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The Gap between Expectations and Reality: Assessing the Water Rebound Effect in Chinese Agriculture

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Abstract

Agriculture is a water-intensive industry; therefore, for policymakers trying to achieve a reduction in water use, the development of agricultural water-saving irrigation technologies to improve water utilization efficiency is of considerable interest. However, the real effect of technological progress on water savings falls short of expectations because of the existence of the rebound effect. This paper estimates the agricultural water rebound effect (AWRE) in China using a sequential Malmquist index and data of 31 provinces from 2002 to 2020. Furthermore, a Logit model is used to analyze the factors influencing the water rebound effect. The results suggest that the average AWRE ranges from -0.43 to 2.41 in Chinese provinces. Twenty-two provinces exhibit a partial rebound effect, while seven and two provinces exhibit a backfire and super conservation effect, respectively. Moreover, AWRE fluctuated around 0.5 from 2003 to 2013 and increased over time from 2015 to 2020. Additionally, water resource endowment has a negative effect on AWRE, while grain-crop ratio, the income of rural residents, and the irrigation infrastructure level have a positive effect on AWRE. Based on these results, policy implications are derived to mitigate AWRE in China.

Keywords: agricultural water use; rebound effect; technological progress; sequential Malmquist index; logit model.

JEL Classifications: E23, Q16, Q25.

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1. Introduction

Water is a basic natural resource that is necessary for human survival and development. With the rapid development of human society and the economy, the contradiction between the supply and demand of water resources has become increasingly prominent (Eliasson, 2015). In China, agriculture has accounted for an average of 63% of total social water use from 2000 to 2020 (China Water Resources Bullet). To reduce agricultural water use, agricultural water-saving irrigation technologies have been widely adopted, such as sprinkler irrigation, micro-irrigation, and drip irrigation under plastic film.[1]

Water intensity—the quantity of water used per unit of yield or output value—is commonly used to measure water-saving technologies. China's agricultural water intensity has decreased substantially, from 0.25 m^3/RMB to 0.11 m^3/RMB from 2002 to 2020; however, agricultural water consumption has not always decreased as expected (Fig. 1). This may be partly due to the water rebound effect (Berbel et al., 2018; Dumont et al., 2013; Li and Zhao, 2018).

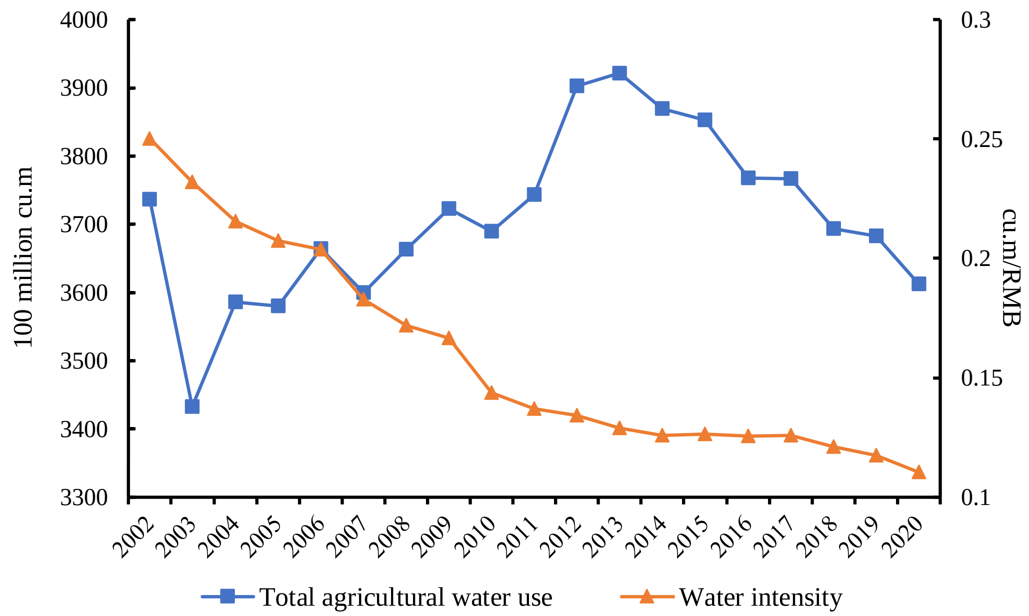

Fig. 1. Total water use and water intensity in China's agricultural sector. Data source: China Water Resources Bulletins 2002-2020 and China Statistical Yearbook 2003-2021.
Note: The water intensity was calculated by using the data of total agricultural water use and total agricultural output value. The total agricultural output value was set at 2002 constant prices.

[1] The related policies are in the China's National Water Conservation Planning Outline (2001-2010) and National Agricultural Water Conservation Outline (2012-2020).

The water rebound effect refers to the phenomenon where the water savings from water efficiency gains are partly or totally offset by an increase of agricultural water use stimulated by the reduced cost of production. Studies have identified the water rebound effect in the USA (Contor and Taylor, 2013), Spain (Berbel et al., 2015; Freire-González, 2019), and India (Fishman et al., 2015). Tong et al. (2014) and Xu and Yang (2022) have also pointed out that a rebound effect may exist in agricultural water use in China, but without quantify this effect.

This paper estimates the water rebound effect for the Chinese agricultural sector at the macro level and examines the impact factors of the water rebound effect. Although there are some studies (Song et al., 2018; Wang et al., 2020) on China's water rebound effect, their assessments of the water productivity and efficiency relied primarily on a production function method. They could not distinguish the different water efficiency improvements among provinces. In addition, Fei et al. (2021) applied a meta frontier data development analysis (DEA) method to estimate water efficiency, however, their analysis did not allow that the technology progressively improves over time. Moreover, they chose agricultural water use, capital, and labor as input indicators for the model, without considering the role of the available land in agricultural production. These limitations may introduce biases into the estimation of the water efficiency. Under this background, this study extends existing literature in two aspects: firstly, we use a sequential Malmquist index to measure the technological progress rate[2] at China's provincial level, which could avoid the phenomenon of pure technical backwardness occurring under technological innovation and thus avoid the potential efficiency biases in the existing AWRE studies; and secondly, we explore the factors that may impact the AWRE and then conduct a quantitative analysis to determine their influence on AWRE. To the best of our knowledge, research has not focused on a detailed and systematical study of this issue so far. Policy suggestions were also derived from the results, which helps to reduce agricultural water consumption.

The paper is organized as follows. Section 2 reviews the relevant literature. Section 3 introduces the methodology and shows the data in detail. Section 4 presents the empirical results. Section 5 concludes the paper and provides policy implications.

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2 Here, "technological progress" refers to generalized technological progress. Generalized technological progress is the contribution of factors other than material factors to economic growth, also known as total factor productivity (TFP). Generalized technological progress can be decomposed into technological progress (or pure technological progress) and technical efficiency change. The former refers to the improvement and innovation of technology, which is also known as pure technical progress. The latter refers to the efficiency of technology utilization in the production process.

2. Literature review

The original concept of the rebound effect can be dated back to the "Jevons Paradox". Jevons found that between 1830 and 1863, technology improvements led to a one-third reduction in coal consumption per unit of iron produced in Scotland. The substantially decreased cost of ironmaking and the associated increased profits, drove more manufacturers to invest in the iron-working industry. The expansion of this industry has resulted in a 10-fold increase in the demand for coal. At the same time, the declined costs have brought down the price of iron, driving downstream industries that use iron as raw material to increase their coal consumption (Jevons, 1865). Since the 1990s, the phenomenon of the rebound effect has widely become a concern for energy economists and energy analysts (Brännlund et al., 2007; Brookes, 1990; Greening et al., 2000; Saunders, 1992; Sorrell and Dimitropoulos, 2008). Other disciplines such as sustainability sciences, industrial ecology, and sociology have also noticed this phenomenon in recent years (Freire-González, 2023). Certain economists have pointed out that efficiency strategies to achieve sustainability often have other unintended effects because changes in behavior may partially offset environmental gains. This effect is known as the "environmental rebound effect" (Alcott, 2005; Hertwich, 2005; Font Vivanco et al., 2016; Font Vivanco et al., 2022).

Certain theoretical studies on agricultural water use also agree that a given efficiency measure has multiple impacts on the environment. These studies hold that water conservation technologies may miss the goal to protect and improve the ecological status of water sources. Gómez and Gutierrez (2011) presented a graphical example showing that contrary to common belief, a higher irrigation water use efficiency may increase pressure on aquatic ecosystems. Contor and Taylor (2013) outlined a mathematical demand function and illustrated a general case; they showed that under any non-zero marginal water cost scenario, improving irrigation efficiency enables rational irrigators (who are willing and able to do so) to purchase a quantity of irrigation water that sustains more consumptive use than in a previously less efficient system.

The occurrence of AWRE is similar to the causes of the energy rebound effect. Theoretically, under the condition of constant planting combination and irrigation intensity, an improvement of irrigation water efficiency should reduce water consumption by the same proportion. However, more effective irrigation systems also make water more productive. Farmers pursue profit maximization, and therefore, they will amend their choices according to the cost and income of production. To be more specific, the last drop of water generates a larger amount of agricultural product than the water used before with a lower irrigation efficiency; therefore, farmers may be willing to use more water in agricultural production than the water efficiency improvement can generate (Gómez and Pérez-Blanco, 2014). This is the same as the "output effect" in the energy rebound effect (Sorrell, 2009). In addition, because of the increase in water use efficiency, the actual irrigation cost decreases. Economic benefits motivate farmers to increase irrigation water use and expand the irrigated area (Contor and Taylor, 2013), thus producing a "scale effect".

Currently, the main methods used to study AWRE are the comparative analysis method (Contor and Taylor, 2013), the production function method (Song et al., 2018; Wang et al., 2020), data development analysis (Fei et al., 2021), and computable general equilibrium (Freire-González, 2019). The comparative analysis method assesses the direct rebound effect by comparing the change in water use before and after the improvement of water efficiency. The production function method and the DEA estimate the contribution of technological progress to economic growth and then calculate AWRE. Computable general equilibrium methods involve an economic simulation model, that is sometimes linked to an environmental model. This is a way to measure an economy-wide rebound effect by studying changes across the whole economic system caused by efficiency improvements. The second and third methods are typically used to study the rebound effect from the macroeconomic perspective because of their advantages of better data availability and simple calculation.

Based on previous studies on the rebound effect, the water rebound effect can be classified into five types according to its magnitude (Saunders, 2000): backfire (AWRE > 1); full rebound effect (AWRE = 1); partial rebound effect (0 < AWRE < 1); zero rebound effect (AWRE = 0); super conservation (or negative rebound) effect (AWRE < 0). Backfire implies that the improvement of irrigation efficiency increases water use. In contrast, super conservation is the ideal situation in which the actual reduction in irrigation water exceeds the expected reduction. This state, along with the zero rebound effect, and the partial rebound effect (to a lesser extent), contribute to the sustainable utilization of water resources.

There are certain disparities in the available empirical studies on the magnitude of AWRE. In the Eastern Snake River Plain, USA, Contor and Taylor (2013) identified a small rebound effect, where an increase of irrigation efficiency from 60% to 80% would result in a reduction in field delivery of irrigation water by 15%, but an increase in the consumptive use from irrigation by 3%. However, Pfeiffer and Lin (2014) obtained a large rebound effect in western Kansas, USA; they found that a shift to more efficient irrigation technology has increased groundwater extraction, which indicates a rebound effect exceeding 100%. Other scholars have also found the existence of AWRE at a macroeconomic level in China. Fei et al. (2021) concluded that the water rebound effect is positive in 30 Chinese provinces, with average short-term and long-term AWRE levels of 49% and 66%, respectively. Fang et al. (2020) found an average economy-wide water rebound effect of 70.3% in agricultural crop farming. They attributed the heterogeneity of the rebound effect between regions to differences in water endowment and irrigation land availability. Wang et al. (2020) found that in the Tianshan region, China, from 1996 to 2015, the agricultural water rebound effect under the macroeconomic level totaled 115%. The main reasons for this variation of results among these studies are differences in studied areas, measurement models, and methods.

In summary, there is a rebound effect for agricultural water use, but its magnitude remains controversially discussed among scholars. It is worth noting that technical progress is generally improving[3]. However, existing research on the irrigation water rebound effect at a macro scale level could not ensure that the technology is progressing over time. In addition, existing research focused on measuring the water rebound effect, while disregarding to analyze its influencing factors empirically. This paper addresses these two gaps in the literature.

3. Methods and Data

3.1. Definition and measurement of the agricultural water rebound effect

The rebound effect (*RE*) is related to the potential resource savings (*PS*) obtained from the efficiency improvement, as well as to the actual resource savings (*AS*) obtained from the technological effect (Dumont et al., 2013; Berbel and Mateos, 2014). To be more specific, *RE* is the ratio of the rebound resource consumption (*RC*) obtained from expanded economic scale to the potential savings induced by efficiency enhancement. This can be expressed according to Equation (1):

$$RE = \frac{RC}{PS} \times 100\% = \frac{PS - AS}{PS} \times 100\% \tag{1}$$

In this paper, AWRE is defined as the ratio of the incremental water consumption to the amount of expected water savings brought by technological progress. Fig. 2 shows a theoretical analysis of the water rebound effect.

[3] Here, "technological progress" refers to pure technological progress.

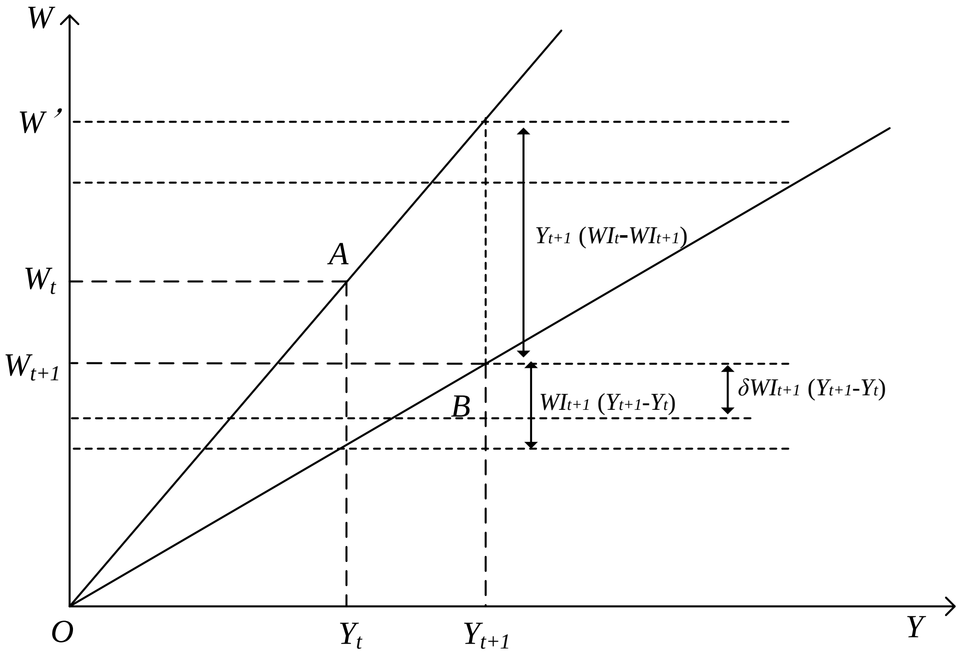

Fig. 2. The rebound mechanism of technological progress.

Assuming that Y_t represents the output of the agricultural sector in year t, WI_t represents the water intensity of the agricultural sector in year t. Then, the potential agricultural water savings caused by a decline in water intensity from year t to year $t + 1$ would be:

$$PS_{t+1} = Y_{t+1}(WI_t - WI_{t+1}) \tag{2}$$

The total additional water consumption can be described as $WI_{t+1}(Y_{t+1} - Y_t)$. Except for technical progress, other factors (such as the scale of input factors) can also promote agricultural growth and cause an increase in water consumption. Suppose that δ is the contribution rate of technological progress to agriculture growth; then, the rebound agricultural water use (*RWU*) can be calculated according to Equation (3) (Zhou and Lin, 2007; Wu et al., 2018):

$$RWU_{t+1} = \delta_{t+1} WI_{t+1}(Y_{t+1} - Y_t) \tag{3}$$

According to the above decomposition, the macro level AWRE in year $t + 1$ is:

$$AWRE_{t+1} = \frac{\delta_{t+1} WI_{t+1}(Y_{t+1} - Y_t)}{Y_{t+1}(WI_t - WI_{t+1})} \tag{4}$$

The next step in the measurement of the water rebound effect is to calculate the indicator of δ in Eq. (4).

3.2. Estimating the contribution rate of technological progress to economic growth

Efficiency can be assessed by the growth accounting method, production function method, stochastic frontier analysis, and DEA. Among them, the first three approaches require the setting of specific function forms. Inappropriate specification of the function form would result in inaccurate results. DEA has attracted much attention in recent years because of its remarkable advantages, which include its lack of requirements for specific production function forms, specific behavioral and institutional assumptions, and pre-determined assumptions of non-efficiency distribution.

Considering that agricultural production is an economic activity with multiple inputs, DEA was adopted to measure water efficiency. Production efficiency can be measured by the Malmquist index[4]. However, under the Malmquist index, the phenomenon of technology backwardness may emerge. To develop the conventional Malmquist productivity index, Shestalova (2003) combined the concept of the successive sequential production possibility set and proposed the sequential Malmquist index. The application of this model in this paper is described as follows:

Assume that *N* types of input factors $\boldsymbol{x} = (x_1, x_2, \dots, x_N) \in \boldsymbol{R}_+^N$ can produce *M* types of desirable outputs $\boldsymbol{y} = (y_1, y_2, \dots, y_M) \in \boldsymbol{R}_+^M$ in the productive process; the input-output combination of the decision making unit (DMU) *k* (*k* = 1, 2, …, *K*) for each period *t* (*t* = 1, 2, …, *T*) is $(\boldsymbol{x}_k^t, \boldsymbol{y}_k^t)$. The sequential production possibility set can be expressed according to Equation (5):

$$P^t(\boldsymbol{x}) = \{\boldsymbol{y} | \textstyle\sum_{t=1}^{T} \boldsymbol{X}^t \lambda^t \le \boldsymbol{x},\ \textstyle\sum_{t=1}^{T} \boldsymbol{Y}^t \lambda^t \ge \boldsymbol{y},\ \boldsymbol{\lambda}^t \ge \boldsymbol{0}\} \tag{5}$$

where $\boldsymbol{X}^t$ is a (*N*×*K*) matrix of inputs, $\boldsymbol{Y}^t$ is a (*M*×*K*) matrix of desirable outputs, and $\boldsymbol{\lambda}^t$ is a (*K*×1) weight vector assigned to different variables.

Then, the directional distance function of a sequential Malmquist index model can be written according to Equation (6) (Chung et al., 1997):

$$\vec{D}_k^t(\boldsymbol{x}, \boldsymbol{y}; g_y) = \max\{\beta : (\boldsymbol{y} + \beta g_y) \in P^t(\boldsymbol{x})\} \tag{6}$$

[4] The Malmquist index was first proposed by Malmquist (1953) for quantitative analysis of consumption. In 1982, Caves et al. (1982) first used the Malmquist index to measure the changes in production efficiency. Färe et al. (1992) combined the index with DEA theory, and since then the Malmquist index has been mostly used for dynamic analysis of input-output efficiency.

where β represents the maximum proportion to which the output combination can expand and shrink simultaneously along the direction vector $g_{\boldsymbol{y}}$, and $\beta \geq 0$. $\beta = 0$ means that this DMU is the most efficient one; otherwise, the DMU is inside the production frontier; the larger the value, the farther the DMU is from the front boundary of $P^t(\boldsymbol{x})$.

The sequential Malmquist index of the *k*th DMU from period *t* to *t* + 1 can be expressed as follows (Färe et al., 1989):

$$M^{t,t+1} = \left(\frac{\vec{D}_k^t(x^{t+1},y^{t+1})}{\vec{D}_k^t(x^t,y^t)} \frac{\vec{D}_k^{t+1}(x^{t+1},y^{t+1})}{\vec{D}_k^{t+1}(x^t,y^t)} \right)^{1/2} \tag{7}$$

Equation (7) represents the changes in total factor productivity (TFP). Here, $M^{t,t+1} > 1$, $M^{t,t+1} < 1$, and $M^{t,t+1} = 1$ indicate that the TFP from period *t* to *t* + 1 has increased, decreased, and remained unchanged, respectively. TFP is commonly used to represent the generalized technological progress; therefore, the rate of technological progress is $\rho_{t+1} = M^{t,t+1} - 1$. The contribution rate of agricultural technological progress to economic growth is:

$$\delta_{t+1} = \frac{\rho_{t+1}}{g_{t+1}} \tag{8}$$

here, g is the agricultural output growth rate.

3.3. Regression model for the influencing factors of the agricultural water rebound effect

Studying the factors that influence the water rebound effect is of great importance for policymakers tasked with controlling the water rebound effect. The influencing factors of AWRE include:

a) Water resource endowment. Water resource endowment is related to the abundance and adequacy of water resources. In general, for farmers in areas with abundant water endowment, it is easier to obtain irrigation water and the regional demand for water can be satisfied easily. Based on previous studies (Fang et al., 2020; Wei et al., 2021; Hamidov et al., 2022), water resource endowment is an important environmental factor that affects AWRE[5].

[5] The existing studies suggests that technological advancements could induce a large-scale rebound effect when the demand of certain resource is not well satisfied; the magnitude of the rebound effect becomes smaller when the demand approaches satisfaction (Fang et al., 2020).

b) Grain-crop ratio. The water requirements and planting patterns are inconsistent between various crops (e.g., grain crops, such as wheat and rice; cash crops, such as cotton and soybeans). With technological advances, farmers reallocate any saved irrigation water according to the characteristics of their crops. Crops that are irrigated far less than their actual water requirements and that can be irrigated easily are more likely to be irrigated. Thus, the grain-crop ratio may be closely related to the agricultural irrigation water use (Li et al., 2021; Zhang et al., 2018) and AWRE.

c) Rural residents' income. Rural household income is related to savings and production endowment. Agricultural output and water use change in case of agricultural capital accumulation (induced by an increase in farmers' income) meets the need for production scale adjustments. From this perspective, rural residents' income also affects farms' irrigation water demand and the rebound effect.

d) Irrigation infrastructure level. Agricultural irrigation infrastructure reflects a region's use of agricultural irrigation technology. The availability of agricultural infrastructure is related to agricultural water use and the rebound effect, as it determines whether farmland can be irrigated. The irrigation infrastructure level can be represented by the ratio of effective irrigation area to cultivated land irrigation area (Zhang et al., 2022), which is an important indicator that reflects the construction of farmland water conservancy[6].

Based on the above analysis, included explanatory variables are water resource endowment (*WE)*, grain-crop ratio (*GR*), rural residents' income (*RRI)*, and irrigation infrastructure level (*IF*). The regression model of the panel data is built as follows:

$$AWRE_{it} = \alpha_0 + \alpha_1 In(WE_{it}) + \alpha_2 In(GR_{it}) + \alpha_3 In(RRI_{it}) + \alpha_4 In(IF_{it}) + \varepsilon_{it} \tag{9}$$

where *AWRE* represents the agricultural water rebound effect, ε is a random error term, i represents the province, and t represents the year.

To examine the effect of these variables on the occurrence of the rebound effect, this paper applies a Logit model to estimate Equation (9); for this, the dependent variable AWRE is redefined. If AWRE is greater than zero, the dependent variable $AWRE_{it} = 1$; if AWRE is less than or equal to zero, the dependent variable $AWRE_{it} = 0$.

3.4. Data

[6] Effective irrigation refers to relatively flat cultivated land that relies on a specific water source and is equipped with irrigation projects or irrigation equipment.

Because of data limitations, this paper uses data of 31 inland provinces (including autonomous regions or municipalities) of China from 2002 to 2020 to study AWRE. The key to the sequential Malmquist model is the selection of input-output indicators. All input and output indicators used in this paper are presented in Table 1. The inputs of agricultural production include land, capital, labor, and resources. Second level indicators include the sown area of crops, the total power of agricultural machinery, and the other six indicators. The output indicator is represented by the total agricultural output value. The total agricultural output value was converted to 2002 constant prices. Water intensity is calculated using data of the total agricultural water and the real GDP.

Table 1
Water efficiency measurement index system.

Index types	First level indicators	Second level indicators	Unit
Input	Land	Sown area of the crops	1000 ha
	Capital	Total power of agricultural machinery	10 thousand kilowatts
		Amount of pesticide	10 thousand tons
		Amount of chemical fertilizer	10 thousand tons
	Labor	Number of labor force in primary industry	10 thousands person
	Resources	Total agricultural water use	100 million cu.m
		Agricultural diesel usage	10 thousand tons
Output	Gross output	Total agricultural output value	100 million RMB

The data in Table 1 were obtained from the China Statistical Yearbook, China Statistical Yearbook on Environment, China Agriculture Statistical Report, and other official data sources including China's Provincial Statistical Yearbook, National Bureau of Statistics, and Provincial Water Resources Bulletins.

Regarding the influencing factors of the water rebound effect, the data on total water resources of each province were obtained from the China Statistical Yearbook on the Environment. The data on the sown area of crops and rural residents' income were obtained from the National Bureau of Statistics, China Statistical Yearbook, and the China Rural Statistical Yearbook. Rural residents' income was transformed to 2002 constant prices. The data on irrigation infrastructure level were obtained from the Compilation of Agricultural Statistics in the Thirty Years of Reform and Opening Up and the China Statistical Yearbook. Table 2 shows the factors affecting AWRE.

Table 2

The impact factors of the agricultural water rebound effect.

Variables	Explanation	Unit	Mean	SD	Median	SE
Water resource endowment	Total water resources	100 million cu.m	915.81	973.43	583.85	47.73
Grain-crop ratio	Ratio of the sown area of grain crops to the total sown area of crops	1	0.66	0.12	0.67	0.01
Rural residents' income	Per capita disposable income of rural households	RMB	4977.43	2691.94	4317.49	131.98
Irrigation infrastructure level	Ratio of effective irrigation area to cultivated land area	1	0.76	0.34	0.65	0.02

4. Results and discussions

4.1. Estimation results for the agricultural water rebound effect

4.1.1. The sequential Malmquist index of the agricultural sector

The sequential Malmquist index was calculated to measure TFP. The average values of the sequential Malmquist index for each province from 2003 to 2020 are shown in Table 3. The average annual TFP growth rate in the Chinese agricultural sector from 2003 to 2020 is 4.8%. Beijing (1.113), Shanghai (1.102), and Qinghai (1.080) have the largest TFP values, while the TFP value in Jilin is the smallest, followed by Gansu and Hainan, with values of 0.996, 1.017, and 1.019, respectively. Among these, the TFP of the agricultural sector in Jilin has decreased. This is mainly due to the low technical efficiency of Jilin in 2016, which lowered both the TFP value of that year and the overall average. Moreover, TFP was all greater than one except for 2015 (Fig. 3). Agriculture is a weak-quality industry that is vulnerable to natural disasters. The decline of TFP in 2015 can be attributed to heavy rainfall and floods in 20 provinces across China in that year. Overall, the TFP of China's agricultural sector showed a fluctuating upward trend during the study period.

Table 3

Average sequential Malmquist index of Chinese provinces from 2003 to 2020.

Province	Value	Province	Value	Province	Value	Province	Value
Beijing	1.113	Shanghai	1.102	Hubei	1.031	Yunnan	1.050
Tianjin	1.060	Jiangsu	1.057	Hunan	1.035	Tibet	1.062
Hebei	1.064	Zhejiang	1.066	Guangdong	1.033	Shaanxi	1.058
Shanxi	1.049	Anhui	1.032	Guangxi	1.040	Gansu	1.017
Inner Mongolia	1.020	Fujian	1.066	Hainan	1.019	Qinghai	1.080

Liaoning	1.034	Jiangxi	1.019	Chongqing	1.046	Ningxia	1.046
Jilin	0.996	Shandong	1.050	Sichuan	1.056	Xinjiang	1.039
Heilongjiang	1.032	Henan	1.048	Guizhou	1.076	Average	1.048

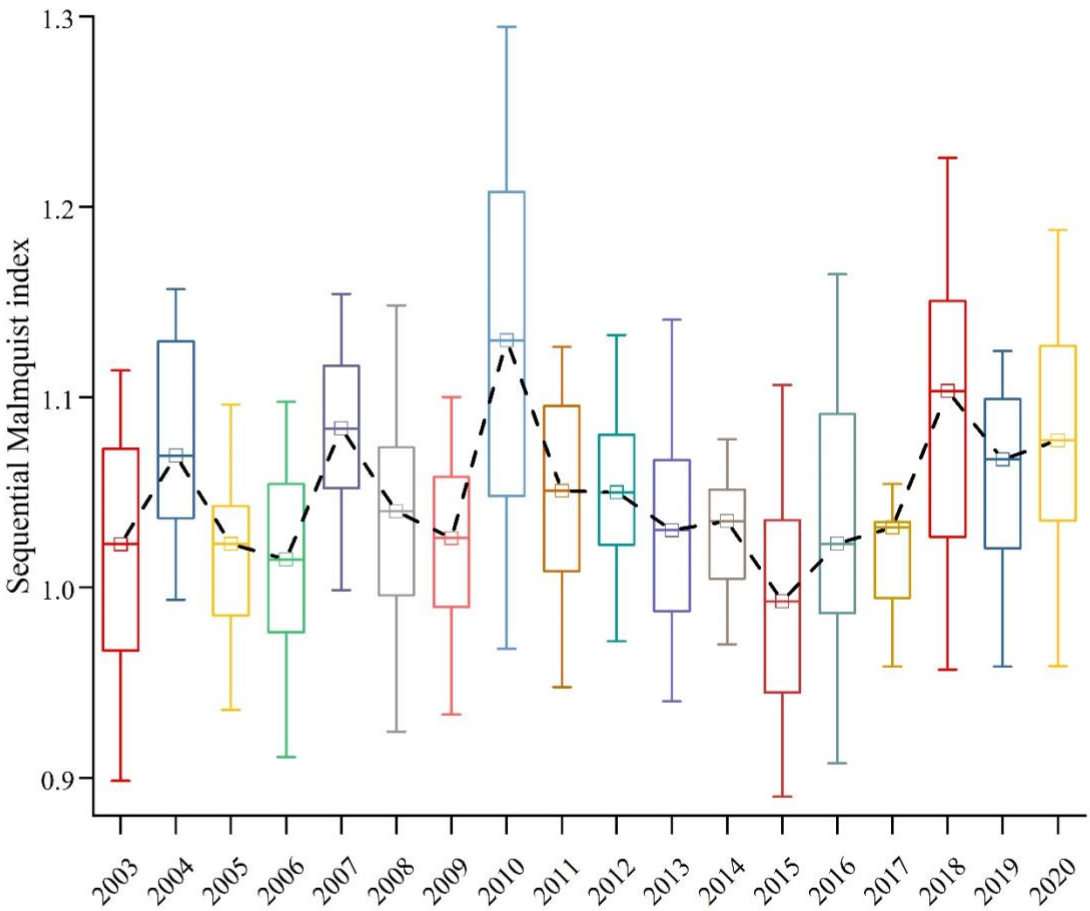

Fig. 3. Average sequential Malmquist index of China during 2003–2020.

Note: The chain-dotted line connection point is the average value of the sequential Malmquist index.

4.1.2. The rebound effect of agricultural water use

According to the definition of the water rebound effect presented in Equation (4), there is a scenario in which the calculated water rebound effect is only numerical but carries no economic meaning: when technology advances, water intensity increases and the expected water saving is negative. This means that technological progress has not contributed to the improvement of agricultural water efficiency. Because this does not meet the hypotheses based on which AWRE is defined, the calculated water rebound effect is nonsensical. Therefore, corresponding abnormal values were excluded when calculating the average water rebound effect in the agricultural sector. In addition, considering data validity, the study period was divided into three sub-periods to discuss AWRE.

The estimated results of AWRE in China over the years are shown in Fig. 4. AWRE was concentrated at around 0.5 in 2003–2013, but experienced an increasing trend over the period of 2015–2020. Fig. 5 visualizes the average AWRE at China's provincial level. The average AWRE at China's provincial level ranges from -0.43 to 2.41, indicating that three types of rebound effects for agricultural water use exist in China: backfire, partial rebound effect, and super conservation. AWRE ranges between 0 and 1 (partial rebound effect) for 22 provinces, indicating that in most Chinese provinces, agricultural water-saving technological progress achieved water savings to a certain extent, and that the water savings were partially offset. However, the water rebound effect was greater than 1 in Hebei, Shanghai, Fujian, Sichuan, Guizhou, Tibet, and Shaanxi. This result indicates that there was backfire (or Jevons' Paradox) in these regions, i.e., technological advances not only did not generate agricultural water savings but also led to an increase in water use. Different from the above regions, the reduction in agricultural water use in Jilin and Xinjiang exceeded the initially expected water savings, showing that in these two regions, technological progress has played a better role in terms of water saving.

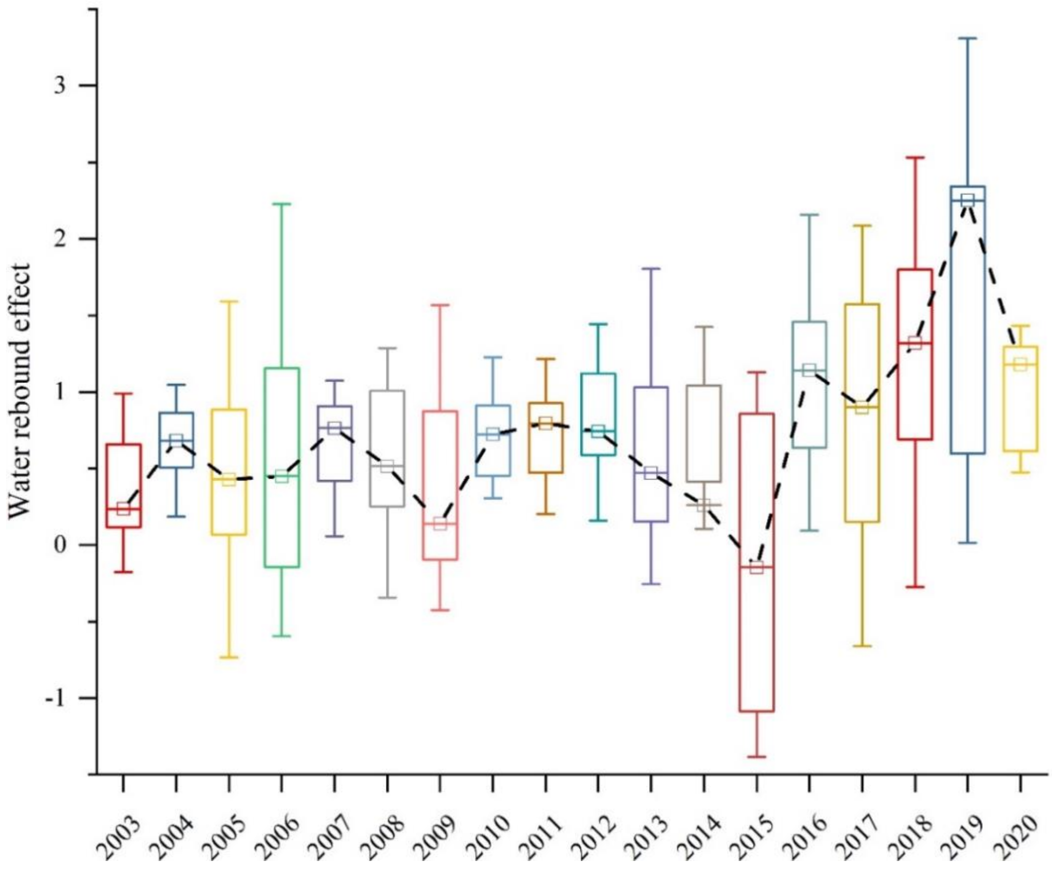

Fig. 4. Average AWRE of China during 2003–2020.

Note: The chain-dotted line connection point is the average value of the water rebound effect

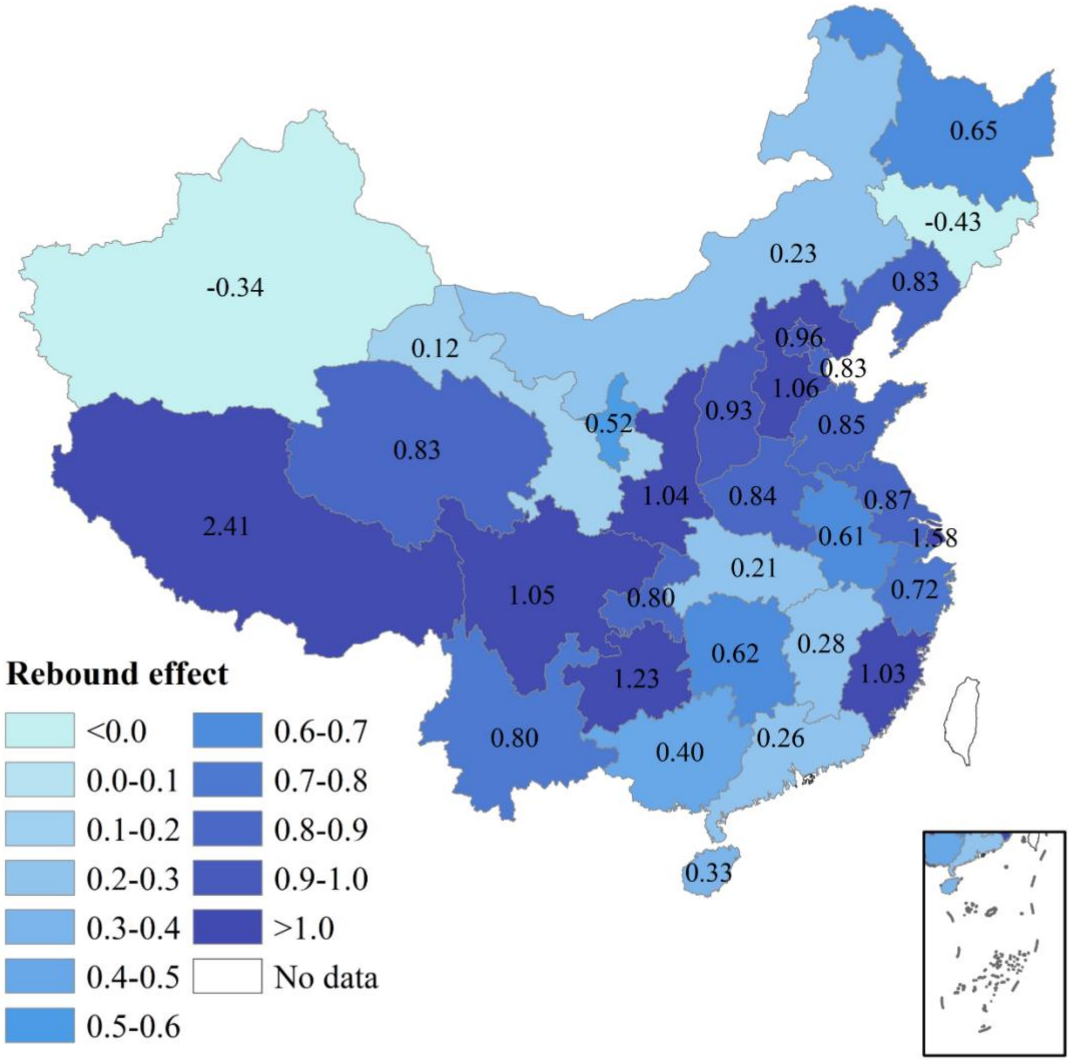

Fig. 5. Average AWRE of Chinese provinces from 2003 to 2020.

From a provincial perspective, there is heterogeneity in the AWRE values between provinces, and in certain provinces, there is even a large difference in the water rebound effect between years (Fig. 6). Inner Mongolia, Guangxi, and Yunnan show different types of rebound effects in the three periods, which are mainly related to TFP growth rate, water intensity, and economic growth. For example, in Inner Mongolia, the negative AWRE (-0.67) in 2009–2014 is caused by a decline in TFP growth in 2009 and a high agricultural water intensity with a relatively small increase in water intensity. The backfire (3.10) in 2015–2020 can be attributed to modest output growth and a large increase in TFP in 2019 and 2020. In addition, Beijing, Hebei, Liaoning, Jiangsu, Chongqing, and Qinghai maintained a stable and high AWRE over the three periods, while AWRE in Tianjin, Shanxi, Jiangxi, Hubei, Sichuan, Guizhou, Yunnan, Tibet, and Ningxia gradually increased over the three periods studied.

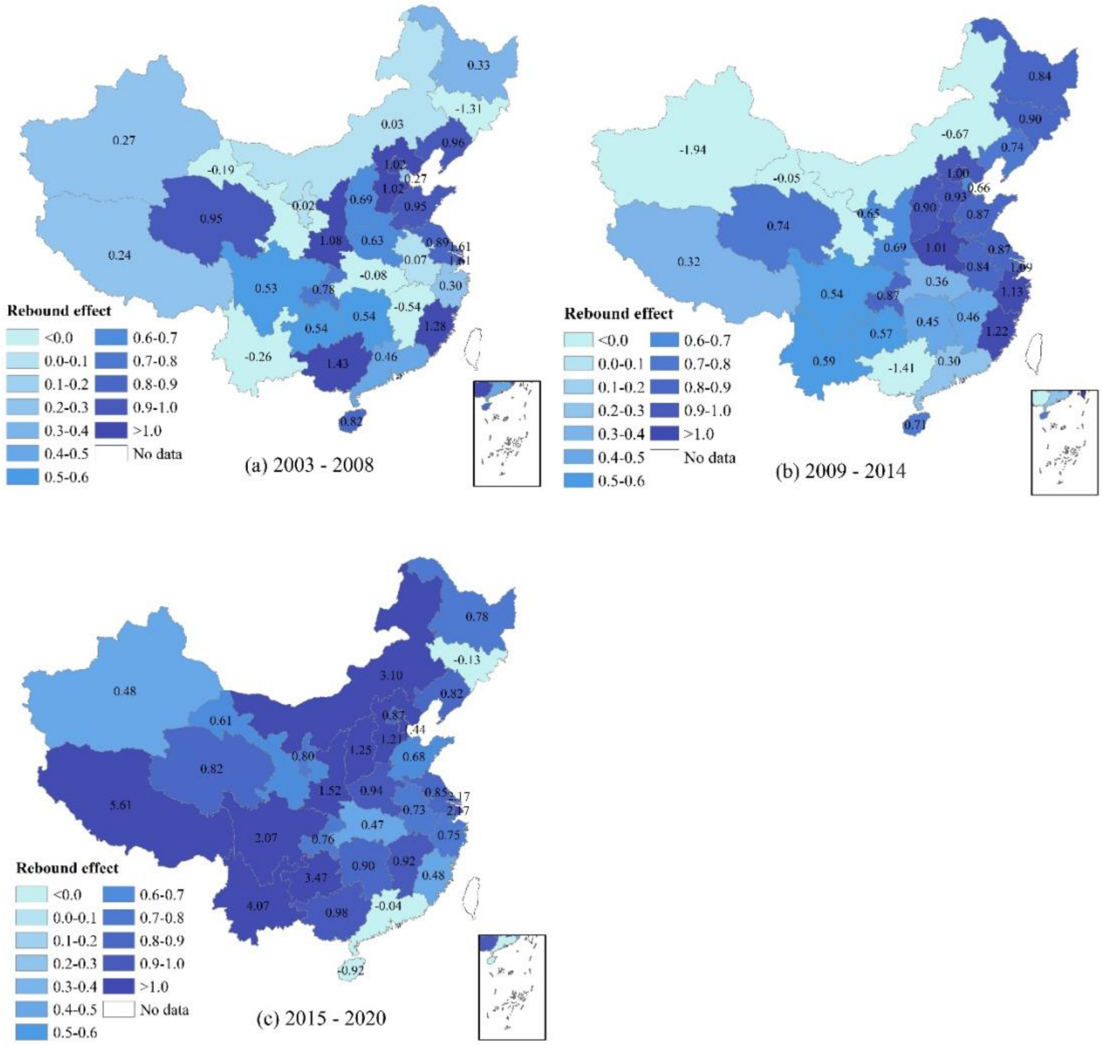

Fig. 6. Values of AWRE of Chinese provinces in different periods.

Note: (a), (b) and (c) represent the average values of AWRE of Chinese provinces in the three periods.

The Comprehensive Agricultural Regionalization of China compiled by the National Committee for Zoning of Agriculture Areas divides China into nine agricultural zones. This division is based on principles such as agricultural production conditions, agricultural characteristics, development directions, and the integrity of administrative units. The provinces included in these nine agricultural zones and the average rebound effect of each zone are presented in Table 4.

Table 4

The AWRE in nine agricultural zones of China.

Zone	Province	WRE
Northeast China Plain	Heilongjiang, Jilin, Liaoning	0.35
Northern arid and semiarid region	Xinjiang, Gansu, Ningxia, Inner Mongolia	0.13

Huang-Huai-Hai Plain	Beijing, Tianjin, Hebei, Shandong, Henan	0.91
Loess Plateau	Shaanxi, Shanxi	0.98
Qinghai Tibet Plateau	Tibet, Qinghai	1.62
Middle-lower Yangtze Plain	Jiangsu, Shanghai, Zhejiang, Anhui, Hubei, Hunan, Jiangxi	0.70
Sichuan Basin and surrounding regions	Chongqing, Sichuan	0.93
Southern China	Fujian, Guangdong, Hainan	0.54
Yunnan-Guizhou Plateau	Yunnan, Guizhou, Guangxi	0.81

Table 4 shows that the largest AWRE appears in the Qinghai Tibet Plateau and the smallest appears in the Northern arid and semiarid region. This may be because the climatic and topographic conditions in the Qinghai Tibet Plateau are favorable for farming; the progress of irrigation technology has mobilized the enthusiasm for water use in agricultural production and therefore, has resulted in a high rebound effect. Water resources are very scarce in the Northern arid and semiarid region. The limited water resources constrain the increase in agricultural water use, and thus, the rebound effect is relatively small (Song et al., 2018). AWRE in water-scarce areas (i.e., the Huang-Huai-Hai Plain, the Loess Plateau, and the Sichuan Basin and surrounding regions) is larger than in water-rich areas (i.e., Northeast China Plain, the Middle-lower Yangtze Plain, Southern China, and the Yunnan-Guizhou Plateau). This implies that the water rebound effect may be related to the water resource endowment, and the unmet needs for agricultural irrigation water are generally more pronounced in water-scarce areas than in water-abundant areas.

Like in previous studies (Song et al., 2018; Fei et al., 2021), this study also confirms the existence of the water rebound effect in the Chinese agriculture sector; however, the utilized methodology and results differ from past studies. Song et al. (2018) used a Hicks-neutral Cobb-Douglas production function to measure the contribution rate of technological progress; they found an AWRE value of 0.62. The approach they used potentially assumes that technological progress is the same across all regions each year, thus ignoring technological differences that exist over time and space. In their calculation of water utilization efficiency in the agricultural sector, Fei et al. (2021) applied the meta frontier DEA method and used related data from 2000 to 2017; they found that the short-term and long-term AWREs of China were 0.49 and 0.66, respectively. However, as mentioned in the introduction, they did not consider the land as an input indictor when they estimated the agricultural water use efficiency. The present study fills the aforementioned gaps, and therefore, the results can be expected to be more robust.

4.2. Regression results of impact factors on the agricultural water rebound effect

Through logit analysis of the AWRE in 31 provinces of China from 2003 to 2020, the regression coefficients of factors were obtained. As shown in Table 5, the LR statistic for the regression is 18.75, with a p-value of 0.00. This result indicates that independent variables are jointly significant in explaining the observed variation in the dependent variable. Moreover, the model was predicted to have a high level of accuracy, i.e., 86.30% correctly classified. To test the robustness of the model, ordinary least squares estimation of a linear probability model and robust standard error estimation were also used in the Logit model (Table 5). For each variable, the estimation results of the three methods are consistent in terms of signs of coefficients. In addition, the coefficients that were estimated using the Logit model with robust standard error and with ordinary standard error are the same. The correctly classified rate is also consistent. Therefore, the estimated results can be considered to be robust.

Table 5

Regression results of the impact factors of the agricultural water rebound effect.

	Logit	Logit (r)	LPM
Variable	Coef.	Coef.	Coef.
ln(*WE*)	-0.133	-0.133	-0.012
	(0.256)	(0.273)	(0.280)
ln(*GR*)	1.779**	1.779**	0.208**
	(0.027)	(0.039)	(0.037)
ln(*RRI*)	0.776**	0.776**	0.085**
	(0.025)	(0.017)	(0.017)
ln(*IF*)	0.380	0.380	0.044
	(0.332)	(0.315)	(0.313)
cons	-2.784	-2.784	0.326
	(0.380)	(0.370)	(0.338)
	LR=18.75 (0.001)	Wald=23.00 (0.000)	F=4.65 (0.001)
Correctly classified	86.30%	86.30%	86.30%

Note: **Denotes the significance at the 5% level. The figures in the brackets are *p*-values.

The results indicate that the regression coefficient of the water resource endowment is negative, which means that the more abundant the water resources, the smaller the water rebound effect; this result is consistent with the analysis of the water rebound effect for the agricultural zones of China presented in Section 4.1.2. This result can be explained because in areas where water resources are relatively abundant, the agricultural irrigation water demand is mostly satisfied. Therefore, famers in water-rich areas are not sensitive to a reduction in effective cost, and the irrigation water use rebound is relatively small after technological progress. However, in water-scarce areas, where water accessibility is difficult and agricultural water use falls short of the water demand for crop irrigation, farmers are willing to increase water use to meet their unsaturated needs; thus, the water savings from technological progress are more likely to be substantially offset. It is worth noting that there may also be an upper bound on the magnitude of AWRE in water-scarce areas, as described in Section 4.1.2. The reason is that the increase in agricultural water use is limited by the amount of water resources and irrigation water can generally not be mobilized.

The effect of the grain-crop ratio on the rebound effect is positive, indicating that the larger the share of the sown area of grain crops, the larger the water rebound effect. This may be due to the simpler management and lower input costs required of grain crops. After irrigation technology has been improved, farmers are more inclined to increase water use to increase grain yields. This result also implies that irrigation technology and cropping restructuring should be developed synergistically to achieve a reduction of agricultural water use.

Regarding the income of rural residents, the results indicate that AWRE increases with increasing income of rural residents. This result is contrary to empirical research regarding the energy rebound effect[7]. This may be attributed to differences between research subjects. Research on the energy rebound effect commonly focuses on consumers (e.g., households or individuals). The higher the income of consumers, the higher their level of utility, and therefore, the smaller the rebound effect. However, farmers are producers; on the one hand, farmers with high income have a high amount of capital available for agricultural production and a powerful production endowment. Thus, when energy efficiency improves, they can plant more crops to maximize profit, which leads to an increase in agricultural water use; on the other hand, farmers with high disposable income can afford more irrigation equipment. They may purchase more equipment to increase crop yield and expand the irrigated area, therefore, resulting in a high water rebound effect.

The level of irrigation infrastructure promotes AWRE. This is a somewhat plausible result, although the regression coefficient for irrigation infrastructure level is not significant. As technology advances, the irrigation efficiency of equipment increases. Regions with a high level of irrigation infrastructure have topographic advantages and are

[7] Most studies found that the energy rebound effect in low-income groups is higher than in high-income groups, e.g., Guertin et al. (2003), Sorrell (2007), Zhang et al.(2017), Shi et al. (2022).

generally equipped with irrigation facilities; they are also more likely to use these advantages to increase water use for irrigation to obtain higher yields.

5. Conclusions and policy implications

Technology advances are considered to be an effective way to reduce water use; however, because of the rebound effect, the actually saved quantities of water may not reach the expected levels. This paper adopts the sequential Malmquist index method to assess China's AWRE for the period of 2002–2020 at the provincial level. The influencing factors of AWRE are also examined.

The estimated results indicate that 22 Chinese provinces have a partial rebound effect, indicating that, for most Chinese provinces, water savings brought by technological advances have partly been offset by the response of farmers. In terms of the changes of the rebound effect, the agricultural water rebound effect concentrated at around 0.5 in 2003–2013 and experienced an increasing trend over the period of 2015–2020.

The exploration of AWRE in nine regions of China showed that the Qinghai Tibet Plateau has the largest AWRE, while the water rebound effect is the smallest in the Northern arid and semiarid region. Overall, in water-scarce areas, AWRE is larger than in water-rich areas. This result implies that, in general, in areas where water resources are scarce, there is a greater unmet demand for agricultural irrigation water compared to areas with abundant water resources. Regarding the factors influencing the rebound effect, the results indicate that water resource endowment has a negative effect on AWRE. Grain-crop ratio, the income of rural residents, and the level of irrigation infrastructure have a positive effect on the water rebound effect.

These findings suggest that improving technology and water efficiency is a useful measure to reduce water use in 22 Chinese provinces from an average perspective. Therefore, financial investment into the research and development of agricultural water-saving technologies is encouraged to improve irrigation water efficiency. However, because of the rebound effect, efficient measures need to be coordinated with other policies to achieve expected water-saving targets. For regions with poor water resources and unsuitable agricultural crop structures, the government should encourage farmers to choose suitable drought-resistant cultivars. Converting grain crops into cash crops is also an efficient way to decrease AWRE. Moreover, as the income of rural residents and the level of irrigation infrastructure can increase AWRE and water cannot be saved by restricting the development of agriculture, farmers should be encouraged to spend less cost savings from technological progress on input indicators that use more water. Water quotas may contribute to restricting the use of irrigation water and ensure water-saving effects of technology enhancement with agricultural economic growth.

Two aspects of this research would benefit from further research. First, changes in agricultural water intensity are not only achieved by irrigation technological progress but also by the crop planting structure effect. Because of data limitations, the effect of irrigation technology progress on water intensity change was not extracted when calculating the water rebound effect. Future research could calculate the irrigation water use of each crop, and then decompose the water intensity to obtain more accurate results. Second, similar to energy efficiency measures, water conservation measures can also reduce the production cost of the agricultural sector. Such cost savings are equivalent to an increase in capital for agricultural production. Whether farmers will increase their use of irrigation water, and whether there will be a rebound effect after water conservation policies have been implemented remains to be studied.

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