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Quality matters: Pollution exacerbates water scarcity and sectoral output risks in China

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ABSTRACT

Pollution exacerbates a region's water scarcity by making water unfit for different uses and reducing freshwater availability. Local water scarcity may lead to economic output losses, and the risk can be transmitted to downstream sectors through reduced input supplies. Previous studies focus on quantity-based water scarcity assessment. It is still unknown how water quality constraints may amplify economic risks of local water-use sectors and distant economies. Here we introduce an integrated method and assess the impacts of both quantity and quality-based local physical water scarcity risks (LWSR) and virtual water scarcity risks (VWSR) in domestic trade system in China. We find in 2017 quality-based LWSR and VWSR in China are ~593 and ~240 billion US$. Inclusion of water pollution constraints almost doubles the risks of economic losses due to insufficient clean water supply. We then identify critical regions and sectors that are highly risky or vulnerable to the supply chains. We find water pollution makes risky VWSR exporters more centralized in a few Northern provinces where available freshwater resources are already limited, e.g. the agriculture sector in Hebei province. VWSR importers span broadly, but water pollution increases concentrations of upstream suppliers that face local water scarcity for most provinces, decreasing overall resilience of China's domestic trade network. Our results underscore the needs to alleviate overall scarcity risks by conserving physical water resources and improving water quality simultaneously.

1. Introduction

Water scarcity poses enormous economic risks to water-use sectors such as energy, agriculture, and manufacturing (Dolan et al., 2021). The imbalance between water demand and water availability is a major contributor to regional water scarcity (Boretti and Rosa, 2019; Yu et al., 2011). Many regions in the world are suffering from economic impacts of water scarcity. As the world's factory, China feeds 20% of the global population but has only 7% of the freshwater resources on the planet (Cheng et al., 2009; Sun et al., 2021). Inequality in water scarcity is even worse within the country. The North China Plain located in the basins of the *Hai, Huai,* and *Yellow Rivers*, contributes to more than a quarter of China's total economic outputs, whereas available water resources in the region account for less than 8% of the country's total amount (Cheng et al., 2009). Assessing spatial pattern of water scarcity is thus fundamental for mitigating economic risks in local sectors.

In addition to insufficient water quantity, water pollution also exacerbates local water scarcity risks. Poor water quality fails to meet the basic requirement of water use sectors, which may constrain water usability and induce economic output losses (Gleick, 1996; Liu et al., 2016). For instance, salinity, chemical oxygen demand (COD), and other pollutants lead to considerable constraints on water usability in sectors such as irrigation, industrial production, and domestic use (van Vliet et al., 2017). As a result, water scarcity risks are expected to worsen considerably in many regions, as both surface and ground water quality have been deteriorated due to rapid urbanization and poorly treated wastewater discharge (Cheng and Hu, 2012). In China, for example, pollutant concentrations observed in 27.6% of China's surface water monitoring stations were not up to Grade III standard in 2018, a water quality level that merely enables people to swim in (Li et al., 2019). Sustainable management of water resources in China and other water dependent economies should not only account for demand in water quantity, but also for water quality (He et al., 2020).

Current indices developed for assessing the levels of water scarcity are made mainly based on water quantity aspects. For example, the Water Stress Index (WSI) is typically defined as the ratio of water

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withdrawal or consumption to water availability (Damkjaer and Taylor, 2017). To quantify the constraint of water quality on water stress, several studies introduce the concept of gray water footprint (Mekonnen and Hoekstra, 2015), which is the amount of water required to dilute pollutants in wastewater to meet the water quality standard. Combining total water demand and gray water footprint, Liu et al. (2017) calculate its ratio to freshwater availability to reflect both quantity and quality-based water scarcity in Chinese thirty provincial administrative units. Also, employing the concept of gray water footprint, van Vliet et al. (2017) evaluate the impact of water quality on sectoral water shortage in the Pearl River Basin of China. They take into account three specific types of water quality indicators, including temperature, salinity, and nitrogen. Ma et al. (2020) perform water scarcity assessment at a high spatial resolution of 0.25 × 0.25 arc-degree for China's three-level river basins, taking the water quality requirement of different sectors into account. Their results confirm that water pollution aggravates regional water shortage and inequality. These research efforts help delineate the threat of pollution on regional water stress, however, few of them comprehensively evaluate the risks of both quantity and quality-based water scarcity on local industrial economy.

While water scarcity is often understood and managed as a local issue, its drivers could be global and its impact could be transmitted to downstream economies through supply chains (Cosgrove and Loucks, 2015; Davis et al., 2021; Pfister et al., 2011; Zhao et al., 2015). Studies have extensively quantified virtual water transfer driven by the demand for goods and services. An early work led by Feng et al. (2014) assesses virtual water flows among Chinese thirty provinces and finds that consumption in developed coastal regions exacerbates the pressure of water shortage in already water-scarce inland provinces. From the supply side, the potential of losing outputs in local water intensive sectors can also exert economic impacts in other distant economies and sectors through the trade system. For instance, Qu et al. (2018) map the impacts of local water scarcity risk on global economy from 1995 to 2009. They identify top nation-sectors in virtual water scarcity risk exports and imports. However, we notice that previous studies have rarely analyzed the impacts of local water scarcity on downstream sectors that consider water quantity and quality constraints simultaneously.

This study aims to reveal how water pollution may exacerbate the impacts of water scarcity on the local economic sectors and the entire supply chain system. We first assessed the risks of losing economic outputs in Chinese provincial sectors due to physical water scarcity by incorporating water quality requirements for agriculture, industry, and domestic sectoral uses. We then mapped virtual water scarcity risks transmitted via domestic trade connections and identified top province-sectors that have significant impacts on downstream economies due to local water stress or are vulnerable to distant water scarcity. Our results emphasize the needs for improving local water use efficiency and enhancing wastewater treatment at the same time to mitigate the entire supply chains risks.

2. Methods

2.1. Quality-included local water scarcity risk (LWSR)

Fig. 1 illustrates our method framework. We first developed a local water scarcity risk (LWSR) index that provides a quantitative measure of water scarcity risk in a sector in a province. Both available water quantity and acceptable quality for sectoral use were included in the formulation. As listed in Eq. (1), LWSR includes three main parameters:

$$LWSR_{m,p} = WDR_p \times WD_{m,\,p} \times k_{m,p} \tag{1}$$

$LWSR_{m,p}$ refers to the potential direct output loss (in monetary unit) of sector m in province p due to water scarcity. Water Depletion Risk (WDR_p) measures the fraction of potentially reduced water use due to insufficient water quantity and deteriorated water quality. Water Dependency ($WD_{m,\,p}$) refers to the water resource dependence of sector m in province p, and is defined as the percentage of output loss caused by 1% water depletion. Parameter $k_{m,p}$ refers to the benchmark economic output of sector m in province p without considering the risk of water resource depletion. Below we explain the estimation of WDR and WD.

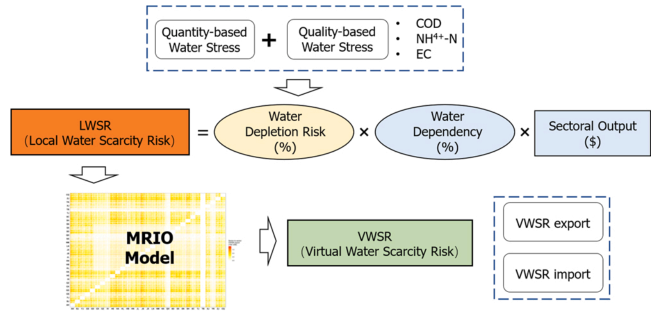

Fig. 1. Graphical representation of the research framework in this study.

2.1.1. Water Depletion Risk (WDR)

Water Depletion Risk (WDR) measures the risk of insufficient water use due to scarcity, which has no direct data or measurement. Its value needs to be inferred from relevant variables. Accordingly, we first calculated a combined Water Stress index (WS_p), defined as the ratio of sectoral consumption of acceptable water quality to the overall water supply in province p. As shown in Eq. (2), WS_p contains both quantity-based and quality-based assessments of water stress. The quantity-based dimension is measured by the ratio of the total amount of sectoral water consumption ($D_{m,p}$) to water availability (Q_p) in province p. The quality-based dimension is calculated as the ratio of the sum of water resources required for dilution to obtain adequate quality for all sectoral water uses ($dq_{m,p}$) to water availability (Q_p) in province p.

$$WS_p = \frac{\sum_m D_{m,p}}{Q_p} + \frac{\sum_m dq_{m,p}}{Q_p} \tag{2}$$

The approach to determine $dq_{m,p}$ is shown in Eq. (3), where $C_{i,p}$ is actual water quality level of parameter i (e.g., chemical oxygen demand) in province p and $Cmaxi,\,m$ represents the maximum water quality threshold for parameter i in water use sector m. We referred to the method proposed by Ma et al. (2020) to calculate $dq_{m,p}$. That is, when water quality meets the requirement, extra water stress caused by pollution was set as 0. When pollution level exceeds the standard, the amount of water for diluting the volume of the sectoral water consumption was calculated to reflect the constraints of poor water quality.

$$dq_{m,p} = \begin{cases} 0, & Ci \le C_{max,\,m} \\ D_{m,p}\left(\frac{C_{i,p}}{C_{max,\,m}} - 1\right), & Ci > C_{max,\,m} \end{cases} \tag{3}$$

For setting sectoral water quality thresholds ($Cmaxi,m$) in Eq. (3), we chose chemical oxygen demand (COD), ammonia nitrogen (NH^{+4}-N), and electrical conductivity (EC) as three typical water quality measures. For agricultural water use, a concentration of 0.7 $dS{\cdot}m^{-1}$ for EC, reflecting a salinity constraint for crop growth, was considered as the maximum water quality threshold for irrigation (Silber et al., 2015). The value is in line with recommendations by Food and Agriculture Organization. According to the *Environmental Quality Standard for Surface Water in China*, 6.0 $mg{\cdot}L^{-1}$ for COD and 1.0 $mg{\cdot}L^{-1}$ for NH^{+4}-N were used as the domestic water use thresholds (Ministry of Water Resources of China, 2017). Meanwhile, 10.0 $mg{\cdot}L^{-1}$ for COD and 1.5 $mg{\cdot}L^{-1}$ for NH^{+4}-N were adopted as the basic water requirements for industry sectors (Ma et al., 2020).

It should be noted that the value of water stress (WS) is not equivalent to the probability of inducing economic losses. A province with WS greater than 1 can still use water through some physical water transfer projects or undermining ecological water requirement (Yevjevich, 2001; Zhang et al., 2015). It is assumed that sectors in high-WS regions are more at risk of output loss due to water scarcity. Therefore, we applied a probabilistic function used by Qu et al. (2018) to convert WS to WDR, the value of which lie in the interval [0,1].

$$WDR_p = f_{WDR}(WS_p;\ \sigma) = E(y_p) \tag{4}$$

With,

$$f_{WDR}(WS_p;\sigma) = E[Y_p],$$

where $\begin{cases} Y_p = 0 \ if X_c \geq 1 \\ Y_p = 1 - X_p \ if X_p < 1 \end{cases},\ X_p \sim Lognormal\left(\frac{1}{WS_p}, \sigma\right)$

As can be seen in Eq. (4), f_{WDR} calculates the expected value of variable Y_p, which is the function of X_p. X_p follows a log-normal distribution with the median being the inverse of WS and standard deviation σ. The value of σ was set as 1 in this study. The value of WDR, in essence, measures the probability that the WSI will be >1 when following the lognormal distribution. Fig. S1 presents calculated WDRs with different WS values in our study. We find the transformation does not change the relative order of WSI but scale the values of WSI into the interval [0, 1]. For a province with WS value higher than 0.20, which was considered as suffering water scarcity in previous literature (Kummu et al., 2016), the function f_{WDR} will output a WDR value over 1%.

2.1.2. Water Dependency (WD)

Water Dependency (WD) measures relative output losses for an economic sector due to less water use. Its largest possible value is assumed to be 1, in which case water is completely not substitutable. Similar to WDR, WD is also not accessible from existing data and should be calculated from Water Intensity (WI). However, water intensity, defined as water consumption for unitary sectoral economic output, varies significantly across sectors and lie in [0, +∞). We therefore used Eq. (5) to convert sectoral WI to sectoral WD, lying in [0.001, 1).

$$WD_m = f_{WD}(WI_m;\ \alpha) = \frac{1}{1 + e^{-\alpha WI_m}\left(\frac{1}{0.001} - 1\right)} \tag{5}$$

As shown in Eq. (5), the WD_m denotes the degree of water resource dependence in sector m, which is the function of water intensity in sector m (WI_m). The parameter α governs a cutoff value of WI above which WD will rise rapidly toward 1. We set α as 0.5 in this study. For province-sectors with very low or even zero water intensity, their WD values are at the minimum value of 0.001, reflecting the general importance of water resources. For province-sectors with water intensity > 20 (ton/\$), their WD values will be very close to 1, as can be seen in the function curve drawn in Fig. S1.

It should be noted that LWSR reflects the probability of output loss due to water scarcity and thus is measured in relative terms (i.e. in%). We should admit the uncertainty for using WSI to represent WDR and using WI to calculate WD. Choosing different parameters may also affect WDR and WD values. Therefore, we have performed sensitivity analysis using different relationship curves and found our conclusions are still robust. The results and explanations for the analysis approach are presented in Fig. S2.

2.2. Virtual water scarcity risk (VWSR)

We then assessed the impacts of LWSR on downstream provinces and sectors through reduced input supplies, i.e. the virtual water scarcity risk (VWSR). The VWSR export reflects the impacts of LWSR transmitted to other province-sectors through exporting water-use goods (e.g., agricultural products) or industrial intermediate inputs. The VWSR import, on the other hand, denotes the provincial or sectoral vulnerability to the local water stress in other regions.

We applied national multiregional input-output (MRIO) analysis to map VWSR exports and imports across Chinese provinces. In the MRIO model, different regions are connected by interregional trade links at the sector level. The MRIO table has the characteristics of column and row balance, indicating that each sector's total input equals its total output. As shown in Eq. (6), each sector's total input equals the sum of its intermediate inputs and value added.

$$x = eZ + v \tag{6}$$

The $1 \times n$ vector x represents total inputs of each economic sector. The $n \times n$ matrix Z denotes transaction flows among province-sectors. The $1 \times n$ vector v denotes value-added creation in each sector. Every element in the $1 \times n$ vector e is equal to one.

To investigate transmission of local sectoral outputs to the whole system, we define an $n \times n$ matrix B as direct output coefficient matrix, representing the product allocation ratio from one province-sector to other province-sectors. The approach to calculate matrix B is shown in Eq. (7), where $\hat{x}$ is the diagonalized matrix of total inputs vector x.

$$B = (\hat{x})^{-1} Z \tag{7}$$

Accordingly, Eq. (6) can be rewritten in the form of Eq. (8).

$$x = v(I - B)^{-1} \tag{8}$$

The $n \times n$ matrix $(I - B)^{-1}$ is the well-known *Ghosh Inverse matrix*, whose element refers to the total production value of sector j generated by unit initial input of sector i. As specified in Eq. (9), we use *Ghosh Inverse matrix* to evaluate the influence of LWSR in the whole national trade network. Elements in vector Δx represent output loss of each province-sector due to LWSR of all province-sectors.

$$\Delta x = LWSR \times (I - B)^{-1} \tag{9}$$

Furthermore, we can get a matrix ΔX by diagonalizing LWSR, as shown in Eq. (10). Elements in ΔX (i.e., Δx_{kl}) stand for the impact of province-sector k's LWSR on province-sector l's economic production. Then, in Eq. (11), We derive n_{pq}, which represents the impact of province p' LWSR on province q's LWSR by summing up Δx_{kl} per province. Finally, we sum n_{pq} to get the values of VWSR imports and exports respectively, as shown in Eqs. (12) and (13).

$$\Delta X = \mathrm{diag}(LWSR) \times (I - B)^{-1} \tag{10}$$

$$n_{pq} = \sum_{\substack{k \in provicne\ p \\ l \in\ provicne\ q}} \Delta x_{kl} \tag{11}$$

$$VWSR_p^{im} = \sum_{p \neq q} n_{pq} \tag{12}$$

$$VWSR_p^{ex} = \sum_{q \neq p} n_{pq} \tag{13}$$

Moreover, to examine relative impacts of a province's VWSR exports on supply chain and VWSR imports on local sectors irrespective of economic size, we measure a risk index and a vulnerability index for each province by normalizing its VWSR by its total output.

2.3. Herfindahl index

Meanwhile, a province's sensitivity to water scarcity risks of upstream suppliers is closely related to concentrations of its VWSR imports. If the origin of a province's VWSR imports are very concentrated, probability of the concurrence of upstream production losses due to water scarcity would be very high. It reduces a province's resilience to water scarcity risks in distant places. To evaluate resilience of supply chain, here we choose the Herfindahl index, represented by $Herf_p$ to measure the intensity of VWSR imports for province p (Ludema and Mayda, 2013). As shown Eq. (14), higher values of the Herfindahl index indicate higher concentrations of its VWSR imports.

$$Herf_p = \sum_{p \neq q} \left(\frac{n_{pq}}{\sum_{p \neq q} n_{pq}} \right)^2 \tag{14}$$

2.4. Data sources

In sum, four types of data were used in this study, including (1) multi-regional input-output (MRIO) data depicting provincial economic transactions in China, (2) pollution monitoring data that reflect Chinese current water quality status, (3) water consumption data of all economic sectors, and (4) water availability data at the provincial level.

MRIO data. We employed the China Multi-Regional Input-Output Table in year 2017, which was compiled by China Emissions Accounting and Data Set (CEADs) (Zheng et al., 2021). The table covers 42 socio-economic sectors in 31 provinces, which is one of the most updated Chinese MRIO tables. The division of sectors in the table was corrected according to the 2017 national input-output table officially issued by the Chinese government. The dataset has been widely used to map the virtual transfer of water and energy among different regions in China (Li et al., 2019; Zheng et al., 2021).

Water quality. The city-level annual average COD, EC, and NH+4-N data in 2017 were obtained from the National Environmental Monitoring Network. We then calculated the annual average concentrations of COD and NH+4-N at the province level, weighted by the total number of monitoring stations per city. Water quality indicators, sectoral water uses quality threshold, data sources, and supporting references are listed in Table S1. Detailed water quality data for each province are reported in Table S4.

Water consumption. We investigated three categories of water-use sectors in this study, namely agriculture, industry, domestic sectors. Water consumption for eco-environmental compensation is relatively small and was not considered in our study. Chinese government releases provincial water use volume of the three sectors every year (officially published in *Water Resources Bulletin*) and we manually collected the data of the year 2017. Next, we estimate water consumption in 42 subdivided sectors used in MRIO. The Chinese official statistical data water uses for specific manufacturing sectors or service sectors at the provincial level. We have to allocate the total amount of water use in provincial industry and domestic sectors to specific manufacturing and tertiary sectors according to the national-level estimated ratio. Therefore, we refer to the Chinese Environmentally Extended Input-Output (CEEIO) database developed by Liang et al. (2017), which provides an environmental satellite account of freshwater use of 45 sectors at the national level. We assume subdivided sectors in different provinces share the same proportion of water use as can be calculated in CEEIO. We then allocate the total amount of water use in industry and domestic sectors at each province to corresponding subdivided sectors accordingly. Fig. S3 presents the ratio of water uses in different manufacturing and tertiary sectors.

Water availability. Water availability reflects water resource endowment of a region. The *Water Resources Bulletin* provides annual accounting of water availability at the province level, which is the sum of surface and groundwater resources. We collected these data published in the year of 2017 (see provincial water consumption and water availability data in Table S3).

3. Results

3.1. Quality and quantity-based local water scarcity risk (LWSR)

We first examine how water pollution exacerbates local water stress at the provincial level. Fig. 2A shows both quality-based and quantity-based Water Depletion Risk (WDR) in 2017. Abbreviations for all provinces are detailed in Table S2. We find provincial WDRs in China exhibit spatial heterogeneity and water pollution exacerbates water scarcity at the national level. Water pollution approximately doubles WDRs in provinces located in Northern China where available water resources are already limited, such as Hebei (HE), Shandong (SD), Henan (HA), and Shanxi (SX). Conditions are even worse in megacities like Beijing (BJ), Shanghai (SH), and Tianjin (TJ), where WDRs increase by 1.93, 1.43, and 1.02 times after considering water quality constraints. When we set 1% WDR as the threshold of local water stress (dashed line in Fig. 2A) (Qu et al., 2018), we find more provinces including Jiangxi (JX) and Hunan (HN) are under risks of lacking sufficient available water. Geographical pattern of WDR in China is consistent with the distributions of water resource endowment, that is, provinces in

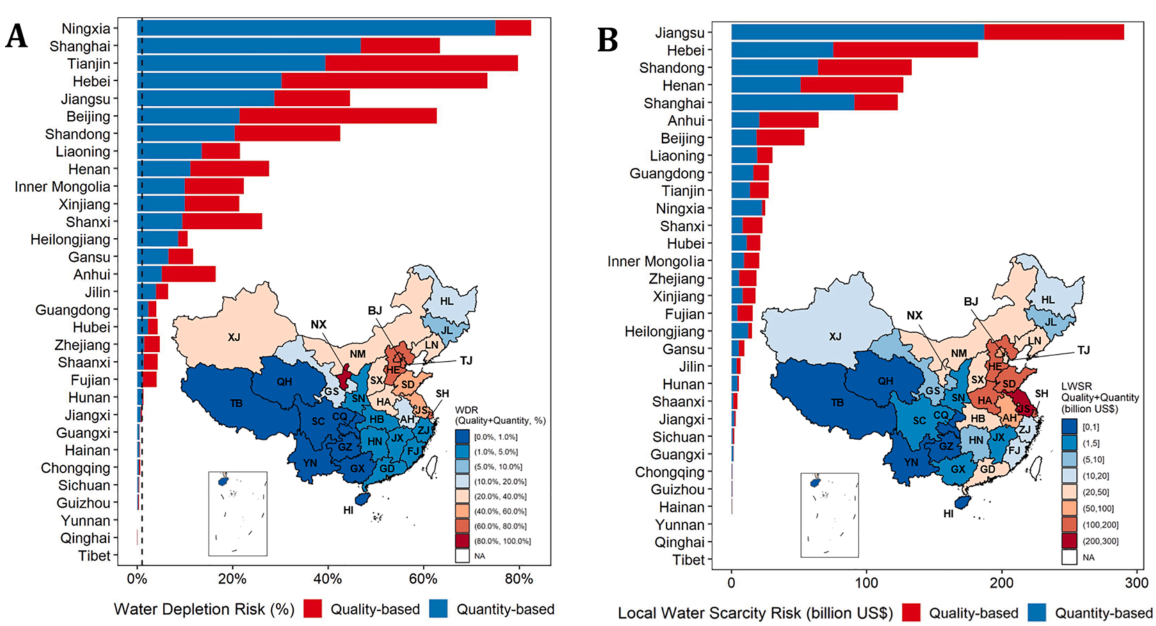

Fig. 2. Quality-included local water scarcity risk assessments at the provincial level. Blue and red bars in ***(A)*** denote quantity-based and quality-based Water Depletion Risk (WDR, in%) in each province. The dashed line denotes 1% WDR, a threshold for local water stress. The map illustrates spatial patterns of combined WDR across the country. Blue and red bars in ***(B)*** denote quantity-based and quality-based Local Water Scarcity Risk (LWSR, in billion US$) per province. The map illustrates spatial patterns of combined LWSR across the country.

Northern China faces more severe water stress than those in Southern China.

However, the geographical pattern of LWSR has changed considerably compared to WDR. As shown in Fig. 2B, provinces in the central and eastern coast of China face higher LWSRs because of their larger size of the economies. Pollution poses extra economic burdens on LWSR. For instance, Jiangsu (JS), Hebei (HE), Shandong (SD), and Henan (HA) are major industrial centers and warehouses of agricultural products in China. They become the provinces with the highest economic risks due to water scarcity after considering the constraints of water pollution. For provinces with abundant water resources like Guangdong (GD) and Fujian (FJ), quality-based LWSR poses more threats on local water-use sectors and economies rather than quantity-based LWSR. National aggregate estimate of quantity-based LWSR is ~660 billion US$ and quality-based LWSR is ~593 billion US$ in 2017, indicating that pollution almost doubles the risks of local economic losses due to water scarcity in China.

Heatmap of LWSR for each province-sector is illustrated in Fig. S4. We can identify sectors that are the most vulnerable to local water scarcity, including agriculture, textile printing, paper manufacturing, gas production, and wholesales. Hotspots of province-sector LWSR are related to the province's economic size and industrial division. For example, while LWSR of agricultural production are common across the country, LWSR of industrial sectors are the most prominent in only a few provinces including Jiangsu (JS), Shanghai (SH), Henan (HA) and Anhui (AH). When water quality constraints are considered, we observe an increasing number of province-sector LWSR hotspots.

3.2. Virtual water scarcity risk (VWSR) in domestic trade

After calculating LWSR in each province-sector, we then input LWSR into the domestic trade model and examine VWSR exports and imports among provinces. Fig. S5 shows the quantity-based and quality-based VWSR at the provincial level. The impact of water pollution on VWSR is not consistent. For example, quality-based VWSR exports in Henan (HA), Hebei (HE), and Shandong (SD) are 1.48, 1.42, and 1.09 times of quantity-based VWSR exports. In contrast, for provinces like Ningxia (NX) and Heilongjiang (HL), where major export sectors are not constrained by local water pollution issues, quality-based VWSR exports are only 10% and 23% of quantity-based VWSR exports. The destinations of VWSR (i.e. importers) span broadly, while the origins are relatively concentrated. In the national aggregate, quantity-based VWSR transfer across provinces in 2017 is ~276 billion US$, accounting for ~41.8% of the national quantity-based LWSR. Quality-based VWSR imports in 2017 are ~240 billion US$, accounting for ~40.4% of the national quality-based LWSR.

We then map combined VWSR exports and imports across provinces, as illustrated in Fig. 3A and Fig. 3B. We find the geographical distribution of VWSR exports is generally consistent with the spatial pattern of LWSR. Provinces in North China Plain including Jiangsu (JS), Hebei (HE), Henan (HA), and Shandong (SD) are four top-ranking exporters of VWSR. On the contrary, VWSR importers are mainly located in Southern China where water resources are more abundant. The two coastal provinces including Guangdong (GD) and Zhejiang (ZJ) take the most economic risks due to water shortages in other distant provinces. For China's two megacities, Shanghai (SH) plays a key role of VWSR

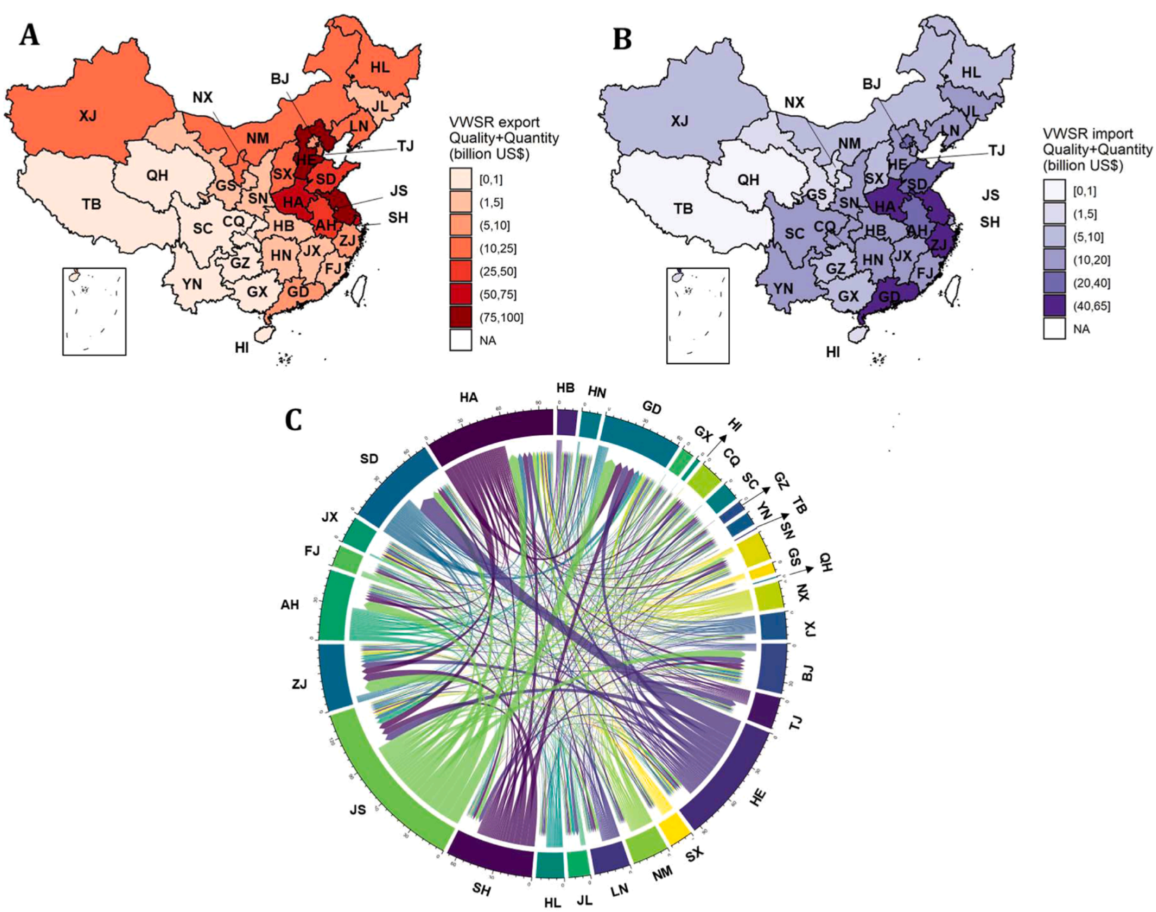

Fig. 3. Virtual water scarcity risk exports and imports at the provincial level. ***(A)*** Map of provincial quality-based and quantity-based virtual water scarcity risk exports (VWSR exports, in billion US$). ***(B)*** Map of provincial quality-based and quantity-based virtual water scarcity risk imports (VWSR imports, in billion US$). ***(C)*** Chord diagram representing flows of VWSR exports and imports among provinces. Degree of the chord thickness is proportional to the volume of VWSR transfer.

exporter whereas Beijing (BJ) is a high-ranking VWSR importer, reflecting their different positions in China's domestic supply chains. Fig. 3C illustrates the transfers of VWSR across provinces and we have identified the largest VWSR flows among them. For example, Hebei (HE) exports 17.8 billion US$ of VWSR to Shandong (SD). Jiangsu (JS) shifts 11.2, 10.8, 9.0, and 8.8 billion US$ of VWSR to Guangdong (GD), Zhejiang (ZJ), Henan (HA), and Anhui (AH), respectively. We have listed the top 50 provincial VWSR flows in Table S6.

The heatmap in Fig. S6 visualizes sector-to-sector VWSR transmissions. Darkest pixels indicate hotspots of sector-to-sector relationships. The distribution of VWSR spreads over a variety of sectors in the national trade system. The top 50 links before and after considering water quality constraints are listed in Table S6. We find origins of VWSR are concentrated. *Agriculture, Hunting, Forestry & Fishing, Production and Supply of Electricity and Heat,* and *Smelting and Processing of Metals* are three major sectors transferring VWSR to other places. Then, the destinations of VWSR span broadly. *Food and Tobacco Processing* is the most top-ranking sector that imports VWSR. After considering constraints of water pollution, we find origins of VWSR become more centralized in a few provinces. Especially for agriculture sector in Hebei (HE).

3.3. Risk indices and vulnerability indices

We then measure risk and vulnerability index by normalizing each province's VWSR exports and imports by its total output, as illustrated in Fig. 4. We find Ningxia (NX), a relatively arid region in Northwest China, has highest risk index due to water scarcity. Local water pollution has largely increased risk indices in many provinces such as Hebei (HE), Xinjiang (XJ), and Inner Mongolia (NM). It indicates that unitary economic output in these regions tends to exert more risks on domestic trade system via VWSR exports owing to insufficient water supply and inadequate water quality.

Vulnerability index, on the other hand, reflects a province's economic sensitivity to water scarcity risks of upstream suppliers. We identify a few provinces that do not rank top in VWSR imports but have highest vulnerability index, including Jilin (JL), Jiangxi (JX), Shaanxi (SX), Chongqing (CQ), and Hainan (HI). Inclusion of water quality in water scarcity assessment has increased vulnerability in most provinces. In general, risky provinces are more concentrated but vulnerable provinces span broadly. Some regions, including Beijing (BJ) and Henan (HA) have large in VWSR both in terms of absolute values and relative vulnerability indices.

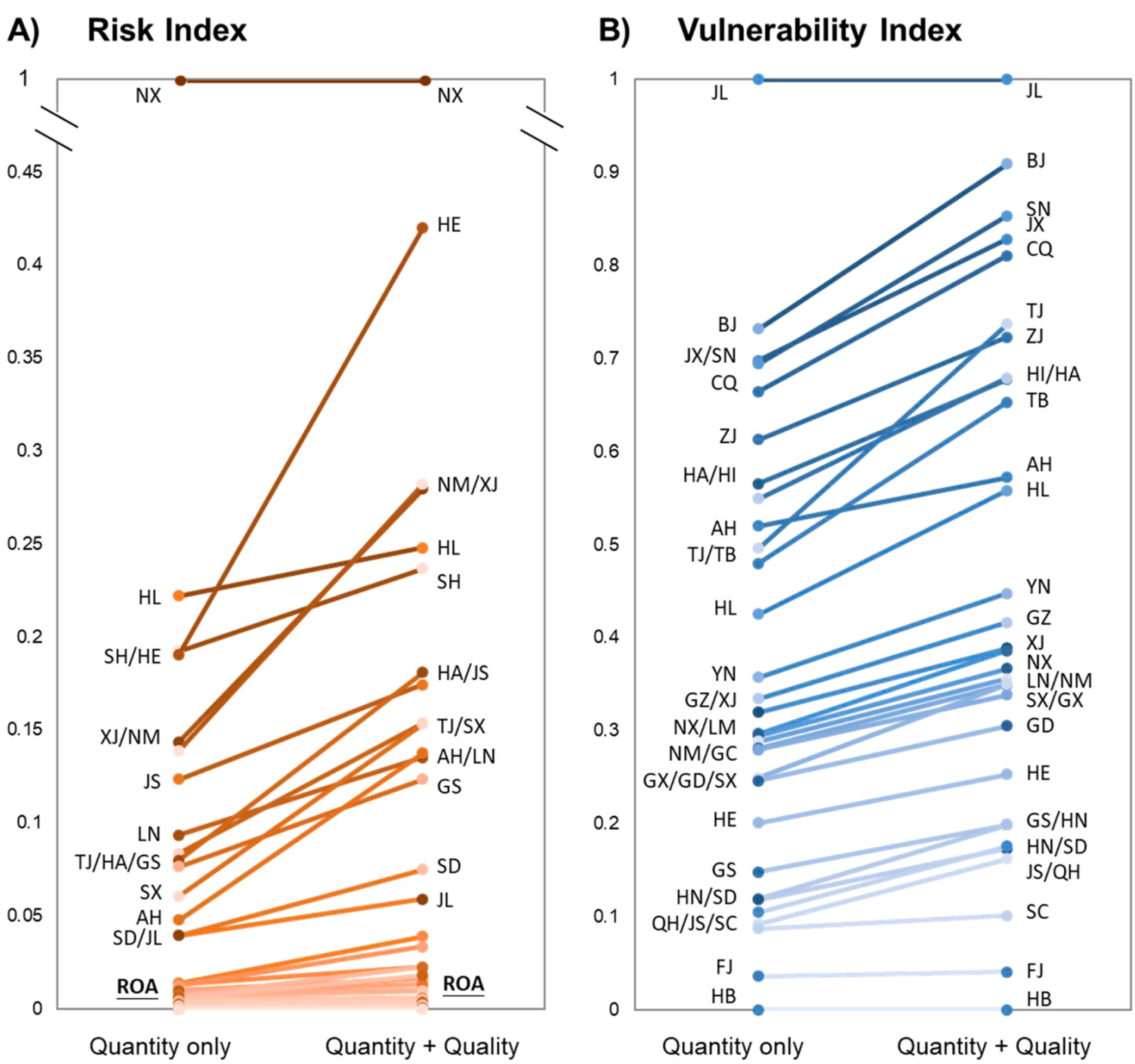

Fig. 4. Risk index and vulnerability index of water scarcity. ***(A)*** Risk index to domestic trade for each province before and after considering the constraints of water quality. ROA indicates the rest of all provinces. ***(B)*** Vulnerability index from domestic trade for each province before and after considering the constraints of water quality. Darker points/lines indicate higher water scarcity risks or vulnerabilities.

3.4. Concurrence of water scarcity risks

Finally, we analyze Herfindahl index of VWSR imports for each province to evaluate the concentrations of upstream trade partners for each province that are vulnerable to local water scarcity risks. If a province imports VWSR from only a few upstream province-sectors, the concurrence of water scarcity risks is much higher. A larger Herfindahl index indicates higher vulnerability and lower resilience of a province in the face of external water shortage shocks. As shown in Fig. 5, when we only consider quantity-based water scarcity, provinces with high Herfindahl index values are concentrated in Tianjin (TJ) and Shandong (SD). When we consider water quality constraints at the same time, the Herfindahl index has increased for most regions but decreased for the top two provinces. Anhui (AH) and Jilin (JL) emerge. On the national average, Herfindahl index has risen from 0.118 to 0.131, indicating that the overall resilience of domestic supply chain has decreased due to widespread water pollution.

4. Discussions

This study provides a comprehensive analysis of how local water pollution may impose risks on economic outputs of local water-use sectors in China. We find that poor water quality increases local water depletion risks (van Vliet et al., 2021) and almost doubles potential local economic losses due to insufficient water supply in China. Risks of water pollution on economic production are not evenly distributed across geographical units. Northern provinces where available freshwater resources are limited face more severe water quality challenges. However, these northern provinces tend to produce water intensive goods for consumption in the south which amplify the scarcity risk (Guan and Hubacek, 2007). Constraints of water pollution also influence VWSR transfers in the domestic trade system. Top VWSR exporters become more centralized in a few provinces whereas vulnerable provinces span broadly and are more likely to be affected by water shortage in distant regions. The concurrence of water scarcity risks, measured by Herfindahl index, becomes higher when water quality is included in the assessment. It indicates that water pollution decreases overall supply chain resilience in China's economic system. Our study highlights the need to reduce economic risks of both quality-based and quantity-based local water scarcity. We find regions that are short in water availability and poor in water quality are largely overlapped. These provinces are spatially located in the North and are key upstream suppliers in China's domestic trade system.

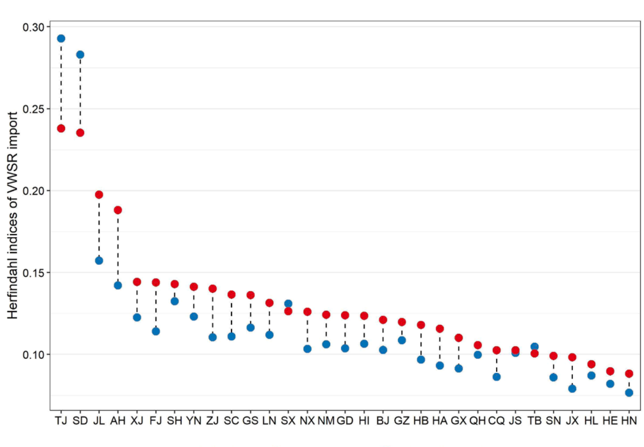

Fig. 5. Herfindahl index for VWSR imports at the provincial level in 2017. Blue dots represent Herfindahl indices of VWSR imports considering only quantity-based water scarcity. Red dots represent Herfindahl indices considering quantity and quality in the meantime.

We then identify critical regions and sectors that may have ramifications on downstream economies or are highly vulnerable to water scarcity in upstream suppliers. Jiangsu (JS), Hebei (HE), Henan (HA), and Shandong (SD) are top-ranking provinces in terms of absolute VWSR exports, whereas Guangdong (GD), Zhejiang (ZJ), Jiangsu (JS) and Henan (HA) are major VWSR importers. When getting rid of the effect of economic size, Ningxia (NX), Hebei (HB), and Xinjiang (XJ) become the most risky provinces, and they are all located in the North. Jilin (JL), Beijing (BJ), Jiangxi (JX), and Shaanxi (SX) are the most vulnerable regions to distant water scarcity risks and they spread all over the country. To lower water scarcity and alleviate overall risks, local authorities should not only focus on conserving physical water resources but also improving water quality (Loucks and van Beek, 2017; Qu et al., 2018). Adaptive solutions include improving water use efficiency (Levidow et al., 2014), increasing water availability by increasing reservoir storage or water diversion projects (Long et al., 2020), and reducing pollutant emissions through better wastewater treatment (Cosgrove and Loucks, 2015; Wang et al., 2020). Meanwhile, for provinces vulnerable to distant virtual water scarcity risks, in addition to switching to upstream suppliers who are not subject to local water stress, provinces should advance regional collaboration and investment on water management and controlling transboundary water pollution (Perry and Praskievicz, 2017).

In terms of hotspots of sectors, our estimates show that *Agriculture, Hunting, Forestry & Fishing, Production and Supply of Electricity and Heat*, and *Smelting and Processing of Metals* are important exporters of VWSR. *Food and Tobacco Processing* is the major destination of VWSR. Water pollution creates more hotspots of sectoral VWSR and makes the origins of water scarcity risks more concentrated in several provinces. These findings inform decision-makers to focus on these hotspots for mitigating risk transmissions. For example, agricultural sector in Hebei (HE) province needs more efforts to mitigate its potential risks to downstream economies due to water scarcity (Long et al., 2020). Yet inequality exists in terms of risks of local water scarcity and shares of economic gains (Dolan et al., 2021). Provinces in the South imports more water-intensive goods from the North but have larger water environment capacity and lower local water stress (Zhao et al., 2015).

Our study develops an integrated method to assess the impacts of quantity-based and quality-based water scarcity on local and distant economies. Quantity and quality-based LWSR calculated in this study for each province depends on its water availability, pollution level, sectoral water-use efficiency, economic size, and industrial structure. It provides an approach to efficiently quantify the restriction of pollution (especially nutrients and major elements) on local available water resources and economic activities. A broader range of water quality parameters could be taken into consideration according to the needs in the future, such as heavy metals and metalloid (van Vliet and Zwolsman, 2008). The indicator could also be used to measure the risks and impacts of extreme climate events such as drought and urban flood on local freshwater supply and output losses. More than that, the proposed method integrates MRIO model and depicts the sources and destinations of transboundary risks in China's domestic trade system. The framework can be extended to investigate how nationwide variability in inland water quality around the globe poses risks on global supply chains. In addition, if multiyear MRIO tables or higher resolution water quality data are available, the model could help support cost-benefits analysis of water management policies by evaluating how improved water quality reduces local and distant economic risks.

Last but not least, several limitations in this study should be noted. First, there are still important water pollution issues that have not fully taken into consideration in this study. For example, increasing water body temperature caused by global warming affects agriculture and fisheries and reduces available cooling water for energy generations. Management of water resources for different water-use sectors needs to account for quality requirements in nutrients, plastics and other pollutants. Second, our water quality data is based on annual average of city-level monitoring stations' records. Provincial sectoral water use data are estimated according to the national-level estimated ratio. MRIO model at the provincial scale is also a coarse measure of the economic activities. The combination of these datasets at provincial levels may not reflect constraints of water scarcity at finer spatial scales in reality. Future research may use high-resolution water quality data and local sectoral economic data to improve the accuracy of water scarcity assessment.

5. Conclusion

This study quantifies the risks of both quantity and quality-based local water scarcity to China's economic performances of local water-use sectors and downstream producers in the domestic trade system. We first reveal that, in the year of 2017, water pollution almost doubles China's local economic loss risks due to water scarcity in China. We also identify the provinces and sectors that are the risky to downstream sectors and find pollution makes water scarcity risk exporters in China become more concentrated. This effect, on the other hand, decreases the overall resilience of China's domestic trade network. This work offers unique insights into the interaction of quality-based water-economy nexus, closing the gap on inadequate attention to water quality constraints on water usability in previous studies. We also offer hotspots that policy-makers should prioritize on for sustainable water management and highlight the need to conserve water resources and improve water quality at the same time.

CRediT authorship contribution statement

Jinling Li: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Jianxun Yang:** Investigation, Formal analysis, Writing – original draft. **Miaomiao Liu:** Conceptualization, Investigation, Writing – review & editing. **Zongwei Ma:** Writing – review & editing. **Wen Fang:** Writing – review & editing. **Jun Bi:** Funding acquisition, Project administration.

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.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.watres.2022.119059.

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