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Quantifying economic-social-environmental trade-offs and synergies of water-supply constraints: An application to the capital region of China

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ABSTRACT

Sustainable water management is one of the sustainable development goals (SDGs) and is characterized by a high level of interdependencies with other SDGs from regional to global scales. Many water assessment studies are restricted to silo thinking, mostly focusing on water-related consequences, while lacking a quantification of trade-offs and synergies of economic, social, and environmental dimensions. To fill this knowledge gap, we propose a “nexus” approach that integrates a water supply constrained multi-regional input-output (mixed MRIO) model, scenario analysis, and multi-criteria decision analysis (MCDA) to quantify the trade-offs and synergies at the sectoral level for the capital region of China, i.e. the Beijing-Tianjin-Hebei urban agglomeration. A total of 120 industrial transition scenarios including nine major industries with high water-intensities and water consumption under current development pathways were developed to facilitate the trade-off and synergy analysis between economic loss, social goals (here, the number of jobs) and environmental protection (with grey water footprint representing water pollution) triggered by water conservation measures. Our simulation results show that an imposition of a tolerable water constraint (a necessary water consumption reduction for regional water stress level to move from severe to moderate) in the region would result in an average economic loss of 68.4 ($\pm$ 16.0) billion Yuan (1 yuan $\approx$ 0.158 USD$ in 2012), or 1.3 % of regional GDP, a loss of 1.94 ($\pm$ 0.18) million jobs (i.e. 3.5 % of the work force) and a reduction of 1.27 ($\pm$ 0.40) billion m^3 or about 2.2% of the regional grey water footprint. A tolerable water rationing in water-intensive sectors such as Agriculture, Food and tobacco processing, Electricity and heating power production and Chemicals would result in the lowest economic and job losses and the largest environmental benefits. Based on MCDA, we selected the 10 best scenarios with regard to their economic, social and environmental performances as references for guiding future water management and suggested industrial transition policies. This integrated approach could be a powerful policy support tool for 1) assessing trade-offs and synergies among multiple criteria and across multiple region-sectors under resource constraints; 2) quantifying the short-term supply-chain effects of different containment measures, and 3) facilitating more insightful evaluation of SDGs at the regional level so as to determine priorities for local governments and practitioners to achieve SDGs.

1. Introduction

In September 2015, 193 members of the United Nations adopted the 2030 sustainable development agenda (United Nation, 2016). This agenda features 169 targets under 17 sustainable development goals (SDGs) in response to rapidly rising consumption de-

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mand, resource scarcity, environmental contamination and climate extremes, with the commitments to implement those by 2030 (Nerini et al., 2018). In aggregate, these SDGs entail a roadmap to ensure human well-being, economic prosperity and environmental protection by tackling multiple challenges faced by humankind, of which, Goal 6 (Sustainable water and sanitation) is the one with high shares of trade-offs and synergies with other SDGs on global and national scales (Pradhan et al., 2017), these interactions emphasize the importance of water resources in determining the achievement of other SDGs (Szabo et al., 2016). The worsening scarcity of water resources has become a threat to the sustainable development of modern society, especially in some rapidly developing regions like India and China (Gosling and Arnell, 2016; Mekonnen and Hoekstra, 2016; Zhao et al., 2015; Liu et al., 2017). Available water per capita in China is only 1,976 m^3 in 2018, which is just one-fourth of the global average (Gu et al., 2017; Ministry of Water Resources of China, 2018). Therefore, water shortages have become "choking points" that potentially restrict economic production in China, especially in the water scarce northern regions such as Beijing-Tianjin-Hebei metropolitan region (the so-called "capital region" or "Jing-Jin-Ji region"). According to the latest statistics, the capital region is feeding 8% of China's population (110 million inhabitants) and producing nearly 10% of China's GDP with only 0.6% of total water availability (18.1 billion m^3 in 2017), and the freshwater endowment per capita is only 165 m^3 (National Bureau of Statistics of China, 2018). The imbalance between economic production and distribution of available water resources has hindered further sustainable development. To alleviate water stress, in 2012, the central government proposed the "the most stringent water resource management system" or so-called "Redline" regulations, which is measured by the "three redlines": Controlling national water use, improving water use efficiency and reducing wastewater discharge to conserve limited water resources (Liu et al., 2013; Li et al., 2020). As a result, the capital region has put forward the "Jing-Jin-Ji integration strategy" in response to this ambitious water strategy and rising water demand (The State Council of China, 2015). The re-evaluation of development options under the special consideration of water supply constraints was the key feature of this integration policy. Thus, planning future economic development from a demand-side perspective based on water endowment is a significant measure in this strategy.

Available water resources assessments focus mainly on assessing the environmental status of water resources in terms of water quantity, quality and scarcity impacts, and rarely consider other environmental aspects (Liu et al., 2017). To model and assess the interactions of economic activities and their impacts on water resources at regional, national and global levels, hydrological models and water footprint accounting are widely used (Hoekstra et al., 2011; Zhuo et al., 2016; Mao and Liu, 2019; Qi et al., 2018; Xu et al., 2019; Liu et al., 2020). A large bunch of global hydrological models forced by climate models, greenhouse-gas concentration scenarios and shared socioeconomic pathways have been developed and integrated to assess climate change impacts on water scarcity from an earth system sciences perspective (Schewe et al., 2014; Wada et al., 2013, 2017; Prudhomme et al., 2014; Wang et al., 2021). Many scholars have also integrated hydrological models with human activities to assess the water footprint distribution and its contribution to the water scarcity at various spatial-temporal scales within the framework of water footprint accounting since the concepts and methodologies of "virtual water" and "water footprint" were introduced (Hoekstra et al., 2011; Allan, 1996). As a result, hydrological models provide a comprehensive understanding on the mechanisms that shape the availability, cycling and quality of water in geological and hydrological terms (Oki and Kanae, 2006), whereas the water footprint approach can be used for accounting water consumption caused by economic production and consumption (Mekonnen and Hoekstra, 2011; Liu et al., 2015). In addition, considerable efforts have been made to simulate the impacts of water use. The approaches for assessing the impacts can be categorized into three main categories: indicator systems (Schlör et al., 2018), system dynamic models (Zhang et al., 2019; Wang et al., 2019), and input-output (Feng and Hubacek, 2015; Feng et al., 2014) or ecological network analysis (Wu et al., 2016; Yang et al., 2012). For instance, Cai et al. (2017) used a composite index approach to demonstrate the spatial-temporal characteristics of China's water resource vulnerability to highlight key challenges of China's water resources. Wang et al. (2019) introduced a comprehensive modeling framework based on system dynamic approach for integrated water resources management (IWRM) to provide users with social, economic and environmental assessments from the perspective of basin-scale water security in the Bow river basin of Canada. Furthermore, many scholars have applied input-output or ecological network analysis to calculate virtual water trade across regions and sectors and quantify the distribution or allocation of water use through complex economic activities (Zhao et al., 2017; Zhao et al., 2015; Fang and Chen, 2015; Guan et al., 2014; Hubacek et al., 2009).

Despite previous studies have provided a solid basis for water resource assessments in endowment, vulnerability and scarcity, they have frequently ignored trade-offs and synergies between protecting water resources and other SDGs. This had led to a growing recognition that water underpins economic and social development, without which it would be impossible to achieve other SDGs successfully (Bizikova et al., 2013). For instance, achieving water sustainability by reducing demand can lead to trade-offs both in terms of economic output (SDG8, 12) and in terms of human well-being (SDG1, 2, 3, 4, 7, 8), but might generate synergies with environmental protection (SDG13, 14, 15). Because of the interconnected nature of water, economic development, social issues and other environmental factors and the aspiration to improve them simultaneously, quantifying the trade-offs and synergies of economic-social-environmental dimensions under water-supply constraints is crucial. The nexus framework has emerged to address the interactions between environmental resources and most recently the links among food, energy and water systems through coupling network analysis, life cycle assessment and footprint analysis to quantify water and other resource footprints at different scales (Liu et al., 2019; Zhou et al., 2019; Newell et al., 2019; Kurian, 2017; White et al., 2015, 2018; Castillo et al., 2019). These methods help to show how these resources or impacts virtually flow through production and consumption networks (Wang and Chen, 2016; Feng et al., 2019; White et al., 2018), but are unable to explicitly consider supply constraints and evaluate trade-offs among different indicators. Some scholars have pointed out that the impacts of supply chain disruption may result in production bottlenecks influencing other sectors and regions via the reduction in the intermediate demands (Sahin and Okuyama, 2009); in turn, this bottleneck could lead to cascading effects resulting from a decline level of activities across the supply-demand chain. For example, Hubacek and Sun (2001, 2005) developed a mixed input-output (IO) model featured by land-supply constraints to evaluate how the changing economy and society of China affect water use and land use at the regional level representing provinces and hydro-economic regions respectively. Liang et al. (2016) proposed an integrated approach based on mixed IO and linear regression models to estimate the overall economic effect and carbon emission under electricity rationing triggered by heat waves in Shanghai, China.

In general, the quantification of the impacts of supply constraints and the associated trade-offs and synergies are of primary importance in mitigating the vulnerability of modern economies.

Fig. 1. Study area.

However, the existing literature has rarely evaluated such compound impacts under resource constraints, often being limited by the chosen indicators (e.g. Galli et al., 2011). More specifically, the literature doesn't take into consideration spillover effects of supply constraints because the studied economy is typically in a closed rather than opening setting, making it impossible to consider interregional trade flows in the analysis. Actually, the teleconnection of water consumption between producers and consumers accompanied by interregional trade is increasingly growing along with the expansion of trade (Cai et al., 2020; Zhao et al., 2015). Therefore, a systematic accounting of water use along the supply–chains and trade network will extend the opportunities for trades-offs and synergies between economic, social and environmental impacts among different trading partners from the perspective of production and consumption (Hubacek et al., 2014). This means that there is an urgent demand for a unifying framework capable of capturing trade-offs and synergies between water and other SDGs in a multi-regional and multi-sectoral setting. This research aims to establish such a framework and demonstrate its utility.

In more detail, we propose a 'nexus' approach that integrates a water supply constrained multi-regional input-output (Mixed MRIO) model, scenario analysis and multi-criteria decision analysis (MCDA) to quantify the trade-offs and synergies of economic, social and environmental indicators under water-supply constraints at the regional-sectoral level. We regard water resources as the bottleneck in the production system. We selected China's capital region as our research area because of the severe water shortages in this region (Fig. 1). First, we developed 120 water-constraint scenarios based on water stress level, sectoral water intensity and economic importance in the region. Second, we mixed MRIO model with water supply constraints to calculate economic losses triggered by rationing water use in individual key sectors in the region, and to estimate trade-offs and synergies between social well-being (unemployment) and environmental protection (grey water footprint reduction) induced by water rationing. Third, we introduced MCDA to select optimal scenarios. Finally, we explored sustainable development pathways of the capital region and the potential of this framework to inform and guide policy.

2. Materials and methods

2.1. Water supply-constrained multi-regional input-output (mixed MRIO) model

The classic MRIO model, which takes the form of $(\mathrm{I}-\mathrm{A})\mathrm{x}=\mathrm{f}$ or $\mathrm{x}=(\mathrm{I}-\mathrm{A})^{-1}\mathrm{f}$, is a demand-driven model, that is, the final demand (f) of the economic sector is an exogenous variable of the economic system that is predetermined by other factors (consumer preferences, government behavior, etc.) outside the model. Accordingly, a change of final demand ($\Delta\mathrm{f}$) will lead to changes in gross economic output ($\Delta\mathrm{x}$). A MRIO model consists of a system of linear equations, which describes the distribution of a region-sector's product throughout the multi-regional economy (Miller and Blair, 2009). This interdependence of regions and sectors makes the approach powerful for assessing the direct and indirect impacts of alternative policy selections across regions and sectors. Additionally, the method can be used to deal with shocks and contingencies across the economy. Policy evaluation based on MRIO analysis can supply new insights to the efforts on searching the most promising policy choice (Garcia et al., 2020).

To calculate resource consumption (water, energy, land, etc.) triggered by $\Delta\mathrm{f}$, we extend the standard MRIO model with a diagonal of sectoral resources requirement coefficients matrix e. Then the sectoral change in resource consumption triggered by $\Delta\mathrm{f}$ can be calculated as follows:

$$\Delta\mathrm{E}=\mathrm{e}(\mathrm{I}-\mathrm{A})^{-1}\Delta\mathrm{f} \tag{1}$$

Equation (1) is used to estimate the changes in economic, social and environmental impacts induced by water rationing from consumption perspective. We selected GDP loss to represent economic impact, employment loss (unemployment) to represent social impact, and grey water footprint reduction to represent environmental benefits. The grey water footprint refers to "the volume of freshwater that is consumed to assimilate the load of pollutants based on natural background concentrations and existing ambient water quality standards" (Hoekstra et al., 2011) Thus, the diagonal elements in variable e is value-added per unit of gross economic output, the number of jobs per unit of gross economic output and grey water footprint intensity respectively.

The standard MRIO model assumes that economy adjusts to changes in spending patterns within a given year, and all production activities are driven by final demand and fully endogenous. That is to say, supply is to be elastic in all regions and sectors perfectly, and a change in final demand is sufficient to stimulate changes in production outputs and incomes across other sectors and regions. However, in this case, the situation is obviously that water rationing sectors will not expand or shrink its output level automatically in proportion with changes in $\Delta\mathrm{f}$. Equation (1) would provide multipliers that are unrealistically large due to an elastic supply response assumption.

Thus, a supply constrained MRIO model may be appropriate for this study in which final demand for some region-sectors and gross outputs for the remaining region-sectors are specified exogenously. This method is a technique that allows the estimation of economic impacts of exogenous changes originating from supply constraints, such as those caused by strikes, natural disasters, pandemics such as the COVID-19, trade barriers or resource shortages (Davis and Salkin, 1984; Arto et al., 2015). To illustrate supply constraints caused by water shortage, we present a case of two regions (I, J) with two sectors (1, 2). Products produced by each region-sector can be merchandised as intermediate inputs or final products (see Table S1), Table S1 can be expressed as a system of linear equations:

$$\begin{bmatrix} X^I \\ X^J \end{bmatrix} = \begin{bmatrix} Z^{II} & Z^{IJ} \\ Z^{IJ} & Z^{JJ} \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} Y^{II}+Y^{IJ} \\ Y^{JI}+Y^{JJ} \end{bmatrix} \tag{2}$$

Where Z matrix is the intermediate use by sector k in region I and J; Y^{IJ} is the final demand of region J for goods produced by sector k of region I; X^I is the total output of sector k in region I, and V^I is the value-added of sector k in region I.

The input coefficients are $A^{IJ} = Z^{IJ}(\hat{X}^J)^{-1}$, and Equation (2) is rewritten as follows:

$$\begin{bmatrix} X^I \\ X^J \end{bmatrix} = \begin{bmatrix} A^{II} & A^{IJ} \\ A^{IJ} & A^{JJ} \end{bmatrix} \begin{bmatrix} X^I \\ X^J \end{bmatrix} + \begin{bmatrix} Y^I \\ Y^J \end{bmatrix} \tag{3}$$

Then, reordering Equation (3) yields the following:

$$\begin{bmatrix} I - A^{II} & -A^{IJ} \\ -A^{IJ} & I - A^{JJ} \end{bmatrix} \begin{bmatrix} X^I \\ X^J \end{bmatrix} = \begin{bmatrix} Y^I \\ Y^J \end{bmatrix} \tag{4}$$

In standard MRIO analysis, the gross output is assumed as endogenous variable and the final demand as exogenous, Equation (4) could be rewritten as follows:

$$\begin{bmatrix} x_1^I \\ x_2^I \\ x_1^J \\ x_2^J \end{bmatrix} = \begin{bmatrix} \left(1-a_{11}^{II}\right) & -a_{12}^{II} & -a_{11}^{IJ} & -a_{12}^{IJ} \\ -a_{21}^{II} & \left(1-a_{22}^{II}\right) & -a_{21}^{IJ} & -a_{22}^{IJ} \\ -a_{11}^{JI} & -a_{12}^{JI} & \left(1-a_{11}^{JJ}\right) & -a_{12}^{JJ} \\ -a_{21}^{JI} & -a_{22}^{JI} & -a_{21}^{JJ} & \left(1-a_{22}^{JJ}\right) \end{bmatrix}^{-1} \begin{bmatrix} y_1^I \\ y_2^I \\ y_1^J \\ y_2^J \end{bmatrix} \tag{5}$$

We assume that some external shocks (e.g. resources shortage, pandemic etc.) happen in sector 2 of region J, which will shrink the production capacity of the affected sector. The initial impact of the external shock is the reduction in the gross output of sector 2 in region J, subsequently, this initial reduction will decrease the demand for goods from the industries supplying intermediate inputs to the constrained sector both directly and indirectly. In this case, the gross output of sector 2 in region J should be exogenous, while the final demand is endogenous; thus, we rearranged Equation (5) to leave the endogenous variables on the left-hand side and the exogenous variables on the right-hand side to obtain the following:

$$\begin{bmatrix} \left(1-a_{11}^{II}\right) & -a_{12}^{II} & -a_{11}^{IJ} & 0 \\ -a_{21}^{II} & \left(1-a_{22}^{II}\right) & -a_{21}^{IJ} & 0 \\ -a_{11}^{JI} & -a_{12}^{JI} & \left(1-a_{11}^{JJ}\right) & 0 \\ -a_{21}^{JI} & -a_{22}^{JI} & -a_{21}^{JJ} & -1 \end{bmatrix} \begin{bmatrix} x_1^I \\ x_2^I \\ x_1^J \\ y_2^J \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & a_{12}^{IJ} \\ 0 & 1 & 0 & a_{22}^{IJ} \\ 0 & 0 & 1 & a_{12}^{JJ} \\ 0 & 0 & 0 & -\left(1-a_{22}^{JJ}\right) \end{bmatrix} \begin{bmatrix} y_1^I \\ y_2^I \\ y_1^J \\ x_2^J \end{bmatrix} \tag{6}$$

by arranging Equation (6), we find the following:

$$\begin{bmatrix} x_1^I \\ x_2^I \\ x_1^J \\ y_2^J \end{bmatrix} = \begin{bmatrix} \left(1-a_{11}^{II}\right) & -a_{12}^{II} & -a_{11}^{IJ} & 0 \\ -a_{21}^{II} & \left(1-a_{22}^{II}\right) & -a_{21}^{IJ} & 0 \\ -a_{11}^{JI} & -a_{12}^{JI} & \left(1-a_{11}^{JJ}\right) & 0 \\ -a_{21}^{JI} & -a_{22}^{JI} & -a_{21}^{JJ} & -1 \end{bmatrix}^{-1} \begin{bmatrix} 1 & 0 & 0 & a_{12}^{IJ} \\ 0 & 1 & 0 & a_{22}^{IJ} \\ 0 & 0 & 1 & a_{12}^{JJ} \\ 0 & 0 & 0 & -\left(1-a_{22}^{JJ}\right) \end{bmatrix} \begin{bmatrix} y_1^I \\ y_2^I \\ y_1^J \\ x_2^J \end{bmatrix} \tag{7}$$

Finally, this mixed MRIO model with supply constraints could be expressed as follows:

$$\begin{bmatrix} X_{no} \\ F_{co} \end{bmatrix} = \begin{bmatrix} P_{(k\times k)} & 0_{(k\times(n-k))} \\ R_{((n-k)\ \times k)} & -I_{((n-k)\ \times\ (n-k))} \end{bmatrix}^{-1} \times \begin{bmatrix} I_{(k\times k)} & Q_{(k\times(n-k))} \\ 0_{((n-k)\times k)} & S_{((n-k)\times(n-k))} \end{bmatrix} \times \begin{bmatrix} \bar{F}_{no} \\ \bar{X}_{co} \end{bmatrix} \tag{8}$$

The sub-matrices in Equation (8) are defined as follows:

$\boldsymbol{P}_{(\boldsymbol{k}\times\boldsymbol{k})}$ is the k × k matrix that is extracted from the first k columns and k rows of matrix (I - A), and represents the average expenditure propensities of the unconstrained sectors in the supply side. The first k sectors are the endogenous and the last (n - k) sectors are the exogenous ones. $\boldsymbol{R}_{((\boldsymbol{n}-\boldsymbol{k})\ \times\boldsymbol{k})}$ is the (n - k) × k matrix from the first k columns and the last (n - k) rows of (-A), which is the average expenditure propensities of the non-supply constrained sectors on the supply constrained sectors.

$\boldsymbol{Q}_{(\boldsymbol{k}\times\ (\boldsymbol{n}-\boldsymbol{k}))}$ is the matrix from the first k columns and last (n - k) rows of A matrix, and represents the expenditure propensities of supply constrained sectors on the non-supply constrained sectors.

$\boldsymbol{S}_{((\boldsymbol{n}-\boldsymbol{k})\ \times\ (\boldsymbol{n}-\boldsymbol{k}))}$ is matrix that is extracted from the last (n - k) rows and columns of - (I - A), and it represents the average expenditure propensities among the supply constrained sectors.

$\bar{\boldsymbol{F}}_{\boldsymbol{no}}$ is column vector of elements from y_1 to y_k, which means the exogenous final demand for the unconstrained sectors in the supply side.

$\bar{\boldsymbol{X}}_{\boldsymbol{co}}$ is column vector of elements x_{k+1} through x_n, which means the exogenous total economic output for the supply constrained sectors.

$\boldsymbol{X}_{\boldsymbol{no}}$ is column vector with elements x_1 through x_k, representing the endogenous total economic output of unconstrained sectors in the supply side.

$\boldsymbol{F}_{\boldsymbol{co}}$ is column vector with elements y_{k+1} through y_n, representing the endogenous final demand of the supply constrained sectors. n is the number of sectors in the IO table, and k refers to the number of water rationing sectors. Equation (8) can be easily converted in a difference form, with $\Delta\bar{\boldsymbol{X}}_{\boldsymbol{co}} = \bar{\boldsymbol{X}}_{\boldsymbol{co}}^0 - \bar{\boldsymbol{X}}_{\boldsymbol{co}}$, i.e., the constraint induced output reduction in comparison to that in the reference economy ($\bar{\boldsymbol{X}}_{\boldsymbol{co}}^0$) without the imposition of the constraint, which will be determined by the scenario calibration in Section 2.2, and $\Delta\bar{\boldsymbol{F}}_{\boldsymbol{no}}$ ***refers to*** the change of the final demand caused by exogenous water shortage, mixed MRIO model is embedded in an opening market, allowing for imports from outside the region to compensate its shrinking final demand. Thus we assume that there is no exogenous change in the final demand for non-constrained sectors ($\Delta\bar{\boldsymbol{F}}_{\boldsymbol{no}} = \bar{\boldsymbol{F}}_{\boldsymbol{no}}^0 - \bar{\boldsymbol{F}}_{\boldsymbol{no}} = 0$), meaning that $\bar{\boldsymbol{F}}_{\boldsymbol{no}}$ remaining the same as in the reference economy ($\bar{\boldsymbol{F}}_{\boldsymbol{co}}^0$) without the imposition of water rationing. $\Delta\boldsymbol{X}_{\boldsymbol{no}}$ corresponds to the change in the economic output of the non-water supply constraint sectors triggered by the indirect impact of the water supply constraint sectors. $\Delta\boldsymbol{F}_{\boldsymbol{co}}$ represents the change in the final demand of the water supply constraint sectors. Finally, we can calculate the impacts in economic, social and environmental dimensions from production perspective based on Equation (8) through pre-multiply e by $\Delta\boldsymbol{X}_{\boldsymbol{no}}$ and $\Delta\bar{\boldsymbol{X}}_{\boldsymbol{co}}$. Hubacek and Sun (2005) described how to formulate this model (Hubacek and Sun, 2005).

2.2. Industrial transition scenarios for evaluating water rationing across sectors

The sustainability consideration in determining production under water supply constraint is that economic development should be aligned with the carrying capacity of local water resources. Trade allows local shortages triggered by water conservation to be offset. To ensure livelihoods and to meet ecological water requirements, the allocation of water resources across different economic uses is an important measure to inform demand-side management. Thus, industrial transition scenarios are designed to reduce water consumption in production activities. In this study, we defined "water supply constraints" as water consumption that must be reduced to mitigate regional water stress by one level in line with water stress index, which is categorized based on the ratio of water consumption to water availability for human, this index originate from Hoekstra et al.(2012) and Mekonnen and Hoekstra (2016), many previous publications has applied this index for their studies (e.g. Chouchane et al., 2020;.Ma et al., 2020; Zhuo et al.,2016; Sun et al., 2016). There are different methods to estimate the envi-

Table 1
Designing water supply constraints in the capital region in 2012.

Row NO.	[Billion m^3]	Beijing	Tianjin	Hebei	Data sources
1	Total available water availability	3.95	3.294	23.553	(Ministry of Water Resourcesof China., 2012)
2	Water availability for human (0.2*Row1)	0.79	0.659	4.711	
3	Total water consumption	1.96	1.55	14.4	(Ministry of Water Resources of China., 2012)
4	Total water consumption in economic sectors	0.95	0.984	15.742	(Ministry of Water Resourcesof China., 2012; Zhao, 2019)
5	Current water stress level (%) (Row 3/ Row 2)	248.1	235.3	305.7	
6	Water stress category	Severe	Severe	Severe	
7	Targeted level (%)	200	200	200	
8	Targeted category	Significant	Significant	Significant	
9	Required reduction in water consumption ((Row 7 – Row 5)/100*Row 2)	-0.38	-0.232	-4.979	
10	Required reduction water consumption in economic sectors (Row 4/ Row 3* Row 9)	-0.184	-0.148	-5.443	
11	The contribution of adjustments in industrial structure (%)	21	21	21	
12	Water supply constraint (Water gap) (Row 10 * Row 11/100)	-0.039	-0.031	-1.143	

ronmental water requirement–regarded as 80% of total water availability is the simplest way (Hoekstra et al., 2012, Mekonnen and Hoekstra (2016)). Several studies have shown that changes to the industrial structure have become the biggest decelerator in driving water consumption in some regions (Liu et al., 2018; Mi et al., 2017; Plank et al., 2018; Zhao, 2019; Cai et al., 2016). For example, Zhao (2019) using structural decomposition analysis showed that structural change in the economy of Beijing led to a reduction in water consumption by 21% between 2002 and 2012. Thus, we assume that 21% of reduced water consumption in Tianjin and Hebei could also be achieved through adjusting the industrial structure in the future (Zhao, 2019). Table 1 shows the step by step process of how we could obtain (tolerable) water supply constraints. Finally, the (tolerable) water supply constraint translates into a reduction of the water consumption by 0.039 billion m^3 (2% of the total) from the reference-year economy for Beijing, 0.031***billion*** m^3 (2% of the total) for Tianjin and 1.143 (8% of the total) ***billion*** m^3 for Hebei (see Table 1).

After determining the necessary reduction to achieve tolerable water constraints based on water stress levels in the capital region in the base year, the next step was to determine the sectoral distribution of the reduction. Referring to the "Measures for industrial structure adjustment with energy conservation" (Song and Liu, 2013) and available literature related to the water footprint at the sectoral scale we designed industrial transition scenarios (Zhao et al., 2017). In order to mitigate the adverse impacts of water shortages on human health and well-being, tertiary sectors such as Freight transport and warehousing; Hotels, food and beverage places (establishments) would not be considered as water supply constraint sectors (Liang et al., 2016). To maintain the safe and necessary functioning of urban systems, the water supply to key sectors such as Gas and water production and supply; Social services and Wholesale and retail would not be rationed (Liang et al., 2016). As a consequence, the water constraints are mainly imposed upon agriculture and some secondary sectors.

Our previous research results showed that some sectors such as Agriculture, Food and tobacco processing, and Textile industries have higher water dependency in terms of direct water consumption and water footprint (Zhao, 2019; Zhao et al., 2017); thus, we identified the top five non-service sectors with highest direct water consumption and water footprint as the water supply constraint sectors to calculate the trade-offs and synergies of economic-social-environmental aspects triggered by water shortage. Agricultural water consumption accounted for more than 60% of total water consumption due to the special production law of agriculture in form of evapotranspiration (ET) during the whole growing period (Zhao, 2019), which had a very large impact on water sustainability. We regarded Agriculture as a mandatory water supply constrained sector, and other selected sectors as additional constrained sectors. We allocated the water supply constraint (see Table 1) across the selected sectors according to their proportions of current water consumption in the total, and then we calculated the direct decline of economic output caused by the hard water availability constraints, based on water intensity per unit of economic output. Finally, we developed 3 scenarios for Beijing, 5 scenarios for Tianjin and 8 scenarios for Hebei (see Table 2), and used a supply constrained MRIO model to calculate the total economic loss across all sectors. At the regional scale, the combination of scenarios used to meet the imposed water supply constraint in the capital region could be "B1+T1+H1" or "B3+T4+H7" in Table 2. Consequently, the total combinations that meet the condition were equal to $C_3^1 \times C_5^1 \times C_8^1 = 120$. Fig. 2 presents the flowchart of this evaluation procedure.

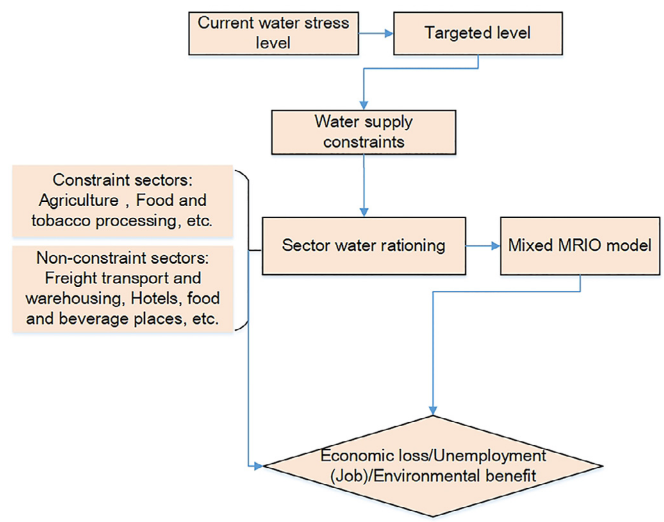

Fig. 2. Flowchart of the evaluation procedure.

2.3. Optimal scenarios/pathways based on multi-criteria decision analysis (MCDA)

MCDA helps balance multiple criteria in a structured way. Allowing different preferences for the criteria is particularly significant for policy decisions, where many assessment criteria and, even more frequently, opposing views of different stakeholders, coexist. Scholars have developed numerous MCDA approaches

Table 2
Industrial transition scenarios based on the (tolerable) water supply constraint.

Beijing			Tianjin			Hebei		
ID	Adjusted industrial sectors	Decline in economic output (10^9yuan)	ID	Adjusted industrial sectors	Decline in economic output (10^9yuan)	ID	Adjusted industrial sectors	Decline in economic output (10^9yuan)
B1	1.Agriculture	2.23	T1	1.Agriculture	1.39	H1	1.Agriculture	37.4
B2	1.Agriculture+6.Food and tobacco processing	(2.19, 5.69)	T2	1.Agriculture+6.Food and tobacco processing	(1.37, 7.56)	H2	1.Agriculture+4.Metals mining and dressing (Cleaning)	(36.7, 32.2)
B3	1.Agriculture+22. Electricity and heating power production	(2.0, 17.53)	T3	1.Agriculture+12. Chemicals	(1.33, 8.08)			
	H3	1.Agriculture+6.Food and tobacco processing	(37.3, 26.2)					
			T4	1.Agriculture+14. Smelting and pressing (processing) of metals	(1.32, 17.1)	H4	1.Agriculture+7.Textile industry	(37.4, 12.1)
			T5	1.Agriculture+24. Construction	(1.37, 11.17)	H5	1.Agriculture+8. Garments, leather, furs, down and related products	(37.3, 10.4)
						H6	1.Agriculture+14. Smelting and pressing (processing) of metals	(36.9, 88.6)
						H7	1.Agriculture+22. Electricity and heating power production	(36.0, 17.5)
						H8	1.Agriculture+24. Construction	(37.1, 38.7)

(for reviews see e.g. Kumar et al., 2017; Wang et al., 2009). In this research, we adopted the most widely used multi-attribute value theory (MAVT) and multi-attribute utility theory (MAUT) (Wang et al., 2009). We set up three kinds of weights to assess the importance of each trade-off and synergy in the context of the capital region: priority to the social dimension (0.3 for the economy, 0.5 for society and 0.2 for the environment), priority to economic and social dimensions (0.4 for the economy, 0.4 for society and 0.2 for the environment) and equal weights (0.333 for each). Then, weighted averages were used to evaluate the scenario rankings (Afgan and Carvalho, 2008; Begić and Afgan, 2007). Santoyo-Castelazo and Azapagic (2014) and Ishizaka and Nemery (2013) provided detailed principles on these two methods. The key equations are as follows:

$$V(s) = \sum_{i=1}^{3} w_i v(s)_i \tag{9}$$

$$U(s) = \sum_{i=1}^{3} w_i u(s)_i \tag{10}$$

Where:

V(s) is the composite value function based on MAVT, representing the total performance score for scenario s; w_i is the weight for criterion i, and three combinations of w_i (0.3/0.5/0.2, 0.4/0.4/0.2, 0.333/0.333/0.333) were used separately in this study; $v(s)_i$ is the ranking value that reflects the performance of scenario s on criterion i using a scale from 1 to 120, where 1 is the best option and 120 is the worst option. Correspondingly, U(s) is the composite value function based on MAUT, $u(s)_i$ is the simulated value of scenario s on criterion i, which has been normalized between 0 and 1, where 1 is the best and 0 is the worst. We selected the weighted average value as the threshold to evaluate scenario sustainability (Liang et al., 2016).

2.4. Data sources

To calculate the trade-offs and synergies of economic-social-environmental pillars at sectoral level based on Equations (1)-(8), we need the MRIO table, water consumption, labor input, grey water footprint and value-added or GDP in capital region and the rest of China (ROC) (see Table S3 and Table S4). We collected the provincial level MRIO table for the year 2012 in China from Mi et al. (2017), and therefore we use this table as the reference economy, the information was converted to 2010 constant prices. For the focus of this research, the provinces beyond the capital region were aggregated into "Rest of China" region. Water consumption data came from the provincial water resource bulletin (Ministry of Water Resources of China, 2012), Zhao (2019) and Zhao et al. (2019). We distribute direct water consumption in 2012 to MRIO sectors based on previous water survey data, economic output and some technical assumptions, the corresponding validation assessment and the works on how to distribute water consumption data to match with MRIO sectors have been done by Zhao et al. (2017) and Liu (2016). Labour data for each sector at the regional scale were obtained from the China Labour Statistical Yearbook (National Bureau of Statistics of China 2013a), the China Statistical Book (National Bureau of Statistics of China 2013) and the China Rural Statistical Yearbook (National Bureau of Statistics of China 2013b). We calculated the grey water footprint based on Hoekstra et al. (2011), Hoekstra and Mekonnen (2012) and Zhao et al. (2016), which is calculated as the volume of water that is required to dilute pollutants to an extent that water quality remains above agreed water environment standards. The chemical oxygen demand (COD) and ammoniacal nitrogen (NH_3-N or $NH^+{}_4$-N) discharge in wastewater were selected as water pollution indicators to estimate the grey water footprint for each sector, the related data is retrieved from the environmental statistical yearbook (National Bureau of Statistics of China, 2013) and Pollution Census Dataset (Editoral Board of First Pollution Census, 2011). Sectoral value-added (GDP) is obtained from Mi et al. (2017).

2.5. Limitations and uncertainties

Some limitations and uncertainties should be included when interpreting the results. First, our supply-constrained MRIO model accounted for trade flows across the three target regions and the rest of China, but does not pay much attention to the evaluation of the spillover effects to international markets or other countries because such an extension goes beyond the scope of this research. To carry out such a comprehensive extension along global supply-chains, a two-tier MRIO model that couples our MRIO with a global MRIO would be needed. Given that the focus of our research is on the impacts induced by water rationing at the capital regions and potential spill over to other regions in China rather than global regions, we deem the national level MRIO to be sufficient for the purposes of this paper. Second, only one indicator was selected for each economic, social and environmental dimension to show how the framework works. In the future, it will be straightforward to add more indicators reflecting different SDGs to extend our analysis using this framework. Third, in this study, we attributed regional-invariant weights to economic development, social well-being and environmental enhancement. It would be more policy-relevant to assign weights for each criterion based on regional endowments and stakeholder inputs (Kumar et al., 2017; Cinelli et al., 2014). Fourth, to some extent, social wellbeing (here number of jobs) is tightly linked to GDP, whereas other SDGs or social targets are less well captured by an input-output framework.

Fifth, the Chinese government publishes input-output tables every 5 years, our analysis is based on the economic structure in 2012, but the technical matrix and thus the production functions will gradually change over time. Trading patterns from 2012 cannot capture future trends, but for the purposes of this paper it is sufficient to keep them constant to show the impacts supply constraints would have everything else kept constant. It should be also noted that Zheng et al. (2020) constructed the 2015 China MRIO table for investigating the regional determinants of China's CO2 emission. However, the interpretation of this 2015 MRIO table are done in the absence of provincial 2015 IO tables and based on a minimization of an entropy function subject to constraints of many assumed relationships on production structure and trading patterns. Given the focus of our research on the response of the intra-provincial industrial structure to water shortage and developing one integrated method framework to quantify economic-social-environmental trade-offs and synergies under water-supply constraints and its potential applications to support environmental policies. Such a purely calibrated 2015 MRIO without the real intra-provincial input-output interactions across industries is not suitable for our research. Therefore, we opted to use the best available MRIO of Mi et al. (2017) and set the base year in 2012. It is worth noting that the exact data on which the application is based is not of major importance, once better data become available, these can be easily used to update the model and apply the framework. In addition, the selection of pollutants will have an influence on grey water footprint to some extent. We select two common pollutants (COD and NH_3-N) in the discharged wastewater as water pollution proxies to estimate the grey water footprints for each sector. On the one hand, this selection is largely determined by the fact that these two pollutants are the most frequently monitored and recorded in China and have been widely employed to evaluate surface water quality (e.g. Ma et al., 2020; Zhao et al., 2016; Guan et al., 2014). On the other hand, these two pollutants accounted for more than 84% of total discharged pollutants in agriculture, industry and domestic sectors in 2012 (National Bureau of Statistics of China, 2013). Finally, the reduction of final demand in the region would inevitably lead to production increase in other regions to meet the demand, the reduction within the region does not necessarily lead to an overall reduction in China because of outsourcing, unless we know where the resources might be outsourced to and that region's economic structure, technology and water use efficiency as well as associated pollution.

3. Results

3.1. Economic loss, employment loss and environmental gains by scenario and region

Fig. 3, Fig. S1 and Table S5 illustrate economic loss (GDP loss), employment loss (unemployment) and environmental benefit (grey water footprint reduction) triggered by hypothetical water supply constraints imposed on China's capital region. The introduction of water rationing in Agriculture (Scenarios B1, T1 and H1) would lead to the least reduction of GDP, which was 1.67 billion Yuan (0.90 billion within the capital region and 0.77 billion in the ROC), equal to 0.1% of Beijing's GDP, 1.15 billion Yuan (0.67 billion within the capital region and 0.48 billion in the ROC), 0.1% of Tianjin's GDP, and 35.5 billion Yuan (22.7 billion within the capital region and 12.8 billion in the ROC), 1.5% of Hebei's GDP respectively. In comparison, the highest loss of GDP was from scenarios B3 (Agriculture + Electricity and heating power production), T4 (Agriculture + Smelting and pressing (processing) of metals) and H6 (Agriculture + Smelting and pressing (processing) of metals), which were 10.8 billion Yuan (3.75 billion within capital region and 7.0 billion in the ROC), equal to 0.7% of Beijing's GDP, 10.6 billion Yuan (4.07 billion within the capital region and 6.56 billion in the ROC), equal to 0.9 % of Tianjin's GDP, and 89.4 billion Yuan (41.7 billion within the capital region and 47.7 billion in the ROC), equal to 3.7% of Hebei's GDP, respectively. The differences in GDP losses by region between scenarios changed from 6.5 times in Beijing (B3/B1) to 2.5 times (H6/H1) in Hebei, which indicates that the output response of non-agricultural industrial products to one unit of water reduction was larger than that of agriculture, and each manufacture sector had different extents of output response because of differences in production recipes and processes. Our results showed that water constraints reduced economic activities not only in the rationed regions and sectors but also in other regions and sectors across the supply-chain upstream and downstream. For example, in Scenario H6, 53% of economic loss was from supply-chain sectors (Freight transport and warehousing, Other services etc.) related to sector 1 (Agriculture) and sector 14 (Smelting and pressing (processing) of metals), thus, an exogenous shock such as limits to water availability would affect the whole economy through supply-chain linkages.

Similar to economic loss, only adjusting agricultural water consumption (Scenario B1, T1 and H1) would have the lowest impact on unemployment, namely 0.11 million jobs (0.10 million within the capital region and 0.01 million in the ROC), accounting for 0.76% of total employment in Beijing, 0.04 million jobs (0.036 million within the capital region and 0.006 million in the ROC), accounting for 0.6% of total employment in Tianjin and 1.43 million jobs (1.265 million within capital region and 0.17 million in the ROC), accounting for 4.2% of total employment in Hebei. In contrast, the Scenario B3 (1.Agriculture + 22. Electricity and heating power production, 0.20 million), T4 (1.Agriculture + 14.Smelting and pressing (processing) of metals, 0.14 million) and H6 (1.Agriculture + 14.Smelting and pressing (processing) of metals, 2.04 million) would lead to the largest losses in employment in this region. The differences in job losses triggered by water rationing across scenarios by region changed from 1.4 times in Hebei (H6/H1) to 3.3 times (T4/T1 in Tianjin, which were smaller than that of GDP because farmers accounted for rather large proportion of the total employment.

In terms of environmental benefits, we found that Scenario B3 (1.Agriculture + 22.Electricity and heating power production), T4 (1.Agriculture + 14.Smelting and pressing (processing) of metals) and H6 (1.Agriculture + 14.Smelting and pressing (processing) of metals) contributed to the largest reduction in the grey water footprint, with values of 0.25 billion m^3 (0.017 billion m^3 within the

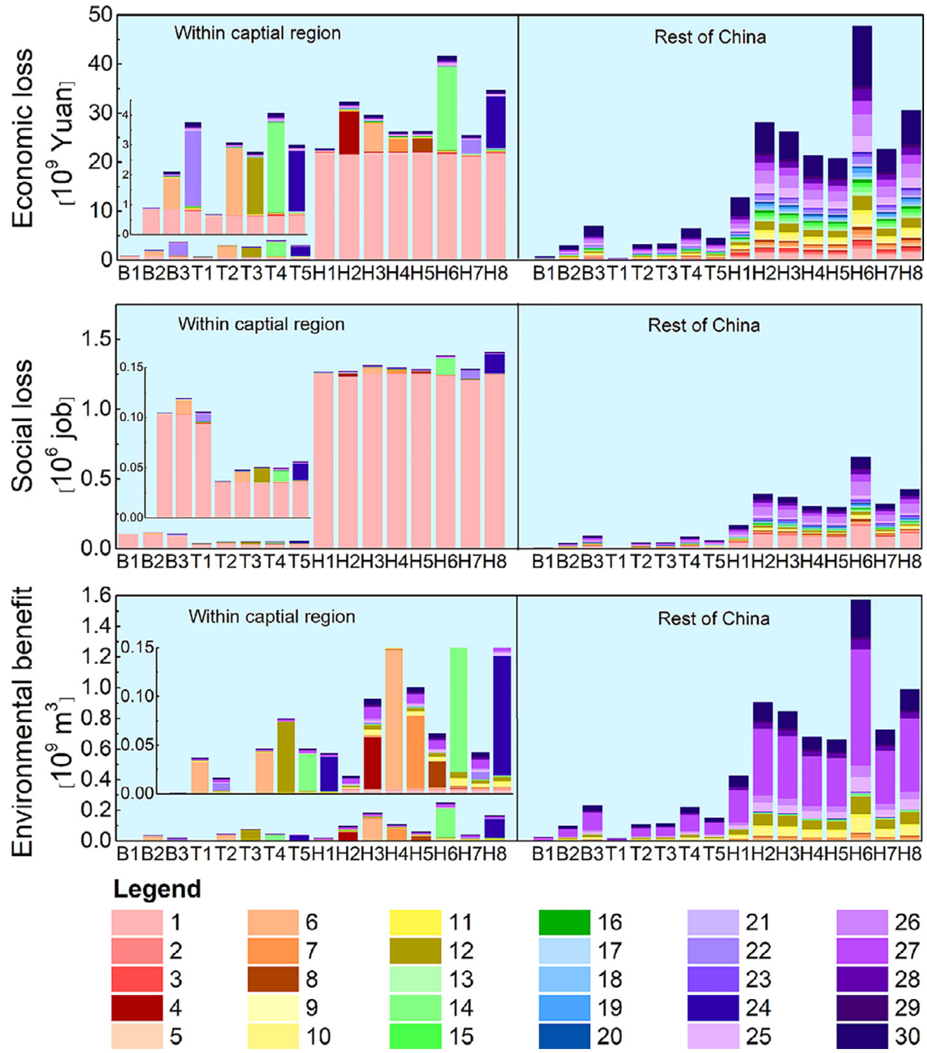

Fig. 3. Economic loss, social loss and environmental benefit under water supply constraint. Legend represents sector IDs in Table S3.

capital region and 0.235 billion m^3 in the ROC), equal to 2.0% of the total grey water footprint of Beijing, 0.27 billion m^3 (0.046 billion m^3 within the capital region and 0.22 billion m^3 in the ROC), equal to 1.9 % of the total grey water footprint of Tianjin, and 1.83 billion m^3 (0.25 billion m^3 within the capital region and 1.57 billion m^3 in the ROC), equal to 5.8 % of the total grey water footprint of Hebei. Restricting only Agriculture (B1, T1 and H1) would have the least effect on environmental protection, which was 0.03 billion m^3 in Beijing, 0.02 billion m^3 in Tianjin and 0.45 billion m^3 in Hebei respectively. The differences in environmental gains triggered by water rationing across scenarios by region varied from 4 times in Hebei (H6/H1) to 16 times (T4/T1) in Tianjin, which were much bigger than in the case of GDP and social losses because of significant water pollution discharge in manufacturing compared with agriculture. Our results indicate that water-rationing in sectors with high grey water footprints per unit of output, such as Electricity and heating power production, Smelting and pressing (processing) of metals, and Chemicals, would have the largest contribution to grey water footprint mitigation.

3.2. Economic and social losses versus environmental gains by sector and region

The heat map in Fig.4 and Table S6 show the average relative shares and absolute values in loss of value added and jobs, and environmental benefits under water supply constraints at the sectoral scale in the capital region. The economic losses vary from 36.4% (or 24.9 billion Yuan) of the total value added in Agriculture (sector 1) to 0.4% (0.27 billion Yuan) of total value added in Nonmetal minerals mining and dressing (sector 5) in the capital region. The second largest ones are from Other services (sector 30, 12.6% of the total value added, with 8.6 billion Yuan) and Smelting and pressing of metals (sector 14, with 5.2% of the total value added, 3.5 billion Yuan). At the regional scale, Agriculture contributed with 17% the greatest share to total economic loss in Beijing, 13% in Tianjin and 41% in Hebei respectively. Similarly, the proportions of job losses ranged from 77.3% (1.50 million jobs) in Agriculture to 0.07% (0.0014 million jobs) in Other manufacturing products (sector 21) of all jobs due to the water constraint, the second largest ones are from Wholesale and retail trade (sector 26, 3.8%) and Other services (3%). At the regional scale, Agriculture still showed the biggest contribution, ranging from 70.5% of all lost jobs in Beijing, 48.4% in Tianjin and 79.6% in Hebei respectively.

In terms of environmental benefits, Hotels, food and beverage places (sector 27) has the largest grey water footprint (0.541 billion m^3), accounting for 42.5% of the total grey water footprint in capital region, this ratio is 43% in Beijing, 36.6% in Tianjin and 43.5% in Hebei. Other services (sector 30) and Chemicals (sector 12) show the second largest relative effects, which are 12.8% and 8.3% respectively, but sector 20 (Measuring instrument & machinery for cultural activity & office work manufacturing) is the smallest one, only 0.026% of the total grey water footprint.

Yet, when looking at distribution of costs and benefits, some interesting patterns emerge. Damages to the economy and jobs are heavily concentrated in food-related sectors (Agriculture, Food and tobacco processing (sector 6)) and service sectors (Wholesale and retail trade, Other services), however, the benefit to the environment is mainly due to sectors with heavy wastewater discharges (Hotels, food and beverage places, Chemicals). For example, under the water supply constraints in our designed scenarios, the resultant economic loss, job loss, and environmental gain in sector 30 (Other services) in the capital regions as a whole will account for 13%, 3%, and 13% of the total economic and job loss, and the total environmental gain, respectively. By contrast, the corresponding shares in sector 27 (Hotels, food and beverage places) will be 3%, 2%, and 43%, respectively. This mismatch shows the hotspots of pollution as well as points for intervention at least costs considering impacts along the entire supply chain.

3.3. Industrial transition scenarios under water constraints

Fig. 5 shows the boxplots of the 120 industrial transition scenarios under water supply constraints in the capital region. The overall economic loss varies from 38.3 billion Yuan (B1T1H1) to 110.8 billion Yuan (B3T4H6), and approximately 70% of these scenarios have economic losses ranging between 50 billion Yuan and 80 billion Yuan. Industrial transitions resulted in an average economic loss of 68.4 ($\pm$ 16.0) billion RMB, accounting for 1.3% of total GDP of the capital region (National Bureau of Statistics of China, 2013). In terms of unemployment, job losses ranged from 1.59 million (B1T1H1) to 2.38 million (B3T4H6), with an average of 1.94 ($\pm$0.18) million jobs lost. This value accounts for 3.5% of the region's total employment in 2012 (National Bureau of Statistics of China, 2013). Meanwhile, the reduction in total grey water footprint fluctuated between 0.49 billion m^3 (B1T1H1) and 2.34 billion m^3 (B3T4H6), which was nearly 5 times the difference between maximum and minimum values, and the average reduction in the grey water footprint was 1.27 ($\pm$0.40) billion m^3, approximately 2.2% of the total grey water footprint in this region.

3.4. Trade-offs and synergies of economic-social-environmental dimensions

Fig. 6 shows the 3-dimensional (3D) scatter plot of the 120 scenario combinations. This 3D scatter plot is designed to provide instructions on the future development pathway selection. We found that water security has trade-off relationships with economic growth and jobs, and some measures induced by water conservation would bring about economic losses and increases in unemployment; conversely, synergic connections exist between water conservation policies and the grey water footprint. For the capital region, scenarios with sectors of Agriculture, Food and tobacco processing and Chemicals (B1T1H1, B2T1H1, B2T3H1, yellow spheres in Fig. 6 etc.) would have less impacts on the economy than scenarios with the sectors of Electricity and heating power production, Smelting and pressing (processing) of metals and Construction (B3T4H6, B3T5H6,golden spheres, etc.). Similarly, some adjusted scenarios including Food and tobacco processing (B1T1H1, B2T2H1, yellow spheres, etc.) would lead to fewer job losses than scenarios with the sectors Electricity and heating power production, Smelting and pressing (processing) of metals (B3T4H6, B3T5H6,golden spheres, etc.). As for environmental benefit, scenarios including Smelting and pressing (processing) of metals, Electricity and heating power production and Construction (B3T4H6, B3T5H6, B3T3H6, golden spheres, etc.) would mitigate the grey water footprint much more than scenarios with the sectors of Food and tobacco processing, and Chemicals (B1T1H1, B2T1H1, B1T2H1,B1T3H1, yellow spheres, etc.).

3.5. Optimal scenarios based on multi-criterion decision aid (MCDA)

We applied the MCDA framework to calculate a composite value as the evaluation index to measure the performance of each scenario in the context of economic, social, and environmental dimensions (see Fig. 7). In MAVT system, the weighted average value was 60.5, and scenarios whose values were smaller than 60.5 were regarded as sustainable in the three dimensions; in contrast, scenarios with higher values were considered unsustainable. Our results show that adjusting the Agriculture and Food and tobacco processing sectors in Beijing, the Agriculture, Food and tobacco processing or Chemicals sectors in Tianjin, and the Agriculture and Electricity and heating power production in Hebei would have a more positive influence on the development of the capital region. Correspondingly, in MAUT system, the weighted average value was 0.54, which means that scenarios with values greater than 0.54 were accepted as reference scenarios for future development, and similar to MAVT, changing the shares of production in the sectors of Agriculture, Food and tobacco processing, Electricity and heating power production and Chemicals would be likely to have the lowest losses and the most environmental benefits. Based on composite values under two MCDA theories, these top 10 scenarios with regard to their performances in terms of economic, social and environmental sustainability could serve as references for guiding future industrial transition policies.

4. Discussion

We proposed a policy support technique that combines mixed MRIO models with MCDA theory to evaluate the consequences of water constraints, and applied it to the largest urban agglomeration in China, the capital region or the Jing-Jin-Ji region. On the one hand, these results on the rank and magnitude of trades-offs and synergies provide useful information for policy makers and planners to effectively identify priority policy selections and balance policy actions in line with policy considerations and value judgements (Kurian, 2017). On the other hand, our mixed MRIO approach coupled with the MCDA allows to evaluate not only the direct impacts of alternative policy options but also the indirect impacts induced by supply-chain effects triggered by exogenous shocks (e.g. resource shortage, natural disasters, emergency events etc.), which have more advantages than footprint accounting or system indicators in impact assessments (Liang et al., 2016; Eiser and Roberts, 2002; Leung and Pooley, 2001). In comparison with the results simulated by a standard MRIO model driven by consumption activities (i.e. Fig.4, Figure S1 versus Figure S2 and Table S5 versus Table S7), the mixed MRIO model driven by production activities under the constraint of resource supply is able to provide a more realistic representation of structural interactions across regions and sectors in response to resource constraints, and thus better facilitating the design of economic development pathways. Despite the persistent concern in the literature on water scarcity, there has been a lack of development of simple and effective tools that can be used to clearly assess the losses and benefits caused by water conservation measures across economic, social, and environmental systems. Our research fills an important niche in water resource field.

Agriculture is a crucial but high water demanding sector. It mainly provides raw products (wheat, rice, soybean, cotton), with low economic value-added, but manifests high-water requirements compared with manufacturing industries. For example, in scenarios B1, B2 and B3 (see Fig. 3 row 1), water rationing reduces the same amount of water consumption, but GDP losses in B2 and B3 are

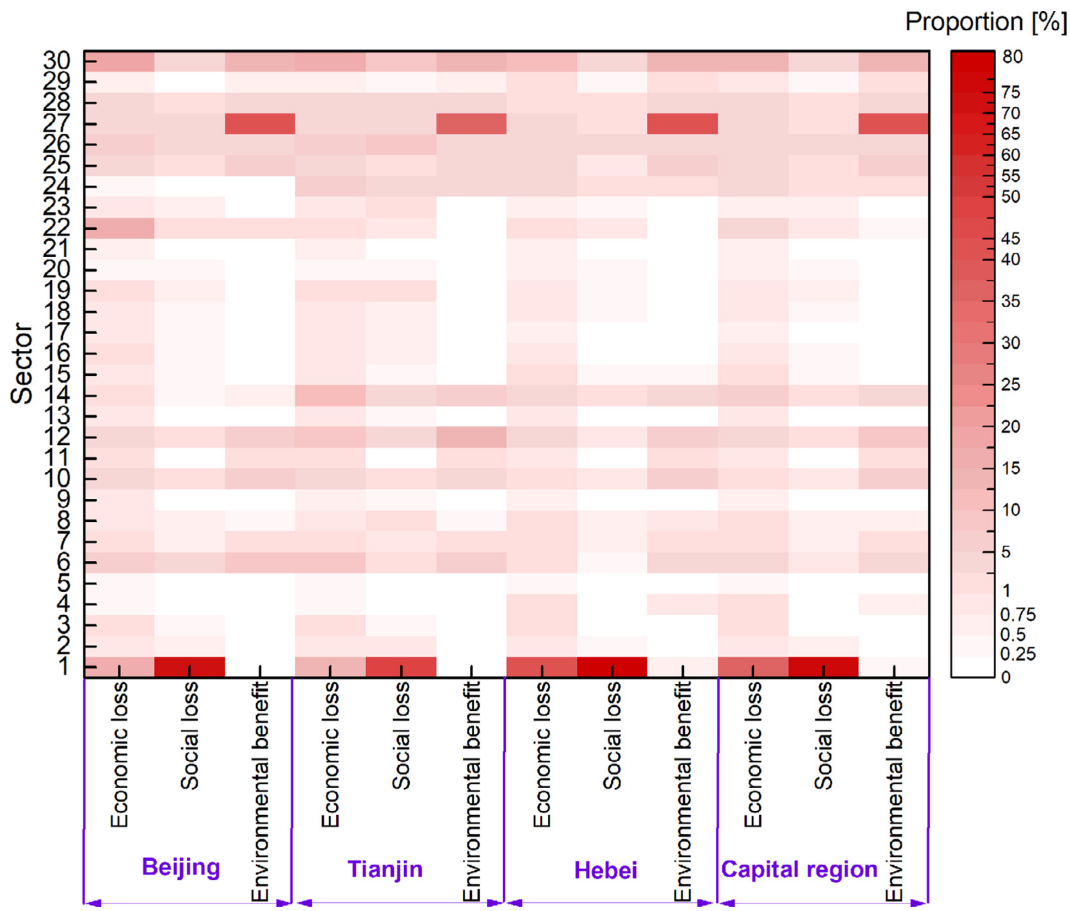

Fig. 4. Proportions in economic and social losses (trade-offs) versus environmental gains (synergy) by sector and region.

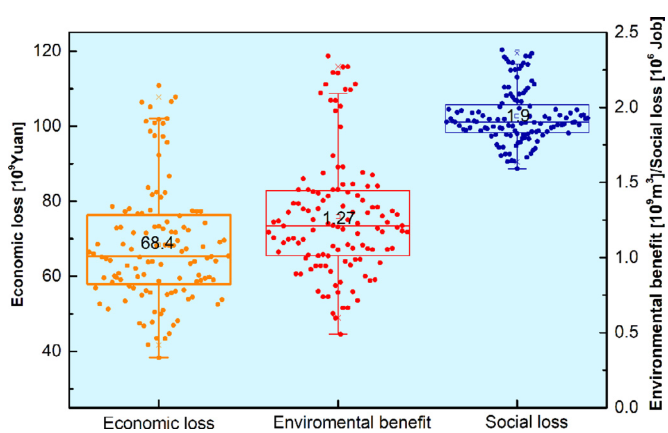

Fig. 5. Boxplots of industrial transition scenarios under water constraints.

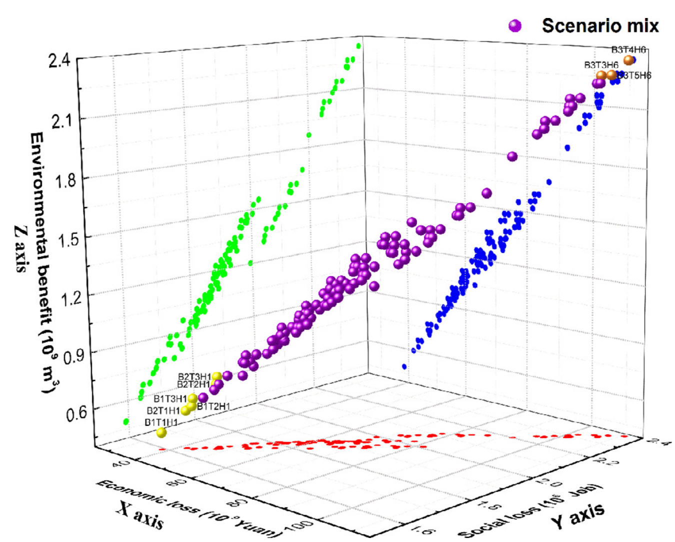

Fig. 6. Trade-offs and synergies of economic-social-environmental dimensions. Note: green plot is Y-Z axis, red X-Y axis, blue X-Z axis, and purple ball is X-Y-Z axis.

bigger than in B1, because scenarios B2 and B3 include industries with higher GDP productivity per unit of water, which means that the elasticity of economic output to water availability is larger in non-agricultural sectors than for agriculture. In other words, reduction in value added from agriculture is lower than in other sectors under the same water reduction scenarios. In addition, agricultural production is labor intensive, and approximately one-third of the labor force is still engaged in agricultural work with low income (farmers, migrant workers) in the capital region (Zhao et al., 2019). As a result, most of the unemployed population in the labor market triggered by water scarcity comes from food-related sectors. Fig. 3 shows that the job loss in agriculture accounted for about 80% of the total job loss in each scenario, but the share of environmental benefit in agriculture is less than 10% of the total, which means that the relatively small extent of economic decline triggered by water rationing in agriculture would lead to large fluctuations on the agricultural labor market and a smaller grey water footprint (Van Arendonk, 2015). There are also some opposite

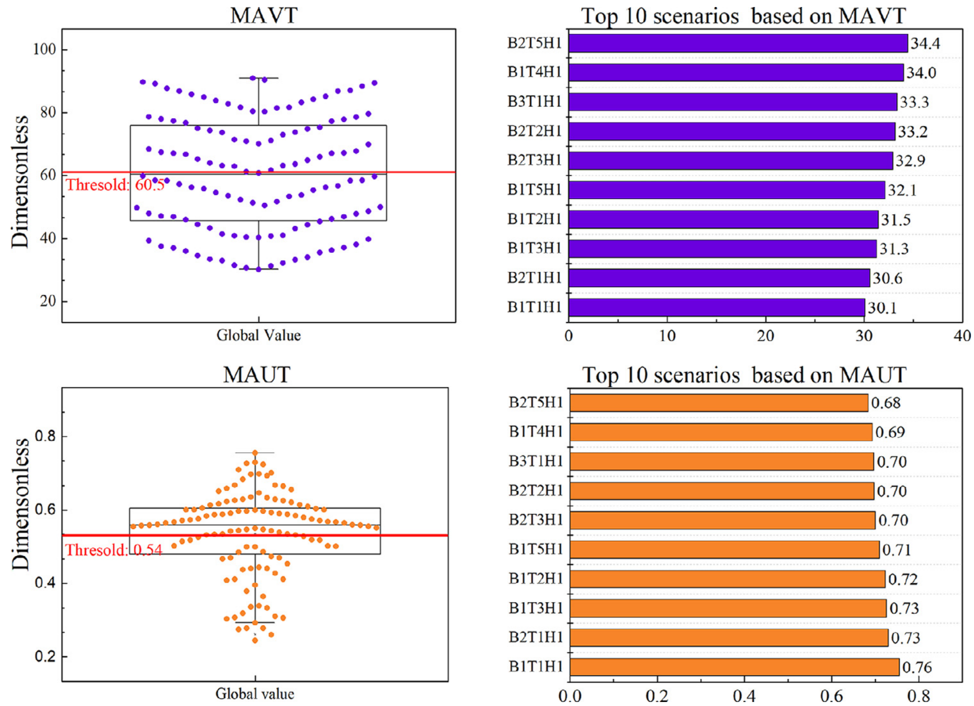

Fig. 7. Scenario evaluation based on two MCDA theories. Note: Scenario ID are showed in Table 2.

cases with small change in labor market but big change in grey water footprint in some scenarios (e.g. B1->B2, T1->T2, H5->H6). These findings indicate that when social and environmental costs are excluded from water conservation planning, policy makers are more likely to promote some water-saving policies at the expense of job losses and unexpected environmental side effects, and this result could be more pronounced in the agriculture sector because of its high water and job intensity. A direct policy implication of this recognition is that although the adjustment in agriculture has the lowest impact on the economy, the responses of social and environmental aspects should also be considered when policy makers propose water policy guidelines.

Fig. 7 shows the overall scores for each scenario with regard to their performance in economic, social and environmental sustainability dimensions for guiding future industrial transition policies in the capital region. It should be noted that we could achieve the goal of decreasing the water stress level to be aligned with the carrying capacity of local water resources based on a range of plausible pathways. In other words, there is space for the stakeholders to join the discussion on the calibration of criterion weights and to choose the most suitable scenario based on their needs. For example, Beijing is on a pathway with an economic structure toward highly advanced services and away from the current water-intensive industries, thus the share of irrigation agriculture could be significantly reduced, even close to zero entirely. Tianjin attempts to become a research center for manufacturing and a pilot region for financial reform, thus some manufacturing with high water intensities and heavy pollutions will be replaced by some high technology industries. Hebei is treated as an important ecological conservation region, with many natural parks surrounding the capital. For this goal, to renew heavy industries by upgrading production processes and modernizing the industrial base will become required in the near future. To some extent, the visualized presentation of the links between policy-relevant requirements and the industrial transitions can better serve the knowledge co-production process between scientists and decision-makers in water demand-side management.

Our findings indicate that trade-offs and synergies exist simultaneously in terms of economic development, social well-being and environmental protection when the economic system is constrained by water resource endowment. Water policies aiming to save water in agriculture will have limited effects on economic development but have negative and significant influences on social and environmental issues. Similarly, shrinking economic output in the Smelting and pressing (processing) of metals and Construction sectors will have significant environmental values but reduced economic and employment benefits. Thus, quantifying the interactions between water and other elements at sectoral scale is very important for water policy planning. Many water studies have been confined to sectorial "silo thinking", without considering the trade-offs between multiple development indicators, which has usually led to inefficient regulatory decisions and spillover and backfire effects leading to environmental and social problems elsewhere (Bizikova et al., 2013). Our research suggests that this well-constructed "nexus" approach has great advantages on impact assessments and scenario selection, and this approach could be a powerful and integrative technique for assessing the trade-offs and synergies among multiple criteria under resource shortages or surpluses, and for addressing the economic, social, environmental, and physical contexts of resource systems to achieve more balanced solutions for policy makers and relevant stakeholders.

The proposed framework can also be applied to modeling potential impacts of supply chain disruptions from external shocks such as the current pandemic (see also for similar modeling approaches Guan et al. (2020) and Shan et al. (2020)). The outbreak of COVID-19, caused by SARD-CoV-2 (severe acute respiratory syndrome coronavirus 2) has become the most disruptive viral public health event since the 1918 influenza pandemic a century ago (Giani et al., 2020). Some strict lockdown measures like travel restrictions, quarantine, closing caterings and entertainment places and social distancing are enforced by many governments with high infection rate and confirmed cases to slow down the spread of COVID-19 (Guan et al., 2020). This newly integrated toolbox with mixed MRIO, scenario analysis and MCDA theory provides decision makers with the ability to assess short-term supply-chain effects of different containment measures to reveal how pandemic-related economic losses will be reallocated along supply-chains across regions and industrial sectors and quantify associated potential economic, social and environmental impacts. For instance, travelling restrictions and closing public places (restaurants, pubs, sports etc.) will bring about external economic shocks in several key service sectors directly, then the impacts of these constrained sectors will be enhanced through complex supply-chain linkages. Subsequently, secondary impacts like unemployment, and changes in air pollution, water resources and biodiversity effects triggered by lockdown measures can be captured by this framework, and allows quantification and comparisons between costs and benefits of various strategies.

The successful achievement of the SDG agenda is a pathway to respond to the global sustainability challenges in ensuring economic prosperity, human well-being, and environmental protection, and the attainment of SDGs will greatly depend on whether synergies can be leveraged and trade-offs are minimized (Pradhan et al., 2017). The UN has established these SDG targets on the global scale; however, assessing these targets at the regional scale in a scientific way is more practical for local governments and practitioners. Our analytical framework can be one tool to assess trade-offs and synergies of SDG targets at the regional level. A coupling of this regional tool with national and global MRIO models in a nested structure in future research would achieve more insightful national overviews, and help determine priorities in supporting SDG targets. The mixed MRIO model results show the necessity of considering the impacts of the disruption triggered by water constraints on the supply chain across region-sectors. Our results indicate that of the total economic loss triggered by the imposition of water rationing in the capital region, 54% occurred in the capital region and 45% occurred in the rest of China. We expect that our integrated approach can serve as a stepping stone for further research into the cascading relationships among food security, energy consumption, and environmental restoration. In these fields, the relative intensities of pressures, trade-offs, and co-benefits will depend on the scope of each analysis and the indicators used to measure the outcomes (Obersteiner et al., 2016). We believe that the simplicity and the rich information provided by MRIO models have advantages in contributing to coherent and comprehensive policy planning, with due attention focused on economic prosperity, resource security and social stability.

5. Conclusion

This study proposed a novel approach that integrates supply constrained MRIO model with multi-criteria assessment to quantify the trade-offs and synergies of economic-social-environmental dimensions at the regional-sectoral level with an application to the capital region of China. We developed 120 industrial transition scenarios including nine industries with the high water-intensities and water consumption under current development pathways. We calculated economic loss, job loss and environmental protection gains triggered by water conservation measures under each of the 120 scenarios. Then, we employed MCDA to select optimal scenarios. The following conclusions were drawn:

1. A tolerable water rationing in Agriculture, Food and tobacco processing, Electricity and heating power production, and Chemicals sectors would result in the lowest economic and job losses as well as the largest environmental benefits to the region.
2. The MCDA procedure recommends 10 reference scenarios with regard to their economic, social and environmental performance that can facilitate the design of future water regulation and industrial transition policies. The visualized presentation of the links between policy-relevant requirements and the industrial transitions can better serve the knowledge co-production process between scientists and decision-makers in water demand-side management.
3. This newly integrated toolbox allows to assess the short-term supply-chain effects of different crisis containment strategies to reveal how pandemic-related economic losses will be reallocated along the supply-chains across regions and sectors and potential other impacts, and allows quantification and comparisons between the losses and gains of various mitigation strategies.
4. This integrated approach could be a powerful policy support tool for assessing trade-offs and synergies among multiple criteria under resource constraints and for evaluating SDGs at the regional level to determine priorities for local governments and practitioners.

Author contributions

J.L., D.Z., L.S., O.V., K.H and K.F. conceived the central idea. D.Z. collected the data, performed the calculations, and created all figures. D.Z. wrote the draft. All authors contributed to the analysis and developed the manuscript.

Data availability

Details on the methodology and data for estimating water consumption in China are summarized in the supplementary information, and any other datasets generated during this study are available upon request from the authors.

Declaration of Competing Interest

None.

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Supplementary materials

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