attributed to the positive correlation between supply chain density, complexity, and critical nodes with the severity of supply chain disruptions (Craighead et al., 2007). On one hand, in the event of a climate-induced disruption at a node within a long and intricate supply chain, the multi-regional involvement of the supply chain often results in slow and incomplete responses to the changes in supply chain nodes (Tang and Tomlin, 2008), hindering timely and comprehensive implementation of effective response measures. On the other hand, when disruptions occur at critical nodes, the

[2] https://ceidata.cei.cn.

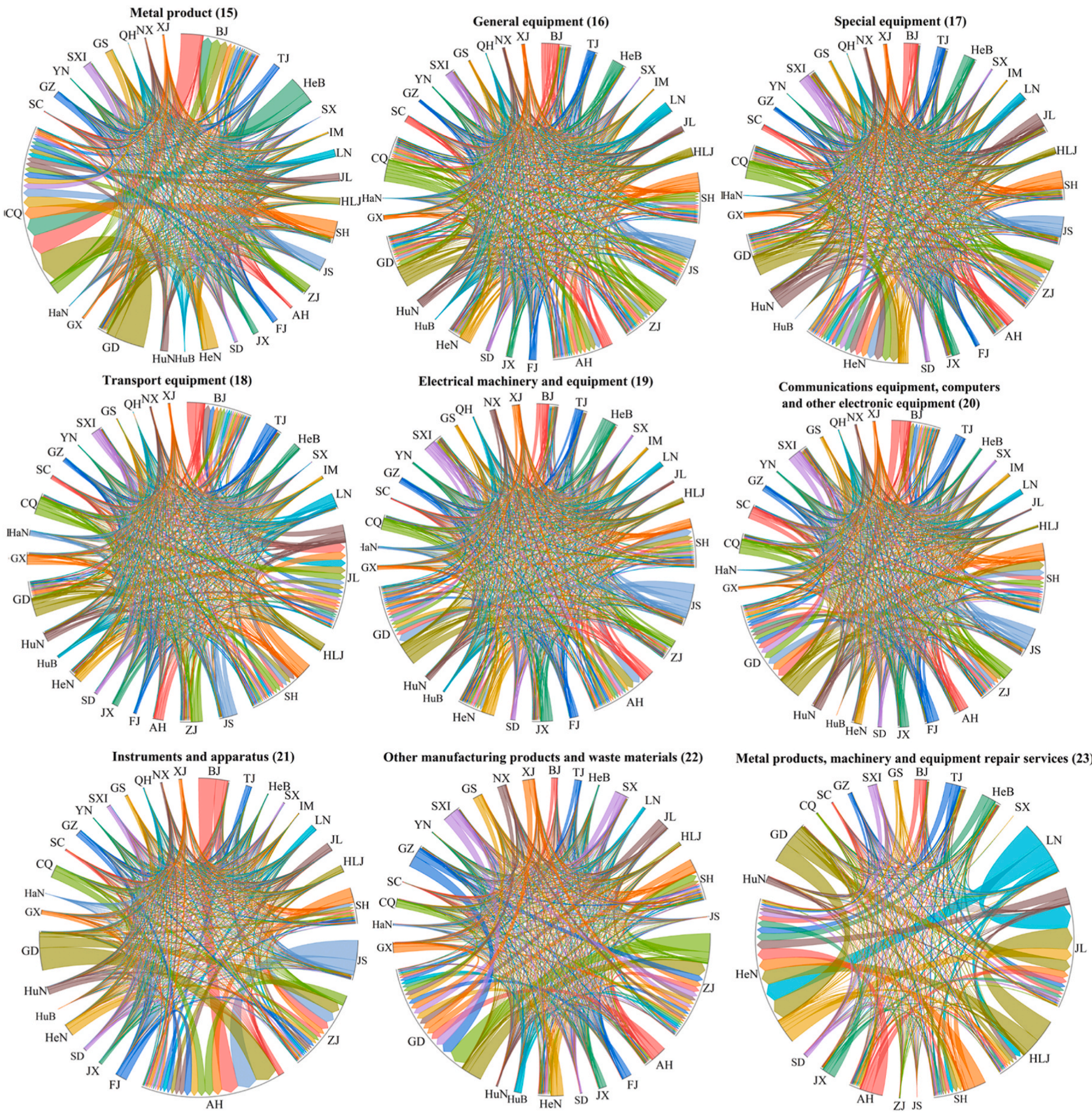

Fig. 5b. The trade flows of Sectors 15–23 in 31 provinces.

adverse effects generated increase proportionally with the number of nodes directly or indirectly linked to them, thereby amplifying the vulnerability of the supply chain. With industrial sectors covering more nodes and handling greater trade volumes, they become more susceptible to the impacts of more frequent and severe extreme weather events (e.g., hurricanes, floods, and droughts) caused by climate change. These events not only affect the availability and costs of raw materials for industrial sectors, but also disrupt the distribution of goods and services, potentially damage infrastructure, disrupt supply networks, and halt production, thereby increasing the costs associated with maintenance, insurance, and productivity losses. Provinces with higher trade volumes experience broader impacts from climate change, leading to higher CCVI. For example, Guangdong, it has consistently held the position of China's leading manufacturing province since 1996. In 2021, The province boasts ten strategically vital industrial clusters for stable economic development, including next-generation electronics and information technology, light industry and textiles, software, and information services. Therefore, as a major manufacturing province, Guangdong exhibits the highest CCVI across multiple industrial sectors (Sectors 8, 10, 12, 16, 19, 22).

5. Conclusions and policy implications

This study assesses the CCVI of 25 industrial sectors across 31 provinces in China from the perspective of SCN. Using MRIO analysis, the study estimates the trade flows among 25 industrial sectors across 31 provinces. Based on this, an assessment framework for climate change vulnerability of industrial sectors is constructed. The paper employs the TOPSIS-Entropy method to assess the climate change vulnerability of 25 industrial sectors across 31 provinces. The findings reveal that, for the manufacturing industry, provinces with higher levels of industrial development and larger trade flows tend to exhibit higher climate change vulnerability. Conversely, provinces with lower levels of industrial development and smaller trade flows demonstrate lower vulnerability. Regarding resource-based industrial sectors, provinces with abundant resources and high outflows to other provinces, or provinces with resource scarcity and significant inflows from other provinces, tend to have greater climate change vulnerability.

Based on the above analysis, we believe that improvements in the following aspects would contribute to reducing the climate change vulnerability of the industrial sector from the perspective of SCN.

(1) In resource-scarce provinces with high dependency, inventory management is conducted on a demand-driven basis. On one hand, it is essential to formulate effective strategies to address climate change, ensuring the stability and continuity of resource supply by establishing collaborative relationships with multiple suppliers, thereby mitigating risks associated with reliance on a single supplier or province. On the other hand, implement an appropriate mechanism for inventory management. This entails flexible inventory management based on market demands and the actual conditions of the supply network, aiming to avoid excessive or insufficient inventory levels.
(2) Establish a collaborative platform to promote coordinated regional development. A multi-provincial collaborative platform can enable participants in SCN to collaborate more effectively, share information, and enhance the reliability and efficiency of SCN. In addition, risks associated with climate change can be mitigated by introducing new technologies. For instance, the Internet of Things (IoT) and blockchain technologies can enhance the traceability and transparency of SCN, contributing to the better management of complex networks.
(3) Establish climate change mitigation measures for key provinces in the SCN. This is particularly pertinent for manufacturing-intensive provinces such as Guangdong and Zhejiang, as well as resource-exporting provinces like Inner Mongolia and Shaanxi, which occupy central positions in the industrial SCN. Regular monitoring and assessment of key provinces are conducted to comprehend local climate change trends and potential environmental risks, to alleviate potential disaster risks.

This study is an exploration of assessing the vulnerability of the industrial sector to climate change from the perspective of SCN. As the input-output tables are compiled every five years, our analysis was limited to the data of the year 2017, making it challenging to achieve a continuous analysis. Future research could be extended along the temporal dimension, unfolding dynamic analyses of climate change vulnerability. For instance, evaluating the performance of the industrial sector in a particular province regarding climate change vulnerability over a period of time, or assessing the climate change vulnerability of a specific industrial sector across various provinces over time. In addition, this research has the potential for extension to other industries. Future studies can draw inspiration from our analytical framework to examine climate change vulnerability in other industries from the perspective of SCN, particularly those significantly impacted by climate change, such as agriculture, forestry, and fisheries. Subsequently, informed by such analyses, effective and industry-specific climate change mitigation strategies can be formulated.

CRediT authorship contribution statement

Qin Li: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Xunpeng Shi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Qunwei Wang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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