

Estimating water scarcity risks under climate change: A provincial perspective in China

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Abstract

Water is a crucial raw material in economic production activities. Research indicates that water scarcity can lead to significant economic output losses (water scarcity risk, WSR), affecting not only the local area (referred to as local water scarcity risk, LWSR) but also causing economic losses to other regions through trade networks (referred to as virtual water scarcity risk, VWSR). With climate change exacerbating this challenge, understanding the water scarcity risk under changing climatic conditions is essential. However, few studies have addressed this issue comprehensively. To fill this gap, we developed a comprehensive model incorporating environmental flow requirements, water withdrawal, supply, economic output, and trade networks to assess LWSR and VWSR among China's provinces under climate change. Our analysis reveals a growth in China's WSR from \$4.6 trillion in 2020 to \$5 trillion in 2030. Specifically, both local water scarcity risk (LWSR) and virtual water scarcity risk (VWSR) amounted to \$0.9 trillion and \$3.7 trillion, respectively, in 2020, increasing to \$1.0 trillion and \$4.0 trillion by 2030. We also identified hot-spot provinces and sectors with high WSR and proposed relevant policy implications. Our findings contribute to China's climate change mitigation efforts, particularly in formulating strategies to address water scarcity risk.

Practitioner points

- Spatial heterogeneity-based environmental flow requirement is considered.
- The water scarcity risk of the Chinese agricultural sector in 2017 amounted to \$1.1 trillion.
- LWSR and VWSR are 0.3 and 0.8 \$trillion, respectively.
- Hotspot Chinese provinces and sectors are identified.

KEYWORDS

climate change, economic output loss risk, trade networks, water scarcity

INTRODUCTION

Under climate change scenarios, by the end of the 21st century, more than half of the world's population will live in environments with extreme water scarcity (Mishra, 2023). As emphasized in the IPCC's Sixth Assessment Report released in 2023 (Lee et al., 2023), climate change poses unprecedented challenges to the global water supply. The report confirms that the 1.1 degrees Celsius of global warming caused by human activities over the past few centuries to thousands of years has led to unprecedented changes in the Earth's climate (Lee et al., 2023). Rising temperatures disrupt precipitation patterns and the hydrological cycle, exacerbating water scarcity and water-related hazards such as droughts and floods (Wang, Bodirsky, et al., 2024). The profound interconnection between water scarcity and climate change is evident, the increase in global average temperatures due to climate change will intensify water stress in water-scarce regions around the world (Zhu et al., 2024). China has been facing challenges such as uneven spatial and temporal distribution of water resources, conflicts between supply and demand, low water use efficiency, and severe water pollution. In 2022, China's per capita water resources were about 1918 cubic meters per year, which is only a quarter of the global average, falling below the "moderate water scarcity" threshold of 2000 cubic meters per year. It is expected that this predicament will worsen under the impact of climate change, putting additional pressure on water availability and exacerbating existing challenges (He et al., 2021).

In addition to the overarching issue of water scarcity, China's extensive territory displays significant spatial heterogeneity in water resource distribution. According to the China Water Resources Bulletin, the water resource conditions exhibited notable disparities across different regions of China (Ministry of Water Resources of China, 2022). In the eastern region, six provinces reported per capita water resources below 1000 cubic meters per year, falling below the "severe water scarcity" threshold defined by the Falkenmark critical value (Zhong et al., 2023), while two provinces were categorized as experiencing "severe to moderate water scarcity" with 1000–2000 cubic meters per year (Ministry of Water Resources of China, 2022). In contrast, only one-third of the provinces in the western and central regions reported per capita water resources below 1000 cubic meters per year (Ministry of Water Resources of China, 2022). Meanwhile, all provinces in the northeastern region reported per capita water resources above 1000 cubic meters per year (Ministry of Water Resources of China, 2022). Hence, conducting a comprehensive analysis at the

provincial level is deemed particularly imperative and urgent to address the water scarcity issues under climate change confronting China.

Water, as an indispensable ingredient in production, not only directly incurs economic losses for local production sectors within a region but also indirectly impacts production sectors in other regions through intricate trade systems, known as water scarcity risk (Chen et al., 2022; Zhao et al., 2020). Water scarcity risk (WSR) encompasses not only local water scarcity risks (LWSR, local economic output loss in water-using sectors due to water scarcity) faced by each province and sector but also includes the indirect threats of water scarcity from the trade system to other provinces and sectors (VWSR, the spread of LWSR through trade systems) (Qu et al., 2018). For example, in 2017, due to water scarcity, the agriculture, forestry, animal husbandry, and fishery industries in upstream of Hebei suffered a loss of \$46.8 billion (LWSR), subsequently affecting the food and tobacco processing industries in Shandong, resulting in a loss of \$5.6 billion through China's trade network (VWSR) (Huang, Shuai, et al., 2024). Therefore, in light of water scarcity and the unequal distribution of water resources due to climate change, it is imperative to evaluate the water scarcity risk encountered by Chinese provinces amidst these changing climatic conditions.

To date, many scholars have assessed the WSR at different levels (Li et al., 2023, 2022; Liang & Zhong, 2023; Yang et al., 2024; Yao et al., 2021). For instance, Qu et al. (2018) proposed a framework for assessing WSR, which employs water stress indices, sectoral economic output, and a multi-regional input–output model to evaluate WSR within the global trade system. Similarly, Zhao et al. (2020) employed this approach to assess both local water scarcity risk (LWSR) and virtual water scarcity risk (VWSR) across Chinese provinces and sectors. Chen et al. (2022) included the consideration of Environmental Flow Requirements (EFR) in the process of quantifying water risk, going beyond the limitations of traditional water stress indices, and providing a method for more accurately assessing WSR on a global scale. Building upon this foundation, Huang, Shuai, et al. (2024) developed an integrated framework that incorporates spatially heterogeneous EFR into the quantification of WSR. Dong et al. (2023) constructed a global VWSR transfer network for the period 2001–2016 based on a multi-regional input–output model and complex network theory, and further explored the determinants influencing the formation of the VWSR transfer network using a time-indexed stochastic graph model. Wei et al. (2023) integrated water quality and quantity factors into the risk assessment system for local water scarcity, analyzing the potential virtual water scarcity risk and its transmission mechanism

faced by cities and industries in the Yellow River Basin of China. Wang, Shuai, et al. (2024) built a nested multi-regional input–output (MRIO) model to assess water scarcity risk, linking the provinces of China with those around the world. Another crucial aspect of conducting this research is to assess water scarcity under the influence of climate change. Previous studies on global water consumption and available water resources have predominantly centered on historical analyses, with only a limited number of scholars venturing into prediction under various climate change scenarios. For instance, the World Resources Institute (2018) estimated future water demand and supply globally under various climate change scenarios using General Circulation Models (GCMs) and Shared Socioeconomic Pathways (SSPs) databases. Khan et al. (2023) combined the Global Change Analysis Model with a land use downscaling model, the global hydrologic framework, and a water withdrawal downscaling model to generate a dataset of global monthly sectoral water withdrawal and consumption for the period 2010–2100 at a 0.5° resolution suitable for multiple scenarios. However, to the best of our knowledge, only a few scholars have predicted water scarcity risk under climate change. Zhao et al. (2019) used a multi-regional input–output (MRIO) model with class water stress index (the percentage of water withdrawal to availability) to delve into how climate change could profoundly impact the global trade system by reducing available water resources in specific regions worldwide. Despite these advancements, traditional methods for calculating water stress indices often overlook the water needed to maintain environmental flows, resulting in underestimated WSR and a failure to accurately reflect the pressure and risks faced by water resources (Mekonnen & Hoekstra, 2016). Additionally, these indices, typically expressed as percentages, lack direct association with economically related decision indicators (Chen et al., 2022). Lastly, by using nations as the research scale, the spatial heterogeneity of water resources within countries is often neglected.

To tackle these challenges, our research adopted a multi-step approach. First, we quantified the Potential Water Shortage Volume (PWSV) under climate change conditions, including water withdrawal, available water resources, and environmental flow requirements. Then, by integrating PWSV with the economic output of various industries, we calculated the situation of Local Water Scarcity Risk (LWSR) for provinces and sectors in China under the context of climate change. Finally, we used the MRIO model to assess the risk of water scarcity in China and identified the key regions and vulnerable industries affected by water scarcity. The novelty and significance of this study are reflected in three aspects. Firstly, we

provide a detailed assessment of potential economic output losses due to water scarcity under climate change, filling an essential gap in predicting the economic impacts of water resource constraints. To address the mismatch between water resource availability and provincial demand, we refined the research scale, enabling a more precise identification of regions most vulnerable to economic losses from water scarcity under climate change. Additionally, this study uses PWSV as a direct absolute value, rather than a proportion, to better align with economic indicators, providing an analytical tool for the national macro-response to water resource risks under climate change. Moreover, we used Class C Environmental Flow Requirements (EFR) in assessing water scarcity, significantly improving the accuracy of LWSR measurements.

METHODS AND DATA

Methods

Considering the fluctuations in water resources attributed to climate change, this study endeavors to evaluate water scarcity risks at provincial sectoral levels in China. The assessment comprises three primary components: (1) examining PWSV under climate change, (2) gauging LWSR-associated PWSV, and (3) assessing VWSR due to LWSR.

PWSV assessment

We utilize the PWSV to assess the water scarcity under climate change, which is calculated by comprehensively considering the availability of water, water withdrawal, and Environmental Flow Requirements (EFR).

$$PWSV_p = \text{water withdrawal}_p - (\text{water availability}_p - EFR_p) \quad (1)$$

Where $\text{water withdrawal}_p$, $\text{water availability}_p$, and EFR_p respectively represent the water withdrawal, available water quantity, and Environmental Flow Requirements (EFR) of province p under climate change. When the PWSV value is negative, it signifies the absence of local water scarcity risk and, consequently, no economic losses due to water shortage. In such cases, the value is set to 0 to accurately reflect this condition (Chen et al., 2022; Huang, Shuai, et al., 2024; Wang et al., 2025). However, it's important to note that regions with a positive PWSV may not necessarily be experiencing an immediate

physical water shortage. Instead, a positive PWSV indicates unsustainable local water usage practices, highlighting the potential for future water scarcity issues if these practices persist (Chen et al., 2022; Huang, Shuai, et al., 2024; Wang et al., 2025).

LWSR assessment

Then, we distribute the PWSV of province p among its sectors according to sectoral water intensity (Chen et al., 2022). To minimize the LWSR value, we initially assign it to the sector with the highest water intensity. If the water withdrawal of this sector is less than the PWSV, we proceed to allocate the remaining PWSV to sectors with lower water intensity until the entire PWSV of province p is allocated (Chen et al., 2022).

$$LWSR_{ps} = \frac{PWSV_{ps}}{\text{water withdrawal}_{ps}} \times x_{ps} \quad (2)$$

where $\text{water withdrawal}_{ps}$ represents the water withdrawal of sector s in province p , x_{ps} is the total economic output of sector s in region p under normal water conditions, and $LWSR_{ps}$ is the economic output loss of sector s in province p due to $PWSV_{ps}$. This study encompasses 31 provinces and 42 sectors. We assume a linear relationship between economic output loss and water scarcity, which is the widely used assumption in input-output analysis. Finally, we can obtain the LWSR for province p as follows:

$$LWSR_i = \sum_p LWSR_{p,s} \quad (3)$$

VWSR assessment

We employ the multi-regional input-output (MRIO) model to depict the trade structure between provinces and sectors, which is widely used in previous studies (Chen et al., 2025, 2024; Fang et al., 2024; Huang, Li, et al., 2024; Jiang et al., 2020; Liu et al., 2021; Shen et al., 2023; Wang et al., 2023; Yang, Li, et al., 2022; Zhang, Ji, et al., 2023). The total input of each sector equals the sum of intermediate inputs and value-added, which can be expressed as follows:

$$x = eZ + v \quad (4)$$

x and v are both $1 \times k$ vectors, representing the total input for each sector and the value-added creation for each sector, respectively. Z is a $k \times k$ vector representing the

transaction flow between provinces and sectors. e is a $1 \times k$ unit vector. In this study, k is 1302.

The $n \times n$ matrix B consists of direct output coefficients, reflecting the distribution ratio of a sector's products to all sectors. Its equation is represented as:

$$B = (x)^{-1}Z \quad (5)$$

We use the Ghosh model to quantify the VWSR imposed by upstream sectors with LWSR on downstream sectors (Ghosh, 1964). The basic equations are as follows.

$$\Delta X = \text{diag}(LWSR) \times (I - B)^{-1} \quad (6)$$

$$\text{diag}(LWSR) = \begin{bmatrix} LWSR_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & LWSR_{kk} \end{bmatrix} \quad (7)$$

The matrix ΔX represents the total economic output loss matrix. The elements in the matrix indicate the loss of economic output for each economic sector due to the LWSR associated with the specific sector represented by that position. We calculate the Water Scarcity Risk (WSR) for China by summing the elements of ΔX . The $k \times k$ matrix $(I - B)^{-1}$ is the Ghosh inverse matrix, which represents the total output of the sectors represented by the sectors due to single value-added creation (direct and indirect sum), $\text{diag}(LWSR)$ is an $k \times k$ diagonal matrix of LWSR.

We use the following formula to calculate the WSR for each province:

$$p_{jm} = \sum_{\substack{l \in \text{province } j \\ r \in \text{province } m}} \Delta x_{lr} \quad (8)$$

p_{jm} represents the economic loss incurred by province m due to water scarcity in province j , and the element Δx_{lr} originates from the matrix ΔX .

The formula for calculating VWSR caused by inter-provincial trade is as follows:

$$VWSR_m^{\text{ex}} = \sum_{j \neq m} p_{jm} \quad (9)$$

$$VWSR_m^{\text{im}} = \sum_{m \neq j} p_{mj} \quad (10)$$

Data

The data utilized in this study primarily consist of national Multi-Regional Input-Output (MRIO) tables,

water withdrawal data for various provinces and sectors, and information regarding water availability and Environmental Flow Requirements (EFR) for each province. We relied on the most recent MRIO tables compiled by the China Emission Accounts and Datasets (CEADs), which encompass the trade networks and economic outputs of 42 industries across 31 provinces in 2017 (Zheng et al., 2021). For projections of future water resource availability and water withdrawal data under climate change for the years 2020 and 2030, we accessed the WRI Aqueduct database (World Resources Institute, 2018). This database, based on the CMIP5 model ensemble, encompasses average water resource changes from the baseline period (1950–2010) to the future period (2020–2030) (World Resources Institute, 2018). To ensure consistency with the “China Water Resources Bulletin” of 2020, we linearly adjusted the data due to variations in statistical calibrations. Our analysis focused on data corresponding to the Representative Concentration Pathway (RCP) 8.5, which represents the business-as-usual climate change scenario. Provincial-level EFR data were sourced from the Global Environmental Flow Information System of the International Water Management Institute (International Water Management Institute, 2017). For this study, we opted for Class C EFR values, which are aligned with the recommendations for China provided by

the Food and Agriculture Organization of the United Nations (Food and Agricultural Organization, 2017).

RESULTS

Potential water scarcity volume at national level

Figure 1a,b demonstrates the potential water shortage volume (PWSV) in China's provinces in 2020 and 2030 under climate change conditions. Among the nine provinces facing potential water shortages in China in 2020, seven belong to the eastern region, with Fujian, Jiangsu, and Guangdong facing the most severe potential water shortages, with PWSV reaching 29 billion tons, 24.8 billion tons, and 24.6 billion tons, respectively. The remaining two provinces are Ningxia in the western region and Henan in the central region, with PWSV reaching 6.1 billion tons and 4.5 billion tons, respectively. The provinces in the northeastern region have abundant available water resources, with a PWSV of 0. Compared with 2020, the number of provinces facing water shortages in 2030 did not change, but the degree of potential water shortages worsened. For example, the PWSV in Henan increased from 4.5 billion tons to 7.1 billion tons, an increase of 58%.

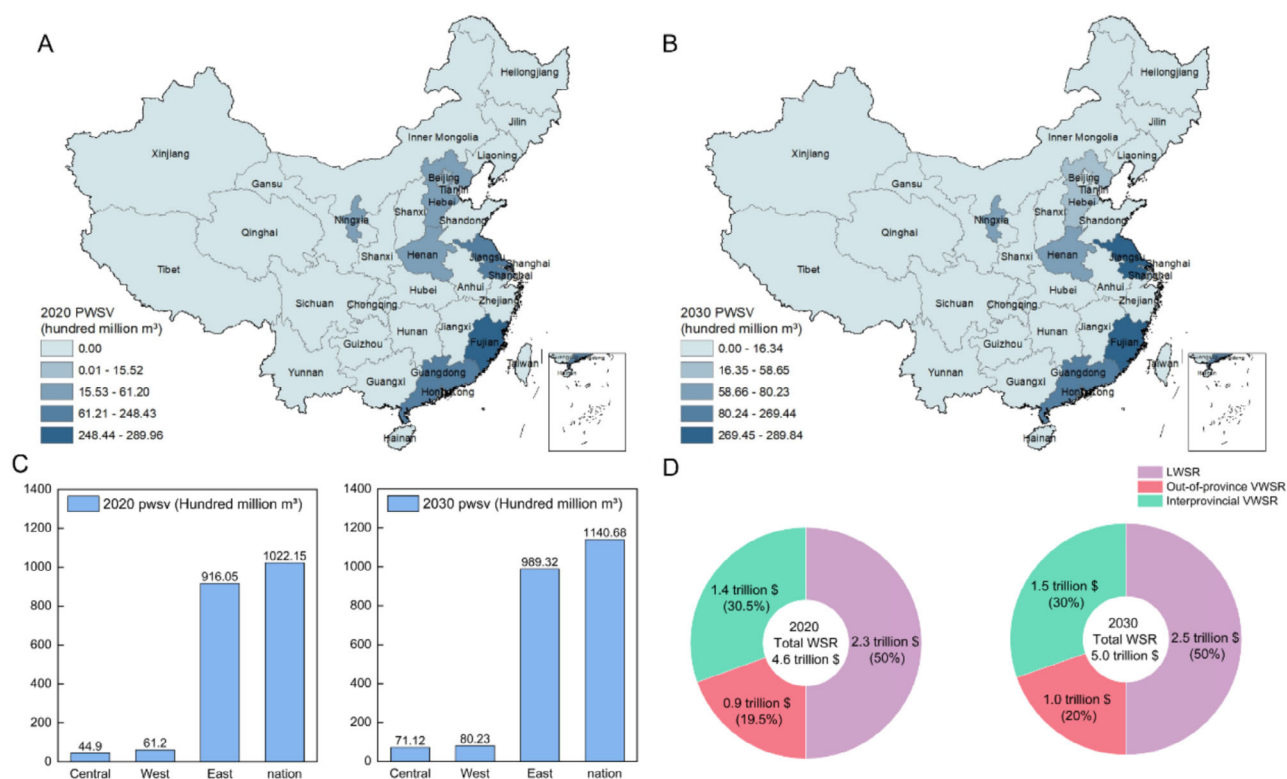


FIGURE 1 PWSV at provincial level in 2020 (a) and 2030 (b), PWSV for four regions (c), and WSR at the country level (d).

As depicted in Figure 1c, China's PWSV in 2020 was 102.2 billion tons, with over 90% of the PWSV coming from the eastern region. The PWSV in the western and central regions were 6.1 billion tons and 4.5 billion tons, respectively, and there was no potential water shortage in the northeastern region. Under climate change conditions, China's PWSV increased to 104.1 billion tons in 2030. The PWSV in the eastern, western, and central regions all increased, reaching 98.9 billion tons, 8.02 billion tons, and 7.1 billion tons, respectively.

As shown in Figure 1d, the total WSR of China in 2020 was approximately \$4.6 trillion. Among the total WSR, LWSR accounted for about 50%, valued at \$2.3 trillion. The remaining 50% constituted VWSR, with inter-provincial VWSR comprising a significant portion at 30.5% (\$1.4 trillion). By 2030, China's total WSR increased to \$5 trillion, with LWSR still maintaining a 50% share, while the proportion of interprovincial VWSR decreased to 30.4% (\$1.5 trillion).

Water scarcity risk at provincial level

LWSR rankings among provinces show some correlation with PWSV, but they are not entirely consistent. As

shown in Figure 2a, in 2020, the top five provinces in LWSR rankings were Fujian, Guangdong, Shanghai, Jiangsu, and Tianjin, with LWSR values of \$1296.2 billion, \$425.4 billion, \$182.8 billion, \$147.8 billion, and \$94.1 billion, respectively. Comparing 2030 with 2020, there were slight changes in LWSR rankings, with increases in LWSR values across provinces (as shown in Figure 2b). For example, Henan rose from ninth to eighth place, with LWSR increasing from \$41.8 billion to \$62.2 billion, mainly due to a significant increase in PWSV in Henan in 2030.

We illustrate the flow of VWSR among provinces. Figure 2c shows that in 2020, Fujian, Shanghai, and Guangdong were the top three exporters of VWSR, with over 70% of VWSR exports coming from these three provinces. Notably, the flow from Fujian to Guangdong was the largest, reaching \$60.5 billion. Additionally, Fujian's exports to Zhejiang were \$39.4 billion. The top five importers of VWSR were Zhejiang, Guangdong, Jiangsu, Henan, and Beijing, with import volumes of \$110.3 billion, \$100.5 billion, \$87.1 billion, \$61.0 billion, and \$55.0 billion, respectively. Comparing 2030 with 2020, there were no changes in the provincial rankings of VWSR imports and exports, but the import and export volumes of VWSR increased across provinces (as shown in

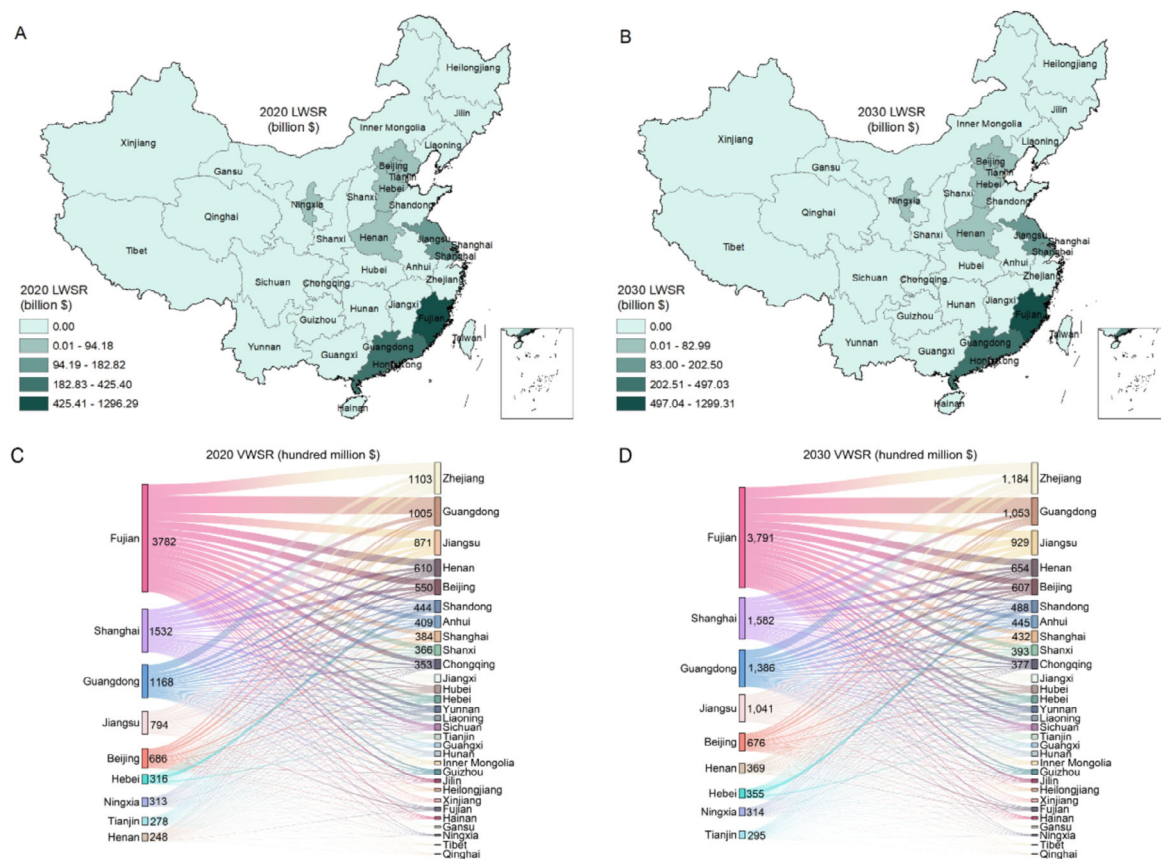


FIGURE 2 LWSR at provincial level in 2020 (a) and 2030 (b) and flows of VWSR import and export among provinces in 2020 (c) and 2030 (d).

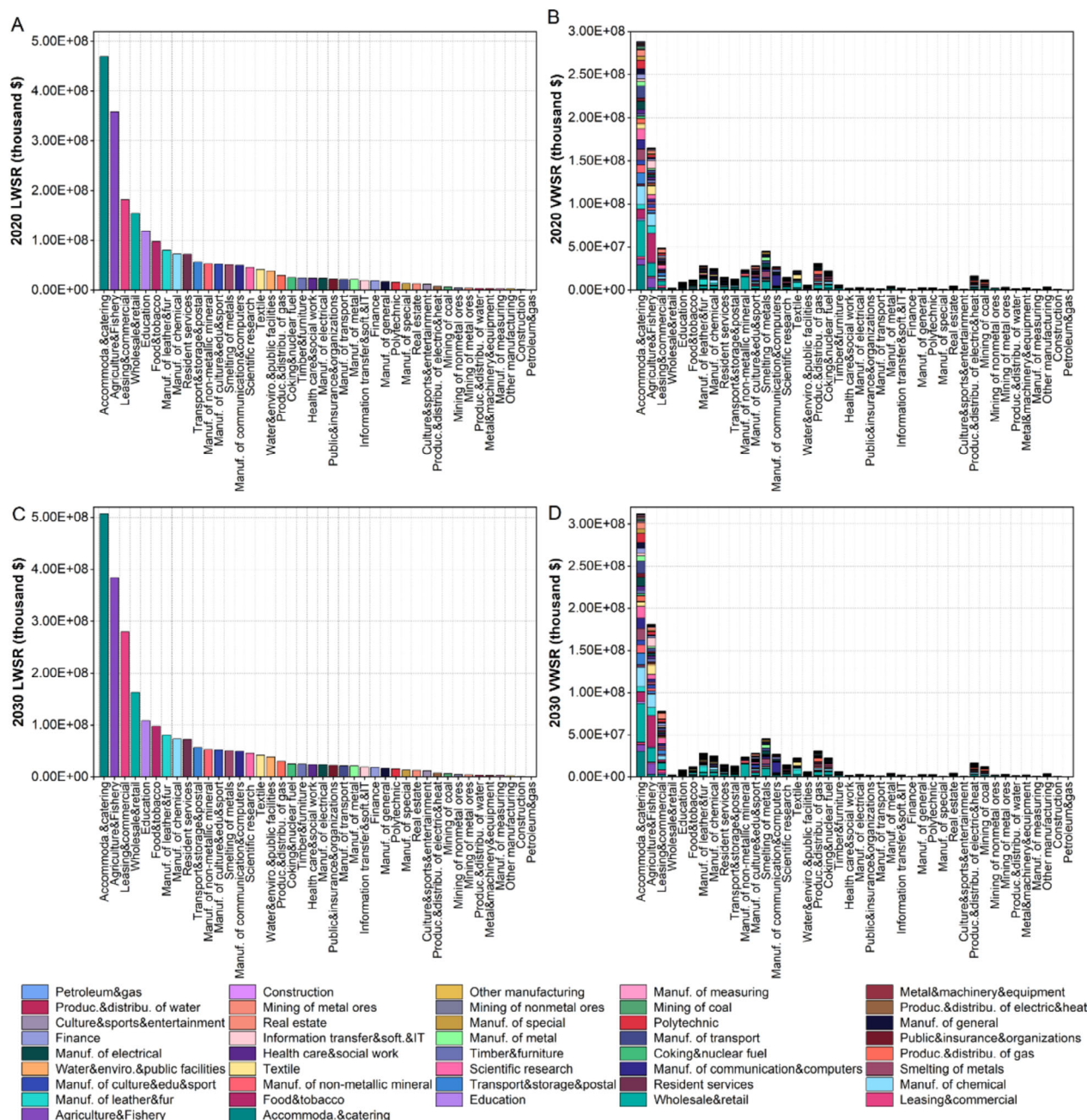


FIGURE 3 WSR at the sector level. (a) 2020 LWSR (thousand \$); (b) 2020 VWSR (thousand \$); (c) 2030 LWSR (thousand \$); (d) 2030 VWSR (%).

Figure 2d). For example, the export volumes of the top three provinces in VWSR exports—Fujian, Shanghai, and Guangdong—increased to \$397.1 billion, \$158.2 billion, and \$138.6 billion, respectively.

Water scarcity risk at sectoral level

Figure 3a shows that in 2020, over 20% of the LWSR (\$469.8 billion) came from the accommodation and food

service sector, followed by \$358.6 billion (15% of LWSR) from the agriculture, forestry, animal husbandry, and fishery sector, and \$181.6 billion (8% of LWSR) from the rental and business services sector. The top three industries for VWSR exports are consistent with LWSR (Figure 3b). Over 30% of VWSR (\$206.5 billion) came from the accommodation and food service sector, followed by \$108.3 billion (18% of VWSR) from the agriculture, forestry, animal husbandry, and fishery sector, and \$35.1 billion (5% of VWSR) from the rental and business

services sector. The transmission types of department-level VWSR mainly present as distributed transmission, with VWSR from various departments being distributed to many other departments. For the accommodation and food service sector, a large portion of VWSR is transmitted to both the accommodation and food service sector and the wholesale and retail trade sector. Specifically, 10% of VWSR (\$20.6 billion) from the accommodation and food service sector is transferred to the accommodation and food service sectors of other provinces, and 15% of VWSR (\$30.3 billion) is transferred to the wholesale and retail trade sector. The agriculture, forestry, animal husbandry, and fishery sector have over 20% of VWSR (\$24.1 billion) transferred to the food and tobacco sector, as the production of food and tobacco products relies on raw materials provided by the agriculture, forestry, animal husbandry, and fishery sector, making the VWSR export to the food and tobacco sector from this sector the highest. Figure 3c shows that in 2030, compared to 2020, the rankings and transmission of department-level LWSR and VWSR remain largely unchanged, with slight increases in amounts (Figure 3c,d). For example, the LWSR of the accommodation and food service sector in 2030 was \$507.1 billion, an increase of 8%.

The key sectors in the critical provinces

We also conducted WSR analysis at the provincial-sector level. Figure 4a shows that in 2020, LWSR originated from 91 provincial-sectors. The wholesale and retail sector in Fujian had the highest LWSR value, amounting to \$145 billion, followed by the accommodation and food service sector in Guangdong with \$131.5 billion, and the agriculture, forestry, animal husbandry, and fishery sector in Jiangsu with \$107.5 billion. Our research findings indicate that the relationship between provincial-sector LWSR and their rankings follows a power-law function (exponent = -0.6 , $R^2 = 0.81$), expressed by the Pareto principle as 80% of the consequences stemming from 20% of the causes (Lipovetsky, 2009). Figure 4b shows that VWSR imports originated from 1302 provincial-sectors. The wholesale and retail sector in Zhejiang received the highest VWSR imports, valued at \$14.6 billion, followed by the communication equipment and computer sector in Guangdong with \$13.3 billion, and the wholesale and retail sector in Guangdong with \$10.2 billion. The Pareto principle similarly applies to the relationship between VWSR imports and rankings (exponent = -0.6 , $R^2 = 0.84$). Figure 4c displays changes in LWSR rankings

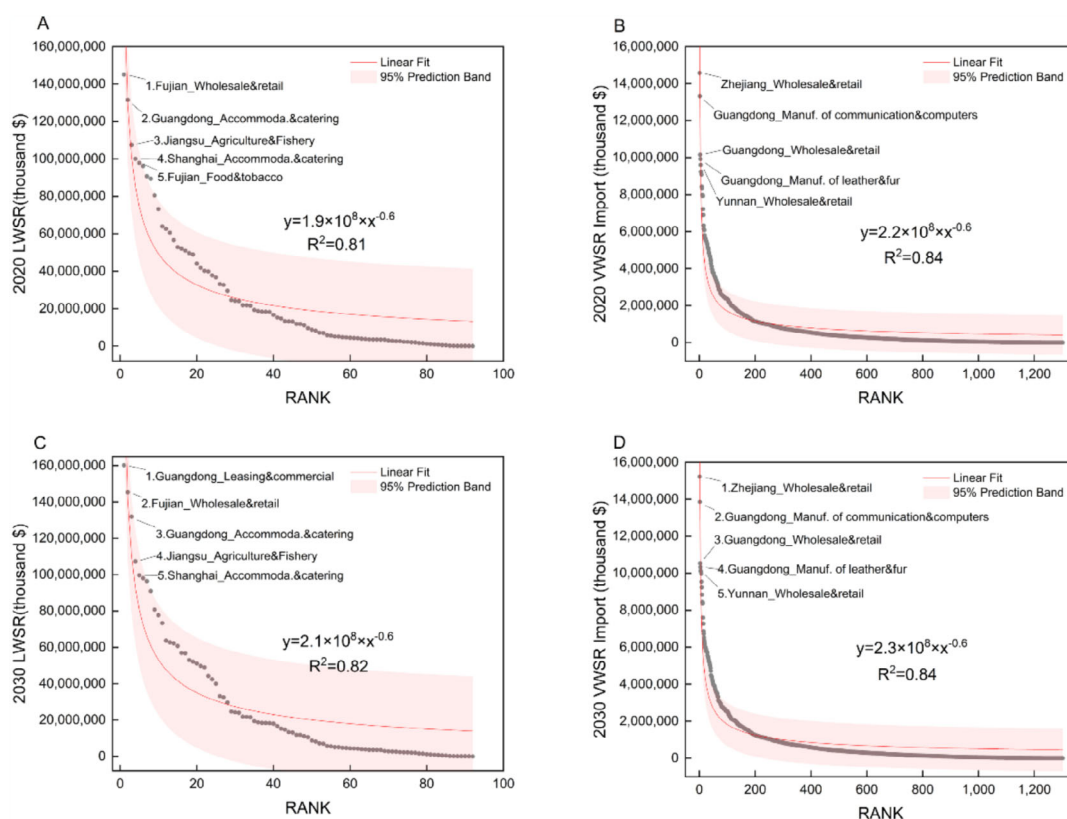


FIGURE 4 WSR at the province-sector level. (a) 2020 LWSR vs. rank; (b) 2020 VWSR import vs. rank; (c) 2030 LWSR vs. rank; (d) 2030 VWSR import vs. rank.

in 2030. The leasing and business services sector in Guangdong had the highest LWSR value, totaling \$106.2 billion, followed by the wholesale and retail sector in Fujian with \$145.4 billion, and the accommodation and food service sector in Guangdong with \$131.9 billion. The top five rankings for VWSR imports remained the same as in 2020 (Figure 4d), with some increase in numbers. For instance, the wholesale and retail sector in Zhejiang experienced an increase in VWSR imports to \$15.2 billion.

DISCUSSION AND POLICY IMPLICATIONS

The traditional water stress index evaluates the scarcity of water resources by comparing the annual water withdrawal to renewable water resources. This method often underestimates water scarcity risk as it does not consider environmental flow requirements. The method used in this study to construct potential water scarcity volume comprehensively considers water withdrawal, water availability, and EFR. Additionally, PWSV, being an absolute value rather than a percentage, provides a clear quantifiable standard, enabling better correlation with economically relevant indicators and facilitating a more accurate quantification of the economic losses caused by water scarcity risks. Considering the spatial heterogeneity of water resources within countries, this study, for the first time, refines the research scale to the provincial level to investigate water scarcity risks under climate change in China.

Our research indicates that under climate change conditions, there will be more WSR in 2030 compared to 2020. This is because climate change leads to reduced water supply while water demand remains unchanged, resulting in an increase in PWSV and ultimately an increase in WSR. This finding is consistent with previous studies, which also demonstrate the decrease in water supply due to climate change (Yang, Zhang, et al., 2022; Zhao et al., 2019). The provinces facing water scarcity risks remained unchanged between 2020 and 2030, namely Fujian, Guangdong, Jiangsu, Ningxia, Shanghai, Hebei, Henan, Beijing, and Tianjin, primarily concentrated in the eastern regions. This is attributed to the higher economic development and urbanization levels in the eastern regions, resulting in greater population, industrial, and societal pressures on their water resource systems (Tian et al., 2021). The ranking and transfer patterns of LWSR and VWSR in these provinces have remained relatively stable, but the total WSR in the country has increased from \$4.6 trillion to \$5 trillion. This suggests that the distribution pattern of provincial water

scarcity risks in China under climate change conditions has not changed significantly, mainly because there have been minor changes in the distribution pattern of PWSV among provinces from 2020 to 2030, coupled with a certain increase in the volume of PWSV. Provinces currently facing water scarcity will face even greater challenges in the future. Therefore, attention should be paid to guiding these provinces to enhance their awareness of water conservation when formulating policies. Estrela-Segrelles et al. (2024) also indicates that climate change will exacerbate water scarcity in areas currently experiencing water shortages. The LWSR and VWSR of industries in 2020 and 2030 have also increased slightly while their ranking and transfer patterns remain relatively stable. For example, in 2020, the LWSR and VWSR export volumes of the agriculture, forestry, animal husbandry, and fishery sectors were \$358.6 billion and \$118.3 billion, respectively, and increased to \$383.9 billion and \$129.6 billion, respectively, by 2030. This increase is due to minor changes in the ranking of water intensity and trade structure of industries between 2020 and 2030, resulting in a slight increase in the proportion of PWSV, leading to an increase in LWSR and VWSR of industries.

We have also identified regional and sectoral hotspots under climate change. In 2030, the two provinces with the highest LWSR are Fujian and Guangdong, at \$1299.3 billion and \$497.0 billion, respectively. Fujian and Shanghai have the highest VWSR export volumes, at \$397.1 billion and \$158.2 billion, respectively, indicating that the water scarcity in Fujian and Shanghai has the greatest impact on other provinces. The two provinces with the highest VWSR import volumes are Zhejiang and Guangdong, at \$118.4 billion and \$105.3 billion, respectively. Their main source of VWSR imports is Fujian, which has severe PWSV. Diversification of import sources can be achieved by reducing reliance on water-intensive products from Fujian. At the industry level, accommodation and food services and agriculture, forestry, animal husbandry, and fishing are the top two industries in both LWSR and VWSR exports, with WSR far exceeding other industries. Accommodation and food services suffered \$507.1 billion in LWSR exports and \$223.0 billion in VWSR exports. Agriculture, forestry, animal husbandry, and fishing had LWSR and VWSR exports of \$383.9 billion and \$129.6 billion, respectively. Li et al. (2022) took into account the impact of water pollution on WSR in their research, and they discovered that agriculture, hunting, forestry, and fishing, as well as the production and supply of electricity and heat, and the smelting and processing of metals are major exporters of VWSR. In this study, although the production and supply of electricity and heat, as well as the smelting and processing of metals, also exhibited significant VWSR export volumes,

they were not among the top three. This discrepancy is due to the method used in this study, which allocates PWSV based on industry water intensity. The water intensity of the accommodation and food services industry and the agriculture, forestry, animal husbandry, and fishery industry is very high, resulting in the highest PWSV experienced. Ning et al. (2023) found that agriculture, accommodation, and catering are industries with low water use efficiency when analyzing water use coefficients. Although accommodation and food services have less PWSV compared to agriculture, forestry, animal husbandry, and fishing, their economic output is higher, resulting in greater economic losses due to water scarcity than the latter. For these water scarcity hotspots industries, policy incentives can be provided to encourage enterprises to adopt effective water-saving measures.

Under the backdrop of climate change, China is facing increasingly severe risks of water scarcity, which pose a threat to both government and corporate decision-makers. The risks of water scarcity include both local water shortage risks and indirect water shortage risks spread through trade networks. This paper offers several suggestions on this matter. On one hand, it is essential to conserve water resources in areas and industries with higher local water scarcity risks. This not only effectively mitigates the economic losses caused by water shortages at the local level but also reduces the economic losses imposed on downstream regions. Strengthening public education and raising awareness of water conservation among the public is crucial. By disseminating water-saving knowledge through various channels, the importance of water conservation can be recognized, encouraging public participation in water-saving actions. Policy incentives can be provided to encourage businesses to adopt effective water-saving measures. For example, the accommodation and food services sector, having the largest LWSR (\$469.8 billion in 2020), can be encouraged to use water-saving equipment such as low-flow faucets, showerheads (Tam et al., 2021), and dishwashers (Belke et al., 2018). The agriculture, forestry, animal husbandry, and fishing sector rank second in LWSR (\$358.6 billion in 2020). In agriculture, water use can be reduced by promoting water-saving irrigation techniques (Han et al., 2023), selecting drought-resistant crops (Lüscher et al., 2022), and rationalizing irrigation water prices (Zhang et al., 2022). Reasonable irrigation quotas can be established based on factors such as crop type, growth cycle, and irrigation needs, with a progressive pricing system for water usage exceeding the quotas. By setting scientifically reasonable agricultural irrigation water prices, farmers can be guided to save water, improving the efficiency of water resource utilization. On the other hand, for areas and sectors with high virtual

water scarcity risks, trade structures can be improved, and the advancement and rationalization of industrial structures can be promoted (Zhang, Zhou, et al., 2023). For instance, more than 50% of Fujian's VWSR exports are destined for Zhejiang and Guangdong. Consequently, policymakers in Zhejiang and Guangdong should commence efforts to reduce their reliance on imports of water-intensive goods, such as agricultural products, from Fujian, and to diversify their import channels. This can be achieved by implementing policy incentives to revitalize regional self-sufficiency in production, or by seeking reliable alternative resources from other provinces like Anhui, thereby enhancing the adaptability and resilience to challenges posed by water scarcity due to climate change.

We have established a framework to predict the economic output losses caused by water scarcity under climate change conditions. This helps assess the impact of climate change on local freshwater resources and economic activities. However, our study still has some limitations that should be addressed in future research. Firstly, although the Chinese MRIO table used in this study is the latest data available, it may be subject to some lag due to its updating constraints. This could affect the prediction of water scarcity risks and timely responses to water scarcity issues. Future research could use machine learning methods to forecast the MRIO table (Chen et al., 2023; Li et al., 2025; Shuai et al., 2022; Zhao et al., 2022). Secondly, the WSR derived from our study based on provincial-level annual economic data in China may be underestimated, and using data with higher spatiotemporal resolution could significantly improve the accuracy of the research. Future studies could consider using data with higher temporal resolution (e.g., monthly grid data) for research purposes. Additionally, future research could explore the use of remote sensing data to enhance spatial resolution (Duan & Duan, 2021).

CONCLUSION

The focus of this study is to estimate the risk of water scarcity in China under climate change conditions. Water scarcity can affect the production of local sectors, leading to economic losses. We found that China's LWSR in 2020 and 2030 under climate change conditions are \$2.3 trillion (accounting for 50% of WSR) and \$2.5 trillion (accounting for 50% of WSR), respectively. Among them, Fujian and Guangdong are the provinces with the highest direct economic loss risk due to regional water scarcity. This impact is transmitted from upstream to downstream through the trade system, causing losses to

downstream regions and industries. Fujian, Shanghai, and Guangdong are the top three exporters of VWSR, with more than 70% of the VWSR export volume coming from these three provinces. The top three industries for VWSR exports are the accommodation and food services sector, the agriculture, forestry, livestock, and fishing sector, and the leasing and business services sector. Our research can help policymakers strengthen water resource management, which is of great significance for reducing economic losses due to water scarcity.

AUTHOR CONTRIBUTIONS

Ying Wang: Formal analysis; visualization; writing – original draft; data curation. **Chenyang Shuai:** Conceptualization; methodology; writing – review and editing. **Xi Chen:** Funding acquisition; writing – review and editing; project administration. **Wei Huang:** Data curation. **Jingran Sun:** Writing – review and editing. **Bu Zhao:** Writing – review and editing; methodology.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

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