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Decomposition methods for analyzing changes of industrial water use

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ABSTRACT

Changes in industrial water use are of the utmost significance in rapidly developing countries. Such countries are experience rapid industrialization, which may stimulate substantial increases in their future industrial water use. Local governments face challenges in formulating industrial policies for sustainable development, particularly in areas that experience severe water shortages. This study addresses the factors driving increased industrial water use and the degrees to which these factors contribute, and determines whether the trend will change in the future. This study explores the options for quantitative analysis that analyzes changes in industrial water use. We adopt both the refined Laspeyres and the Logarithmic Mean Divisia Index models to decompose the driving forces of industrial water use. Additionally, we validate the decomposition results through a comparative study using empirical analysis. Using Tianjin, a national water-saving city in China, as a case study, we compare the performance of the two models. In the study, the driving forces of changes in industrial water use are summarized as output, technological, and structural forces. The comparative results indicate that the refined Laspeyres model may be preferable for this case, and further reveal that output and technology have long-term, stable effects on industrial water use. However, structure may have an uncertain influence on industrial water use. The reduced water use may be a consequence of Tianjin's attempts to target water savings in other areas. Therefore, we advise the Tianjin local government to restructure local industries towards water-saving targets.

1. Introduction

Changes in industrial water use are of the utmost significance in rapidly developing countries such as China (Geng et al., 2012). The fast growth in industrial output (annual rate of 10%), is expected to exponentially increase the use of industrial water, even after accounting for a drastic reduction in water use per unit of output (Shang et al., 2016a). However, we have reason to doubt the accuracy of such a prediction. According to the experience of developed countries, industrial water use will not continue to increase (Jia, 2001). Specifically, when an economy reaches to a certain stage of development, industrial water use will stop rising and exhibit a downward trend. For example, industrial water use began to decline in Sweden in 1964, in Japan in 1974, and in the US in 1981. China also experienced a decline in industrial water use in some of its economically developed areas, although the nation remains in state of rapid industrialization (Shang et al., 2016b). Wang et al. (2012) predicted a continued increase in global industrial water use, and these results were confirmed by Flörke et al. (2013) using the Water Global Assessment and Prognosis (WaterGAP) model. Based on the results of water demand forecasting, the development of many the water conservancy projects for storage, diversion, pumping, and transfer is required in the future to provide incremental water supplies (Wang et al., 2012). Researchers have reach a consensus that the promotion of water saving and an increase in investment in water conservancy projects are measures that have helped the developed countries to overcome the constraints of limited water resources on their socioeconomic development (Jia et al., 2006). However, such projects may entail huge investments, which challenges developing countries characterized by poverty (Wang et al., 2015). Therefore, developing countries attempt to solve water shortage crises through administrative legislation rather than building water conservancy projects (Fujii

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et al., 2012). For example, China has implemented strict control over total water use by industries (Zuo et al., 2014), and shows remarkable results proving the controls to be effective but far from sufficient. Additional efforts to improve levels of water saving and water use efficiency are required (Alnouri et al., 2014).

Industries produce large amounts of wastewater during their production processes while the discharge of wastewater can be reduced by increasing water use efficiency. Industrial wastewater discharge typically increases with an increase in industrial water use (Kirkpatrick et al., 2011), and the discharge to rivers without treatment will inevitably cause serious water pollution (Englert et al., 2013). Extensive sewage treatment requires considerable money and energy (Arani et al., 2012), and industrial wastewater in developing countries is often directly discharged into rivers without treatment (Yi et al., 2011), which further exacerbates water shortages. To increase the amount of available water for industrial purposes, recent literature on industrial water use has been focused on planning methods for coordinated development between industries and water resources, regulatory policies to improve water use efficiency, or specific techniques to reduce pollution. Lévová and Hauschild (2011) developed a planning approach to determine the maximal development scale of the biotech industry based on the lifecycle evaluation of water use. Pham et al. (2016) found that a current water management system was not conductive to industrial water savings using a case study of an industrial park in Vietnam. This study recommended "reducing wastewater discharge" and "improving water reuse," to address the high water use by industries. Agana et al. (2013) posited that effective integrated management of industrial water use could contribute towards targets including minimizing wastewater discharge and improving water use efficiency. To promote the reuse of industrial waters, Marianne et al. (2012) optimized the water supply network using the mixed-integer linear programming approach.

The above-mentioned studies mainly focused on the assessment of available industrial water, regulatory policies to mitigate water shortage, or specific techniques to reduce pollution. The studies consider water a factor of industrial production and conduct quantitative analyses of the scale of industrial development or industrial wastewater discharge using input–output or similar static models. However, the industrial structure of a city is by no means static; rather, it constantly undergoes change (Bao and Fang, 2012). The structure includes industries that will be eliminated, new industries that will be included, and other traditional industries that will be transformed. Therefore, a dynamic analysis of the driving forces of changing industrial structure is required. Researchers have realized that changes in industrial structure are driven by multiple factors (Saboori et al., 2012), and all of the driving forces may substantially influence industrial water use (Yoo et al., 2007; Shang et al., 2016c). Although a complete understanding of the nexus between industries and their water use has not yet been achieved (He et al., 2014), a linkage was found between industrial development and industrial water use, which can be depicted by the Kuznets curve (Tate, 1986; Muhammad et al., 2012; Foster, 2015). Merrett (1997) pioneered the use of Kuznets curves to describe the relationship between continuous socioeconomic development and the demands for water resources and found that, with continuous socioeconomic development, the demand for water grows, then exhibits zero growth and, finally declines. Shang et al. (2016c) introduced a "partiality to high water use" method to describe the influence of industrial structural adjustment on industrial water use. Shang et al. (2016c) found that the decline may be attributed to a combination of a reasonable industrial structure and high water use efficiency. Reynaud (2003) studied the changes in industrial water use though field investigation and data analysis. The study found that regulation policy can significantly influence industrial water use, and the price of water may also provide powerful water-savings incentives. Steven (2005) suggested the use of economic instruments within a legal framework to promote industrial water savings. Shang et al. (2016b) may have been the first to introduce the Laspeyres model to decompose industrial water use. In their study, the factors affecting and contributing to the change of industrial water use was quantitatively analyzed. However, quantitative analyses of the contribution of different factors to incremental industrial water remain limited, although the quantitative analysis methods have been widely used in various fields of economics and social studies (Armknecht and Silver, 2014; Zhang and Da, 2015). Most studies are restricted to a qualitative description of the laws of industrial water use and the broad exploration of influencing factors.

The Laspeyres model and the logarithmic mean divisia index (LMDI) model are the two typical approaches for quantifying the driving forces behind change (Ang et al., 2015). Among the approaches, the Laspeyres model may be the most widely used because it is simple and easy to use (Richard, 2012; Kieran et al., 2013). However, the model is unable to fully decompose all factors, and the remainder (or residual error) of the decomposition results increases with factors. When a factor significantly changes in the short term, the remainder can be significantly large and, if ignored, can undermine the model's accuracy (Ang and Zhang, 2000). To achieve complete decomposition, Sun (1998) proposed a refined method to optimize the Laspeyres model. In the refined model, all the remainders were assigned to their source items under the "jointly created and equally distributed" principle (Zhang et al., 2009). Through a comparative study, Ang (2004) argued that the LMDI model was superior because it allows the complete decomposition of factors by building a log-mean formula. The main purpose of this paper is to explore additional options for quantitatively analyzing the driven changes of industrial water use. This study adopts both the refined Laspeyres and LMDI models to quantitatively assess the factors influencing industrial water use changes. We selected Tianjin, "national water-saving city" of China, as the study area to verify the results of the models. In addition to model verification, we also provide a theoretical basis and supporting data required to help China build more water-saving cities. Fig. 1 shows the location of Tianjin in China.

China has been known to have scarce water resources; this is particularly true for Tianjin. Tianjin records the lowest per capita water resources at 182 m^3/a in mainland China, equivalent to one-fifteenth of the national average and significantly less than the internationally recognized poverty line of 500 m^3/a. This water scarcity has hindered socioeconomic development and further aggravated the ecological environment in Tianjin. To ease the increasingly prominent water shortage crisis, Tianjin has set targets for water use efficiency that must be achieved within a given period (Xinhua, 2015). This regulatory policy showed remarkable results. In 2013, water use per 10,000 yuan of gross domestic product (GDP) was reduced to 17.52 m^3 (less than one-sixth of the national average,) and water use per 10,000 yuan of industrial added value was lowered to 8.3 m^3, which represents the highest level of national water use efficiency (Shang et al., 2015). The remainder of this paper is structured as follows: Section 2 introduces the modeling methods and data used in this study; Section 2.1 discribes Laspeyres model and derives the LMDI model; Section 2.2 gives an overview of the data; Section 2.3 introduces industrial water use in Tianjin, China; Section 3 analyzes the results; Section 3.1 compares the decomposition results of the two models; Section 3.2 qualitatively analyzes the statistic of Tianjin's industrial water use; Section 3.3 validates the two modeling methods using a case study. Section 4 concludes the paper.

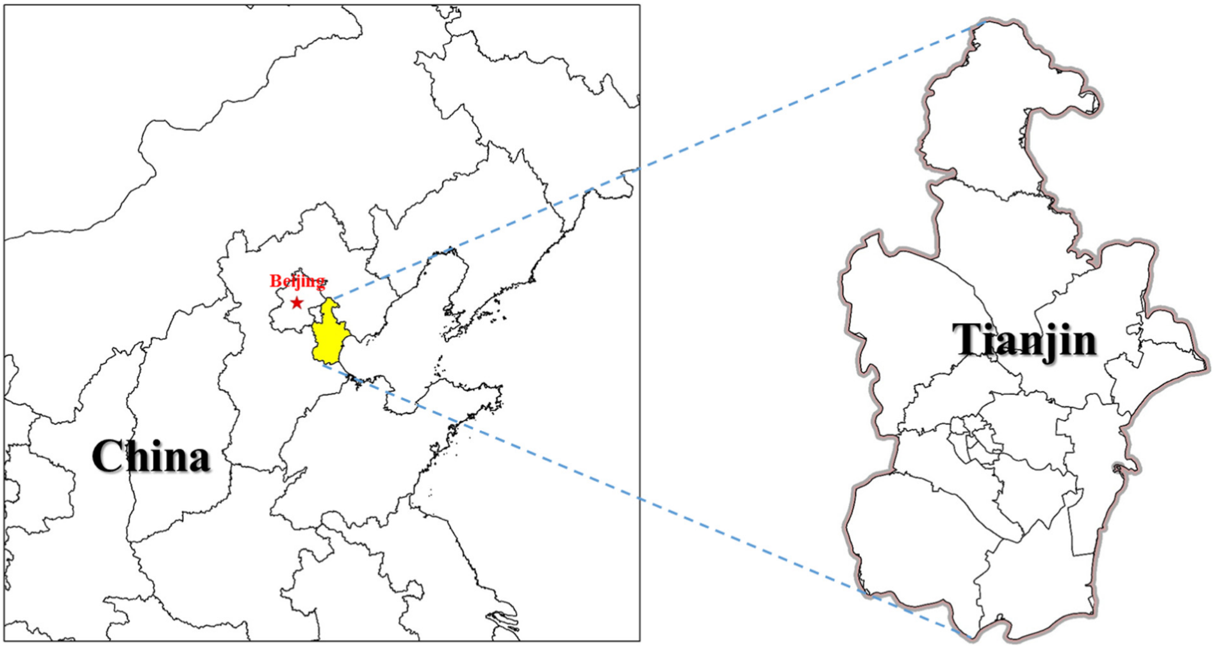

Fig. 1. The location of Tianjin in China.

2. Methodology and data

2.1. Decomposition models

2.1.1. Laspeyres model

The Laspeyres decomposition model was first proposed by Lasperyers in 1864, and was improved by Sun (1998). Shang et al. (2016b) extended the use of the refined model to decompose the driving forces of changes in industrial water use. The refined Laspeyres model described here is derived by Shang et al. (2016b).

For complete decomposition, we explicitly assume that industrial water use is subject to three factors including industrial output, water use per unit of output, and the three factors equally contribute to industrial water use. Therefore, the resulting decomposition formula can be written as:

$$Q = \sum_{i=1}^{n} \mu_i \cdot M \cdot q_i \tag{1}$$

where Q represents the total quantity of industrial water use; n is the number of total industrial sectors, and i starts from 1; M is the total industrial output of Tianjin; q_i represents water use per unit of output in sector i, and μ_i is the proportion of sector i within total industrial output.

For the interval [0, t], when Q changes from Q^0 to Q^t, the amount of change in ΔQ can be written as follows:

$$\Delta Q = \Delta Q_M + \Delta Q_q + \Delta Q_\mu \tag{2}$$

in which,

$$s\Delta Q_M = \sum_{i=1}^{n} M^0 q_i^0 \Delta\mu_i + \frac{1}{2}\Delta\mu_i(q_i^0 \Delta M + M^0 \Delta q_i) + \frac{1}{3}\Delta\mu_i \Delta M \Delta q_i \tag{3}$$

$$\Delta Q_\mu = \sum_{i=1}^{n} \mu_i^0 q_i^0 \Delta M + \frac{1}{2}\Delta M(q_i^0 \Delta\mu_i + \mu_i^0 \Delta q_i) + \frac{1}{3}\Delta\mu_i \Delta M \Delta q_i \tag{4}$$

$$\Delta Q_q = \sum_{i=1}^{n} \mu_i^0 M^0 \Delta q_i + \frac{1}{2}\Delta q_i(M^0 \Delta\mu_i + \mu_i^0 \Delta M) + \frac{1}{3}\Delta\mu_i \Delta M \Delta q_i \tag{5}$$

where ΔQ represents the change in industrial water use; ΔQ_M represents the change in industrial water use because of output, which, in other words, is the increment of decrement of industrial water use along with the change in industrial scale or output; ΔQ_q represents the change in industrial water use brought about by technology. Specially, ΔQ_q refers to the amount of water savings from the changes in water use efficiency and the application of water-saving technique; ΔQ_μ represents a change in industrial water use brought about by industrial structure or, specially, the increment of decrement of industrial water use along with the adjustment to the share of industrial sectors; M^0 is the value of industrial output in the previous year; q_i^0 is water use per 10,000 yuan of industrial added value in industrial sector i in the previous year, and μ_i^0 is the proportion of Tianjin's total industrial output value that came from industrial sector i in the previous year. ΔM, Δq_i, and $\Delta\mu_i$ refer to the changes in industrial output value, water use per 10,000 yuan, and the output proportion of industrial sector i, respectively.

2.1.2. LMDI model

Mahony Tadhg (2013) applied the LMDI model to decompose carbon emissions, where the three driving forces including policy, population, and economy factors were considered respectively. Our study extends the use of this model to the field of industrial water use. The derivation of the LMDI model is given as follows.

Here, we define industrial water use in the previous year as Q^0 and in the tth year as Q^t, and the industrial water use in year t can be expressed using the following formula:

$$Q^t = \sum_{i=1}^{n} Q_i^t = \sum_{i=1}^{n} M^t \times \mu_i^t \times q_i^t = \sum_{i=1}^{n} M^t \times \frac{M_i^t}{M^t} \times \frac{Q_i^t}{M_i^t} \tag{6}$$

where M^t is the total industrial output in year t, that is, output-driven force. M_i^t and Q_i^t are industrial output and water use of sector i. μ_i^t stands for the percentage of sector i in total industrial output, that is, structure-driven force. q_i^t is water use per 10,000 yuan of output in sector i, or technology-driven force.

First, we apply a differential calculus for time to formula (6); then, the formula can be written as follows:

$$\frac{dQ^t}{dt} = \sum_{i=1}^{n}\left(\frac{dM_t}{M_t} \times \frac{Q_i^t}{dt} + \frac{d\mu_i^t}{\mu_i^t} \times \frac{Q_i^t}{dt} + \frac{dq_i^t}{q_i^t} \times \frac{Q_i^t}{dt}\right) \tag{7}$$

We apply the integral calculation for time period [0, t]. The change in industrial water use for the interval [0, t] are, therefore, expressed as follows:

$$\Delta W = W_t - W_0 = \sum_{i=1}^{n}\left(\int_0^t dlnM_t \cdot Q_i^t + \int_0^t dln\mu_i^t \cdot Q_i^t + \int_0^t dlnq_i^t \cdot Q_i^t\right) \tag{8}$$

Finally, we apply the integral mean value theorem to formula (8) and obtain the following formula:

$$\Delta Q \cong \sum_{i=1}^{n} \varphi_i^t \left(ln\frac{M_t}{M_0} + ln\frac{\mu_i^t}{\mu_i^0} + ln\frac{q_i^t}{q_i^0}\right) \tag{9}$$

where φ_i^tstands for the weight of sector i.

According to Ang (2004), φ_i^t can take the following form:

$$\varphi_i^t = \frac{Q_i^t - Q_i^0}{lnQ_i^t - lnQ_i^0} \tag{10}$$

Therefore, the change in industrial water use for the tth year can be rewritten as follows:

$$\Delta Q = \Delta Q_M + \Delta Q_\mu + \Delta Q_q \tag{11}$$

in which,

$$\Delta Q_M = \sum_{i=1}^{n} \frac{Q_i^t - Q_i^0}{lnQ_i^t - lnQ_i^0} ln\frac{M_t}{M_0} \tag{12}$$

$$\Delta Q_\mu = \sum_{i=1}^{n} \frac{Q_i^t - Q_i^0}{lnQ_i^t - lnQ_i^0} ln\frac{q_i^t}{q_0^t} \tag{13}$$

$$\Delta Q_q = \sum_{i=1}^{n} \frac{Q_i^t - Q_i^0}{lnQ_i^t - lnQ_i^0} ln\frac{q_i^t}{\mu_0^t} \tag{14}$$

2.2. Data source

In this study, water use data for Tianjin are sourced from the *Tianjin Water Resources Bulletin* (Tianjin Water Authority, 1995 to 2013). The statistics on water use by industrial sectors are adopted from the *Tianjin Industrial Energy Efficiency Guide* (Tianjin Development and Reform Commission, 2004 to 2013) and the Tianjin Municipal Bureau of Statistics, and the statistics on output are from *Tianjin Statistical Yearbook (1995–2013)* (Statistical Bureau of Tianjin, 1995 to 2013).

Industrial water use refers to water supply for plant workers and water used in (or during) the industrial production process, for example, in boilers and manufacturing, processing, cooling, air conditioning, and washing. Industrial water mainly consists of surface water, groundwater, recycled wastewater, and desalinated water. However, seawater directly used in industrial production is excluded. To avoid errors caused by price fluctuations between years and to facilitate the longitudinal comparisons, industrial output data are converted according to the 1990 constant prices before being incorporated into the model.

2.3. The change in industrial water use in Tianjin, China

Fig. 2 shows that total industrial output increased more than 10 times from 173.82 billion yuan in 1994 to 2.41 trillion yuan in 2012, while industrial water use showed significant segment features with turning points in 1999 and 2008. Fig. 2 shows a gradual increase in Tianjin's industrial water use after a period of rapid increase (1994–1999) and slow decline (1999–2012), and the trend is indicated in Fig. 2 by a red[1] dashed line. Specifically, industrial water use decreased during the period 1999–2003 and gradually increased during the period 2008–2012. The trend is indicated in Fig. 2 by a black dashed line.

We used long time series of industrial output and water use data to find the relationship between industrial output and industrial water use. Fig. 3 shows no obvious linear relationship between industrial output and industrial water use. However, three distinct correlation stages can be observed based the level of industrial output. For low level output, industrial water use is negatively correlated with industrial output. That is, industrial water use decreases as industrial output increases, indicating that substantial water savings are generated during industrial restructuring processes. For intermediate levels of output, the amount of water use does not changes significantly while industrial output increases significantly, indicating that an increase in water use from expansion in industrial scale may be counteracted by a water use decrease from improvements in water use efficiency. For high levels of output, water use is positively correlated with industrial output, implying that industrial water use will remain level with industrial output growth. This may indicate that there is little room for improvement in water saving from improvements in water use efficiency.

As analyzed above, a change in industrial water use may be subject to multiple driving forces. The water availability is a strict constraint for industrial development. Additionally, a change in industrial water use could be considered a joint effect from industrial scale expansion, technological advances, and industrial restructuring. At different periods, these driving forces exert effects to varying extents, leading to complex changing trends in industrial water use. Only by decomposing the driving forces, can we accurately grasp this trend and make a scientific pre-judgment.

3. Results and analysis

3.1. Differences in the calculation results of different models

This study chronologically decomposes water use change using the refined Laspeyres and LMDI models. Both models have passed time reversal and factor reversal checks, which proved the decomposition effective. Moreover, no residual items are observed in the Laspeyres and LMDI decomposition results. Therefore the decomposition results of synergies are entirely consistent, indicating that the decomposition results could reflect the actual situation of Tianjin's industrial water use. Table 1 shows the decomposition results.

Table 1 shows that the two models produce consistent decomposition results with a small difference of 1–2% for most years. This implies that the decomposition results produced by the two models agree, although anomalies were found for the years 2009, 2010, 2011, and 2012. The difference in model results for those years may exceed 10%. The level of difference is attributed to drastic changes in the share of industrial sectors or water use efficiency. There may be statistical errors because change for both the share of industrial sectors and water use efficiency should not be excessive. Fig. 4 provides a clearer display of the decomposition results for the effects of output, technology, and structure in each year plotted as x and y values in Cartesian coordinates.

[1] For interpretation of color in Fig. 2, the reader is referred to the web version of this article.

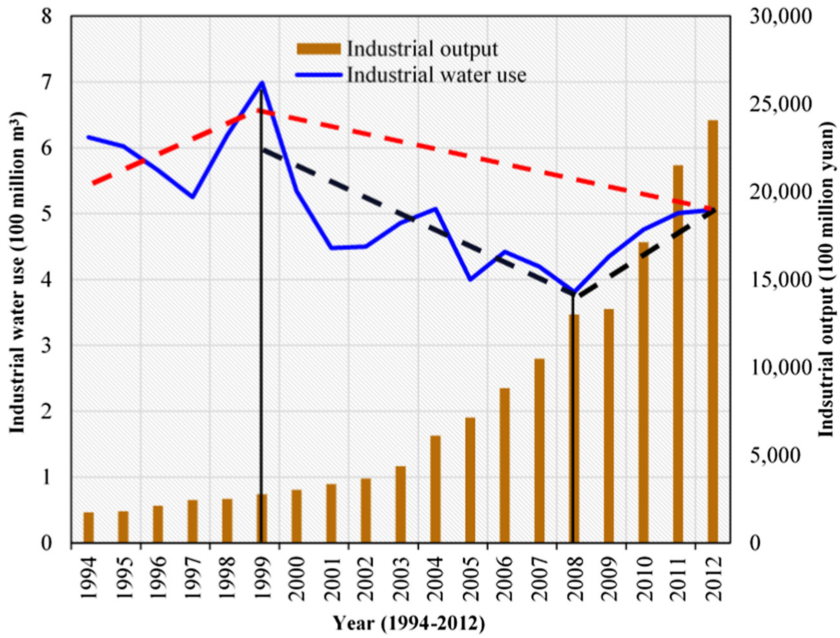

Fig. 2. Industrial output and industrial water use in Tianjin (1994–2012).

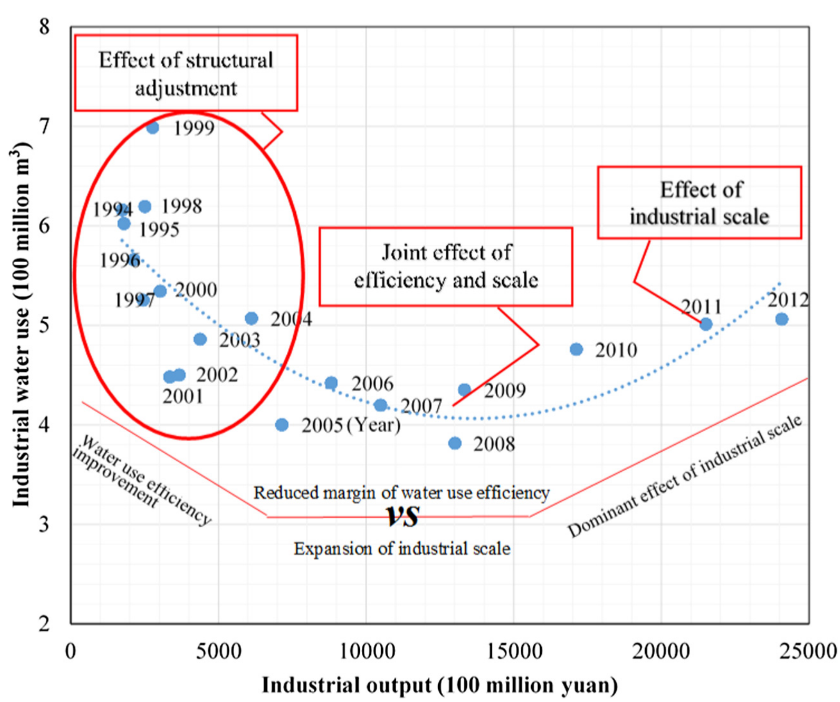

Fig. 3. Diagram of the correlation between industrial output and water use.

Table 1
Decomposition of Tianjin's industrial water use using the refined Laspeyres and LMDI models Unit: 10,000 m^3.

Year	Output		Technology		Structure		Synergies	Total water use
	Laspeyres	LMDI	Laspeyres	LMDI	Laspeyres	LMDI		
2003								48,600
2004	9732	9589	−5349	−5273	−2283	−2216	2100	50,700
2005	7960	7715	−14,367	−14,007	823	708	−5584	45,116
2006	6744	6686	−5160	−5136	−2500	−2467	−917	44,199
2007	6866	6787	−10,627	−10,513	1536	1500	−2226	41,973
2008	6930	6842	−9386	−9278	−1387	−1407	−3843	38,130
2009	6874	6818	−2118	−2021	616	575	5372	43,502
2010	89m26	8529	−9336	−10,521	4493	6074	4082	47,584
2011	8662	8610	−5682	−5591	−464	−503	2516	50,100
2012	7294	6489	−9564	−8599	3057	2897	787	50,887

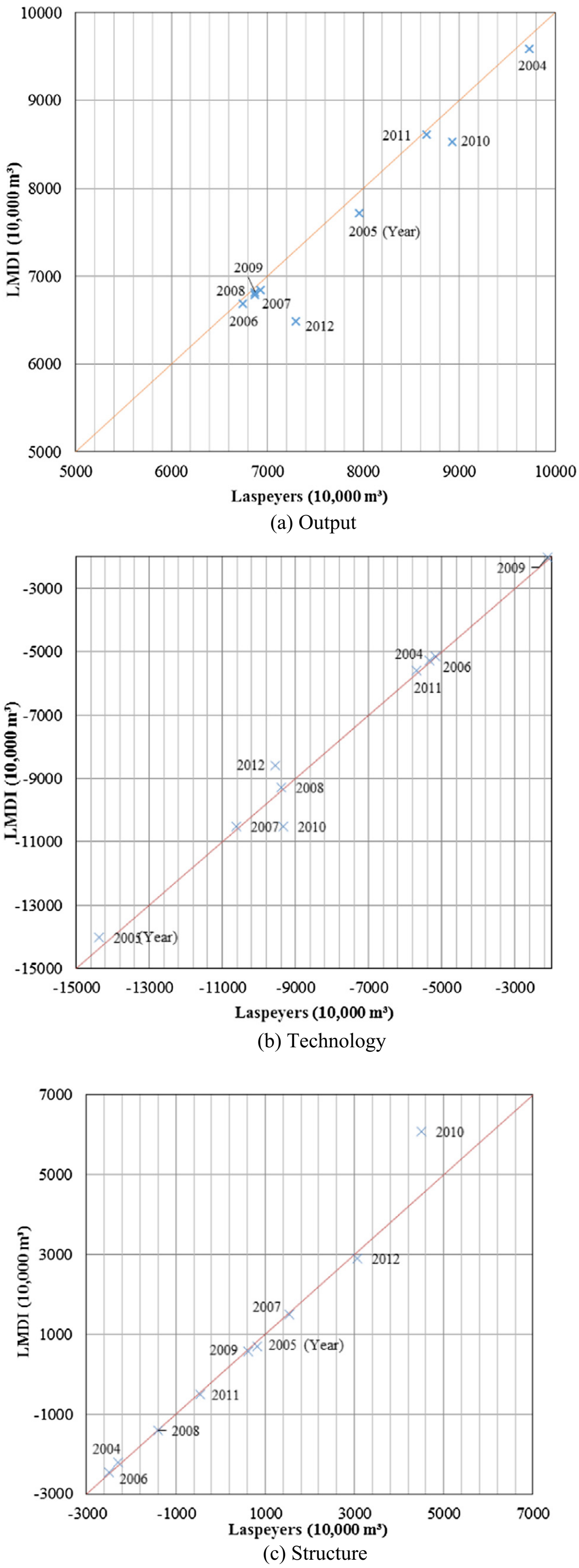

Fig. 4. Laspeyres–LMDI comparison of decomposition results :(a) output; (b) technology; (c) structure.

Fig. 4 also shows the performance differences between the two models. The figure shows that the decomposition results for output using the two models scatter near, mostly below, the straight line $x = y$. The values obtained using the Laspeyres model are slightly larger than those derived using the LMDI model. For technology, the values obtained mostly scatter above the straight line $x = y$ and, thus, the values from the Laspeyres model are marginally smaller than those of the LMDI model (except during the period of 2009–2010). For structure, the values obtained are located on the straight line $x = y$ (except during the period 2011–2012), which implies a small difference in the decomposition results of the two models.

3.2. Empirical analysis of driving forces

To validate the decomposition results and further compare the performance of the two models, this study conducted qualitative analysis based on statistics. This study focuses on the period from 2001 to 2012, with particular attention to industrial adjustment during the period 2003–2012). We also analyze data for the earlier period of 1994–2002 to better grasp the law of long-term industrial development in Tianjin.

3.2.1. Empirical analysis of output-driven force

Total industrial output is introduced as an indicator to describe the scale of industrial development in Tianjin, producing output-driven force. A rise in output is the most direct driving force in the upward trend of water use. In the absence of other driving forces, industrial water use is directly proportional to industrial output. The greater the effect of the output-driven force the more obvious the linear correlation with industrial water use. Fig. 5 shows the correlation of industrial water use with total industrial output for the period 1994–2012.

Fig. 5 shows that the correlation can be divided into two stages. Before reaching 1 trillion yuan (1994–2007), industrial output gradually increased with an average annual increment of 67.3 billion yuan, and its impact on industrial water use was not obvious. Although the industrial production increased annually, industrial water use exhibited a clear downward trend. From 1995 to 2006, industrial water use fell from 740 million m^3 to 420 million m^3 while industrial output quadrupled from 190 billion yuan to 890 billion yuan. This indicates that, at this stage, the driving force of output in water use was offset by the water-saving effect of other factors. After reaching 1 trillion yuan (2008–2012), industrial output markedly expanded with an annual increment of 273.8 billion yuan and the coefficient of the positive correlation with industrial water use was up to 0.81. This implies rigid growth in industrial water use in this stage driven by industrial scale expansion.

3.2.2. Empirical analysis of technology-driven force

Technology-driven force refers to the reduction of water use per unit of product caused by the advancement of water-saving technologies, the use of water-saving devices, water-saving publicity, and system development. The force is manifested in improvements in water use efficiency and expressed by water use per 10,000 yuan of output. Improvements in water use efficiency can restrict increases in industrial water use. In the absence of other driving forces, water use efficiency is inversely proportional to industrial water use. The greater the effect of a technology-driven force, the more obvious the inverse proportion. In terms of industrial water use efficiency, Tianjin has been taking the lead in China since 2006. This can be attributed to the small proportion of

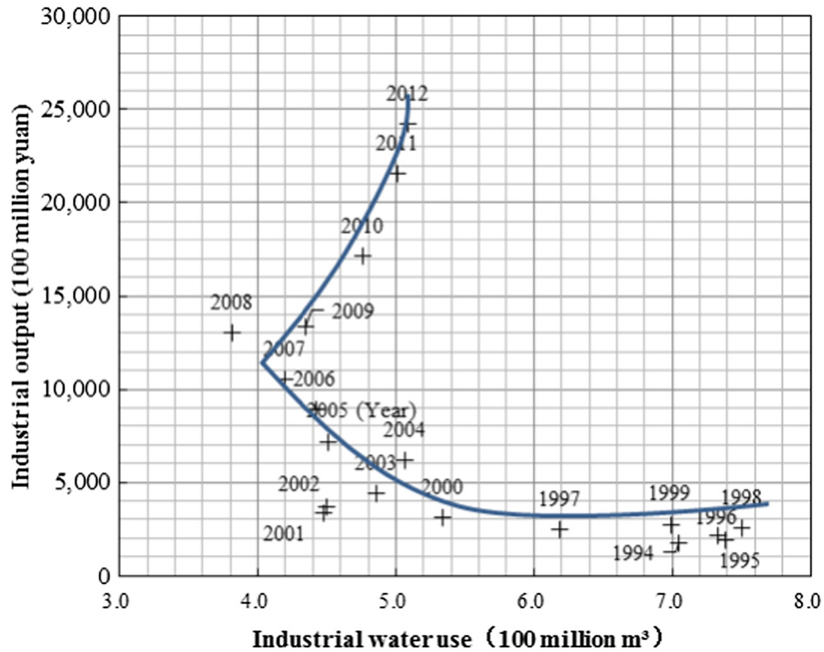

Fig. 5. Correlation between total industrial output and industrial water use in Tianjin (1994–2012).

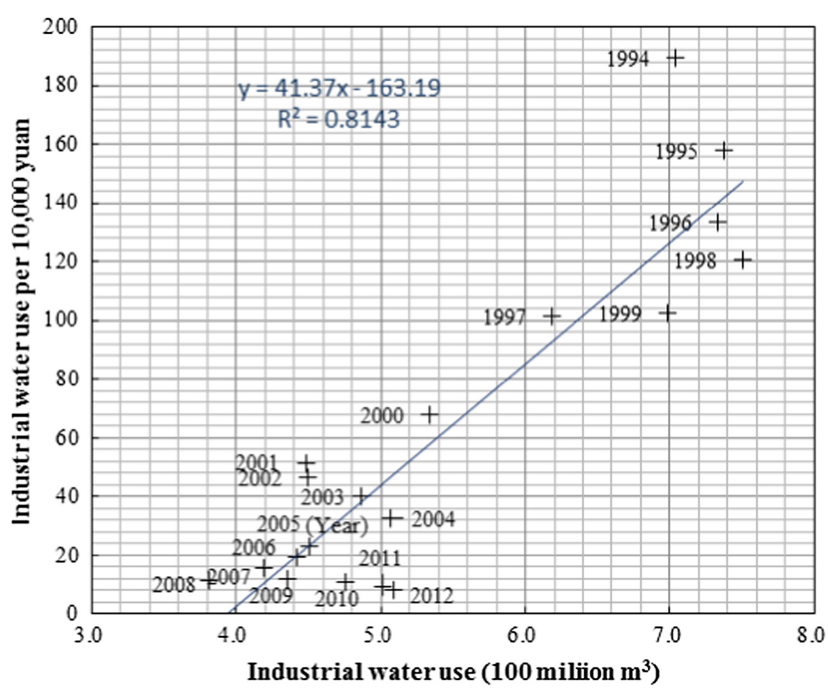

Fig. 6. Correlation between water use per 10,000 yuan of industrial output and industrial water use in Tianjin (1994–2012).

water-consuming industries in the overall industrial structure and importantly, to technological and process improvements in the industrial sectors and the implementation of water-saving measures. Fig. 6 shows the correlation of industrial water use with water use per 10,000 yuan of output in Tianjin during 1994–2012.

Fig. 6 shows a significant linear correlation between water use per 10,000 yuan of output and industrial water use in Tianjin, and the positive correlation coefficient is up to 0.83. The correlation can be divided into three stages. The first stage is the rapid increase in water use efficiency and a fast decline in industrial water use. During 1994–2001, the water use per 10,000 yuan of output plummeted from 40 m^3 to 13 m^3 with an average annual decline of 3.8 m^3, implying rapid improvements in water use efficiency. Industrial water use also fell sharply to 450 million m^3 from 700 million m^3. This indicates that technology played a key role among all the driving forces and significantly curbed the rise in industrial water use. The second stage is the slow increase in water use efficiency and the slight decline in industrial water use. During the period 2002–2008, water use efficiency gradually improved with water use per 10,000 yuan of output down by 1.5 m^3 on an annual basis and industrial water use dropped from 450 million m^3 to 380 million m^3. Here, although the technology-driven force

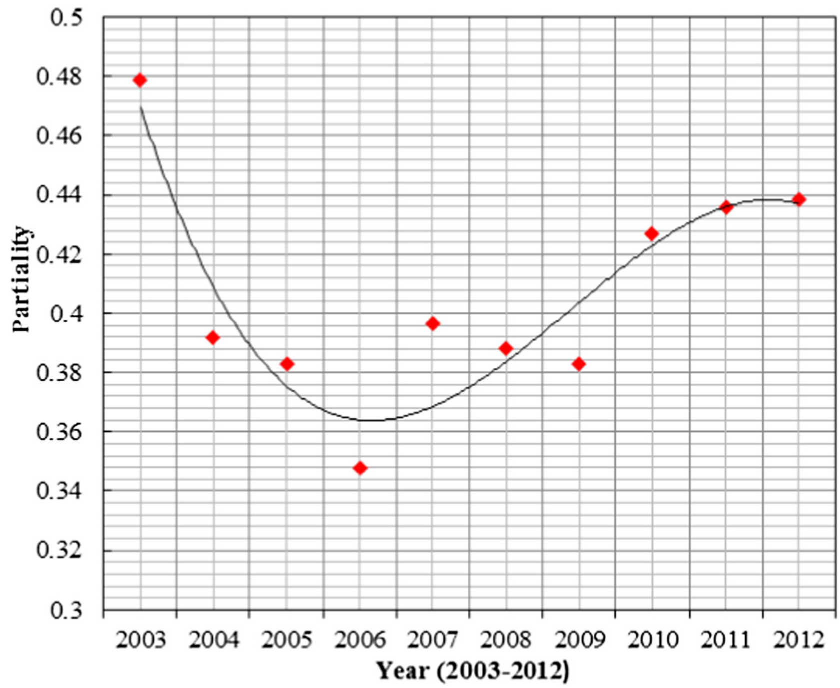

Fig. 7. Partiality of Tianjin's industrial structure to high water use (2003–2012): Data are adapted from Shang et al. (2016c).

began to weaken, it was not overshadowed by the other forces. The third stage is stagnant water use efficiency and increasing industrial water use. There was little room to improve water use efficiency after water use per 10,000 yuan of output reached 3 m^3 in 2008. With the expansion in industrial scale, industrial water use began to gradually rise. In this case, the technology-driven force was overshadowed by the other forces.

3.2.3. Empirical analysis of structure-driven force

Structure-driven force mainly refers to the effect that changing structures of different industrial sectors exert on industrial water use. To visually characterize this impact, Shang et al. (2016c) introduced the indicator (p) of partiality of industrial structure to high water use. A p-value closer to one indicates more partiality to high water use, and a value closer to zero denotes higher partiality to low water use. Fig. 7 shows the partiality of Tianjin's industrial structure to high water use during the period 2003–2012. Fig. 7 shows that the p-value remained below 0.5 throughout the period of 2003–2012, indicating that the current industrial structure is ideal for water savings. In terms of the curve's trend, the partiality first declined and then increased during the period 2003–2012. Specifically, the partiality decreased by 27.3% during the period 2003–2006 and increased by 26.1% during the period 2006–2012 to the pre-2003 level.

Fig. 8 shows a weak positive correlation between partiality and industrial water use, indicating that structure-driven force has a limited effect on industrial water use. Figs. 7 and 8 show that the constraint of water resources is not a dominant factor in Tianjin's industrial restructuring. The reform accounts for energy saving, efficiency improvement, and economic development. Industrial restructuring is not necessarily directed toward water conservation. Noticeably, the size of water-intensive industries demonstrated the tendency to expand after 2007.

3.3. Validation and application of decomposition results

From 2003 to 2012, Tianjin's industrial water use first exhibited a trend of decline, then a rise. Specifically, industrial water use shrank by 21.5% from 48.6 million m^3 to 381.30 million m^3 during 2003–2008 but later rebounded to 508.87 million m^3 in 2012. Based on the decomposition results illustrated in Table 1, we conducted a driving force analysis of this time span.

For the study period from the year 2003 to the year 2012, industrial output stimulated industrial water use in Tianjin and accounted for an average annual growth of 77 million m^3, which, on average, was 76 million m^3 before 2008 and 79 million m^3 after 2008. This indicates that, driven by fast industrial scale expansion, industrial water use grew consistently after 2008, which is in line with the correlation analysis results in Fig. 5. Technology, on the other hand, inhibited industrial water use in Tianjin and contributed to an average annual reduction of 79 million m^3. Notably, technology-driven reduction registered at 90 million m^3 before 2008 and 67 million m^3 after 2008. This implies that the improvement in industrial water use efficiency slowed down and stagnated after 2008, which is consistent with the analytical results in Fig. 6. The effect of structure on industrial water use was not stable; that is, structure could serve as a promoting factor in some years and an inhibiting factor in others. In the study period, promotion and inhibition occurred alternately, but promotion stood out after 2008, indicating increasing partiality of industrial structure to high water use. These results are also consistent with the results described in Figs. 7 and 8.

Based on the analytical results of Tianjin's industrial water use, we further compared the performance of the two decomposition models. As mentioned in Section 3.2, after 2008, industrial output grew markedly with an annual increment of 273.8 billion yuan, and industrial water use showed a positive correlation with output with a coefficient of up to 0.81. The industrial water use per 10,000 yuan of output, already low at 3 m^3 in 2008, indicated limited room for further improvement in water use efficiency. Consequently, with the expansion of industrial scale, industrial water use tended to gradually increase. In this case, technology-driven force is overshadowed by the other forces. From this viewpoint, a larger value of output and smaller value of technology should be reasonable at this stage. The Laspeyres decomposition results show that, during the period 2009–2012, the cumulative effect of output and

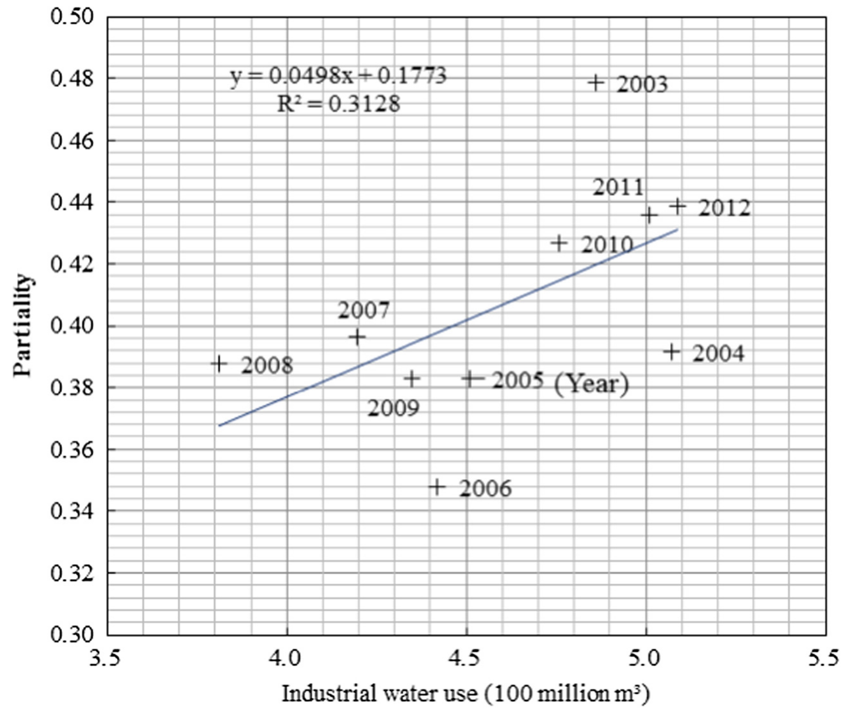

Fig. 8. Correlation between partiality and industrial water use (2003–2012): Data are adapted from Shang et al. (2016c).

technology was 317.56 million m^3 and 267 million m^3 and, according to the LMDI decomposition results, these numbers were 304.46 million and 267.32 million. Therefore, the Laspeyres decomposition results seem more reasonable.

In summary, the decomposition results obtained for the two models are consistent with analytical results obtained from quantitative analysis, justifying the validation of the two models. Moreover, the decomposition methods show superiority in analysis because they provide accurate numerical results rather than descriptive sentences that are typically used in quantitative analysis.

4. Conclusion and discussion

The Laspeyres model and the LMDI model are the two typical approaches for quantifying driving forces behind change. In this study, we used both models to decompose industrial water use and further validated the models through empirical analysis. The accuracy of the decomposition results is ensured because both refined Laspeyres model and LMDI model pass the time reversal and factor reversal checks. Additionally, the decomposition results of the two models agree with each other, with obvious differences for certain years. Nevertheless, the refined Laspeyres model for the case of Tianjin presents more reasonable results according to the qualitative analysis of industrial water use.

This study analyzed factors driving industrial water use in Tianjin during the period 2003–2012 and described changes in their effects at different stages in the recent decade, clarifying the contributions of industrial scale, structure, and water use efficiency. In terms of time scale, two distinct stages before and after 2008 were observed. Before 2008, technology was the primary factor causing changes in industrial water use, and its hindrance to the growth of industrial water use outbalanced the stimulating effect of output. In addition to structure inhibiting water use, industrial water use as a whole exhibited a downward trend. After 2008, however, output became the main factor influencing industrial water use, and its stimulation to industrial water use overshadowed technology-caused inhibition. At the same time, the improper adjustment of industrial structure increased water use. Overall, industrial water use showed an upward trend during this stage. The decomposition results of this study change the initial opinion that Tianjin has considered the rise in water use efficiency to be the primary goal of local industry restructuring over the past decade. Reduced water use may have resulted from Tianjin's development towards targets other than water savings. The availability of water resources are a major constraint factor to industrial development but in many cases, various factors including GDP growth, energy conservation, and emission reduction are considered in the adjustment of industrial structure. Hence, industrial restructuring is not necessarily oriented to saving water. When the share of water-intensive industries increases, restructuring can stimulate water use growth and, when the share decreases, restructuring can hinder water use growth. Considering the current water scarcity in Tianjin, this study advices the Tianjin local government to restructure local industries towards water-saving targets.

The change in the industrial water use can be attributed to changes in industrial output, water use per unit of output, and industrial structure. Therefore, this study summarized those contributors as output, technological, and structural factors. For empirical analysis, the output factor is expressed by industrial output. The larger the industrial scale, the larger the total industrial output and, thus the stronger the demand for industrial water. Industrial scale is an uncontrollable factor. The scale of local industries is expected to continually increase along with local socioeconomic development. The technological factor involves production technology and water use efficiency of industrial sectors. For empirical analysis, it is typically expressed by water use per unit of output, which varies significantly between industrial sectors. The greater the water use per unit of output, the more water is demanded. However, the water use efficiency is a controllable factor and can be improved by adopting water saving production techniques and strengthening total water use controls. The structural factor refers to adjustment of industrial structures, which is described by the proportion of different industrial sectors. Because the water use efficiency varies between sectors, any adjustment to the proportion of industrial sectors will lead to a change in water use. Industrial structure is controllable, and the shutdown or rectification of water-intensive industries and encouragement of low-water industries can be conducive to water saving.

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