Oasis Agriculture: Improving Water Usage Efficiency Within River Basin

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X. Deng, J. Gibson (eds.), *River Basin Management*, Ecohydrology,
https://doi.org/10.1007/978-981-10-6949-9_4

Abstract

The Heihe River Basin (HRB) in Gansu Province is the second largest inland river basin in the arid region of Northwest China. An agricultural oasis is a typical landscape in arid regions providing precious fertile soil, living space, and ecological services. The agricultural oasis change has been one of the key issues in sustainable development in recent decades. In this chapter, we examined the changes in the agricultural oasis in HRB and analyzed the socioeconomic and climatic driving forces behind them. It was found that the agricultural oasis in HRB expanded by 25.11% and 14.82% during the periods of 1986–2000 and 2000–2011, respectively. Most of the newly added agricultural oases in HRB were converted from grassland (40.94%) and unused land (40.22%). The expansion in the agricultural oasis mainly occurred in the middle reaches of HRB, particularly in the counties of Shandan, Minle, Jinta, and Jiuquan. There has been very limited research on the water-use efficiency for soil conservation in the lower Heihe River Basin, a typical water-scarce area where the soil conservation service plays a key role in guaranteeing the ecological safety of the northern part of China. The soil conservation service based on soil conservation amount was estimated with an experiment-based model in this study. The water-use efficiency has direct impacts on the water consumption of agriculture production and is vital for water conservation at both local and regional extent. Taking the HRB as the case study area, this study also explores the changing trajectories of agricultural water use based on the input-output data of 2003–2012 and estimates the water-use efficiency using data envelopment analysis, Malmquist total productivity index, and the decomposition of total factor productivity. Further, the influence of driving factors on the water-use efficiency is analyzed with the Tobit model. The research results indicate that the average agricultural water-use efficiency in different counties is all lower than 1 during 2003–2012, indicating that there is still improvement space in the agricultural water-use efficiency. In addition, there is obvious heterogeneity in the agricultural water-use efficiency among different counties, especially prior to 2009. The research results from the Tobit model indicate that agricultural investment and production, economic growth, industrial restructuring, and agricultural plant structural adjustment have significant influence on the agricultural water-use efficiency. The research results can provide significant references for agricultural water-use management in the middle reaches of the HRB and other similar regions in Northwest China.

Keywords
Water-use efficiency · Oasis · Soil · Agriculture

Introduction

Water resource is one of the most basic and critical elements for the living and production of human beings. The stable supply and efficient use of water resources play an important role in guaranteeing the sustainable socioeconomic development (Deng and Zhao 2014). Water is usually the single most limiting factor for provision of ecosystem services, and water scarcity is impacting human welfare worldwide, especially in arid and semiarid regions that are very sensitive to climate change and land use and land cover change. UN World Water Development Report reveals that 66 countries with 21% of the world population would turn from moderate water shortage to severe situation by 2050, indicating great differences occur in global water distribution with severe water disequilibrium, which brings great challenge to the regional water supply. Although an oasis covers less than 5% of the total area in arid and semiarid regions in China, it holds more than 90% of the population and 95% of social wealth in these regions (Wang et al. 2008).

An oasis not only provides precious fertile soil and living space for human beings in the barren desert but also regulates the regional climate by the vegetation and water resources within it. Therefore, the oasis ecosystem directly influences the environmental and social security in arid and semiarid regions. As a country with large population, China has been evaluated as one of the major countries with apparent unbalanced water supply and demand in the Millennium Ecosystem Assessment report (Duraiappah et al. 2005). The utilization of water resource, especially agricultural water resource, plays an important role in the economic development. Agricultural water consumption accounts for the largest proportion in China. According to the Statistics in the Ministry of Water Resources of the People's Republic of China, 51.5% of the cropland production depends on irrigation in 2014 (Deng et al. 2014). Arid and semiarid regions cover more than 30% of the land on the earth's surface and 22% of the land area in China. However, coincident with rapid growth in water demand is the potential for substantial reduction in water supplies in arid regions. Runoff of many rivers in arid regions showed a declining trend under the influence of the climatic and land use change during the past decades. Besides, rapid socioeconomic development that drives land use change, which is altering the hydrologic system and increasing water needs for industrial, domestic, and environmental uses, has potentially large impacts on water resources (Zhang et al. 2011). As a result, the traditional water utilization approach in these arid and semiarid regions is now facing a big challenge, which appeals to people to develop water-saving irrigation and enhance water-use efficiency for sustainable water use.

An agricultural oasis is defined as cultivated land that can be irrigated by human activities (Bai et al. 2014). Since an agricultural oasis can provide the necessary grain for population growth, it plays a vital role in sustainable social development. Enhancing water-use efficiency is a critical response to growing water scarcity, and it is necessary to carry out in-depth research on water-use efficiency, which can provide valuable reference information for scientific water resource allocation to make more efficient use of limited water resources.

There have been extensive researches on water resources, including water protection, effective utilization of water resources (Huang et al. 2013), and evaluation of water security (Chen et al. 2013); particularly, the water-use efficiency has always been the core issue in different countries (Abu-Allaban et al. 2015). The research on the agricultural water-use efficiency started in the middle of the twentieth century. Departments within UN specially established research institutions for water resource issues (Chen et al. 2015a). There have also been many scholars attempting to find out ways to improve the agricultural water-use efficiency. For example, Li et al. (2015a, b) reveal that water-use efficiency was uneven in the 31 provinces of China, with the irrigation efficiency in Hunan and Jiangsu Province (irrigation land) reaching only 60% during 2005–2012. In addition, the average water-use efficiency was 30% in Northwest China in 2006, where only 3% of the water was effectively used and the rest water was wasted (Zhang et al. 2014), while the water-use efficiency has improved significantly in some regions of Northwest China. For example, Minqin County, a typical agricultural area of Northwest China, has experienced three stages to achieve the comprehensive agricultural water use during 2000–2003, and the water-use efficiency proliferated from 22% to 42% during 2004–2008, while the water-use efficiency increased with 6% annually; and from 2009 to 2012, the efficiency finally reached 76%.

Water-Use Efficiency and Oasis Farmer Income

Uneven Water Use in China

According to the National Agricultural Water-Saving Outlines for 2012–2020 published by the Ministry of Water Resources of the P.R. China in year 2012, water-saving programs efficiently retarded the consumption of water stock. Water-use efficiency had increased about 20% from year 2000 to 2013. However, irrigated water use per ha decreased from 15 cubic meter in year 2000 to 24 cubic meter in year 2013. Further, with the increasing demand of water in urban area, the proportion of water use has changed in both agricultural and nonagricultural sectors which fluctuated under 3% over time, and the growth rate of the total amount of water use continually increased about 1% per year (Fig. 1).

Water-saving programs have pushed the industries toward transformation. Through advanced drought-enduring seeds along with their fostering and widely sown, the average yield of crops had arisen from 1.33 kg in year 2000 to 1.75 kg in

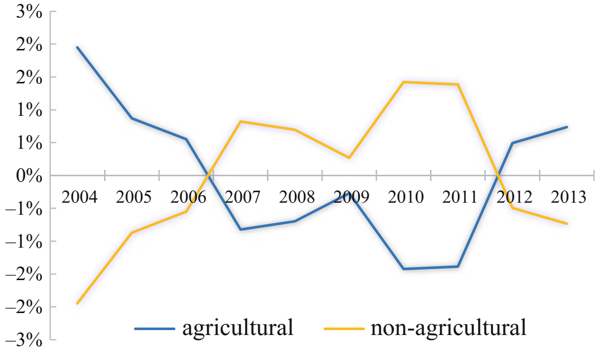

Fig. 1 Water-use proportional changes of agricultural and nonagricultural sectors in the years 2004–2012 (Reprinted from Zhan Wang et al. (2015) with permission of Physics and Chemistry of the Earth) (Data source: National Bureau of Statistics of China (NBSC) in years 2004–2013)

year 2013 from per cubic meter water input. The efficiency of fertilizer and pesticide use with respect to yield was improved around 15%. Over 2000 firms had invested on research and development of water-saving technique and equipment, which successfully supported annual increase of irrigation facilities covering over 200 million ha per year. Until year 2013, irrigated area was 63.47 million ha, about 43% of them covered by irrigation facilities. Moreover, regulations of regional water quota, implementation of forced water-saving technique, installation of water-saving equipment for industrial water consumption, and retreatment including some state subsidies collectively had impacted positively on related industries to save water consumption cost to some extent (Deng et al. 2014).

Impacts of sparing use of water on farmer income of China are rarely researched. Blanke et al. (2007) tended to study household behaviors to irrigated water-saving against drought resistant of cultivation and discussed water-saving technology development and its acceptance in China. Gilg and Barr (2006) did survey research to find evidence that motivation of household behaviors for water-saving through the purchase investment decision of water-saving facilities and their water-use actions. These ideational research designs probe into perception of respondents on water-saving facilities that were practically used in daily living or agricultural production. Wang et al. (2015) analyzed economic welfare of rural and urban residents can benefit from water projects at regional scale that supposed to be achieved by either regional or national government investments to irrigation facilities. However, we do not know yet how much farmer income benefit from sparing use of water at the national level.

Spatial distribution of the total amount of water use is uneven in China. According to regional division of China in geographical categories, there were three large regions: Eastern China, Central China, and Western China. Overall, the consumption of water in China was 556 billion ton in year 2012. Eastern China consumed 218 billion ton of water which accounts for 40% of the total amount of water use in year 2012. Jiangsu (55 bt), Guangdong (45 bt), and Shandong (22 bt) were the top three highest provinces in water use in Eastern China, as shown in Table 1. In Central China, the consumption of water amounted to 196 billion ton in

Table 1 Total amount of water use in each province of China in year 2012

Eastern China		Central China		Western China	
Beijing	3588	Shanxi	7339	Inner Mongolia	18,435
Tianjing	2313	Jilin	12,982	Guangxi	30,301
Hebei	19,531	Heilongjiang	35,890	Chongqing	8294
Liaoning	14,223	Anhui	29,264	Sichuan	24,592
Shanghai	11,598	Jiangxi	24,254	Guizhou	10,082
Jiangsu	55,223	Henan	23,861	Yunnan	15,183
Zhejiang	19,812	Hubei	29,929	Tibet	2981
Fujian	20,008	Hunan	32,880	Shaanxi	8804
Shandong	22,179			Gansu	12,305
Guangdong	45,102			Qinghai	2740
Hainan	4533			Ningxia	6935
				Xinjiang	590
Total	**218,110**		**196,399**		**141,242**

Note: Amount of water used is measured in million ton
Data source: NBSC in year 2012 (Reprinted from Zhan Wang et al. (2015) with permission of Physics and Chemistry of the Earth)

year 2012. Heilongjiang (36 bt), Hunan (33 bt), and Hubei (29 bt) were found to be the top three highest provinces in water use in this region. Similarly, Western China consumed 141 billion ton of water, and the provinces of Guangxi (30 bt), Sichuan (24 bt), and Inner Mongolia (18 bt) were ranked as top three in water use.

Spatial distribution of per capita water use is uneven in China. The per capita water use is the amount of total water use per person, which is the total amount of water use in year 2012 divided by the total population of each province in China. Population of China was 1347.89 million by the end of year 2012.The highest average per capita water use was in Central China (462 t) as shown in Table 2. That was quite close in Eastern China (390 t) and Western China (388 t) in year 2012. Per capita water uses of Shanxi (203 t), Henan (254 t), and Jilin (472 t) were the three lowest in Central China; Tianjing (164 t), Beijing (173 t), and Shandong (229 t) were the three lowest in Eastern China; and Xinjiang (26 t), Shaanxi (235 t), and Chongqing (282 t) were the three lowest in Western China in year 2012.

The relationship between water use and farmer income is ambiguous. According to the statistics of NBSC year 2004–2013, the average farmer income in each province of Eastern China was about 1871 in 2012 USD, which was the highest among three large regions, and that of Central and Western China was sequentially about 1215 and 952 in 2012 USD as shown in Table 3.

Obviously, Eastern China has the highest water use and the highest average farmer income. It seems that there is a linear positive relationship between the total amount of annual water use and the average of contemporaneous farmer income during years 2004–2012. However, this relationship is uncertain with population distribution and may vary over time, as shown in scatter plot in Fig. 2, indicating there is no any observable relationship from year 2002 to 2012.

Table 2 Amount of per capita water use in each province of China in year 2012

Eastern China		Central China		Western China	
Beijing	173.4	Shanxi	203.2	Inner Mongolia	740.4
Tianjing	163.7	Jilin	472.1	Guangxi	647.2
Hebei	268.0	Heilongjiang	936.1	Chongqing	281.6
Liaoning	324.1	Anhui	488.7	Sichuan	304.5
Shanghai	487.3	Jiangxi	538.5	Guizhou	289.4
Jiangsu	697.3	Henan	253.7	Yunnan	325.9
Zhejiang	361.7	Hubei	517.9	Tibet	967.9
Fujian	533.8	Hunan	495.3	Shaanxi	234.6
Shandong	229.0			Gansu	477.3
Guangdong	425.7			Qinghai	478.2
Hainan	511.1			Ningxia	1071.9
				Xinjiang	26.4
Average	**390.5**		**462.0**		**387.7**

Note: Amount of water used is measured in million ton
Data source: NBSC in year 2012 (Reprinted from Zhan Wang et al. (2015) with permission of Physics and Chemistry of the Earth)

Table 3 Average farmer income in each province of China in 2012 (USD)

Eastern China		Central China		Western China	
Beijing	2610.0	Shanxi	1007.0	Inner Mongolia	1205.8
Tianjing	2221.9	Jilin	1362.1	Guangxi	951.7
Hebei	1280.2	Heilongjiang	1363.0	Chongqing	1169.6
Liaoning	1486.5	Anhui	1134.3	Sichuan	1109.1
Shanghai	2820.4	Jiangxi	1240.3	Guizhou	753.0
Jiangsu	1933.0	Henan	1192.1	Yunnan	858.1
Zhejiang	2305.3	Hubei	1243.8	Tibet	906.0
Fujian	1579.0	Hunan	1178.6	Shaanxi	912.9
Shandong	1496.5			Gansu	713.9
Guangdong	1670.1			Qinghai	849.8
Hainan	1173.5			Ningxia	979.1
				Xinjiang	1012.9
Average	**1870.6**		**1215.2**		**951.8**

Data source: NBSC in year 2012 (Reprinted from Zhan Wang et al. (2015) with permission of Physics and Chemistry of the Earth)

Empirical Study Between Water Use and Farmer Income

Key Variables

Farmer income is mainly from selling agricultural production. Water usually is considered as a kind of special goods either as common-pool goods with low price or as free public goods attributed to water rights in an agricultural production process (Perry et al. 1997). Classic economic theory addresses that total consumption demand drives the

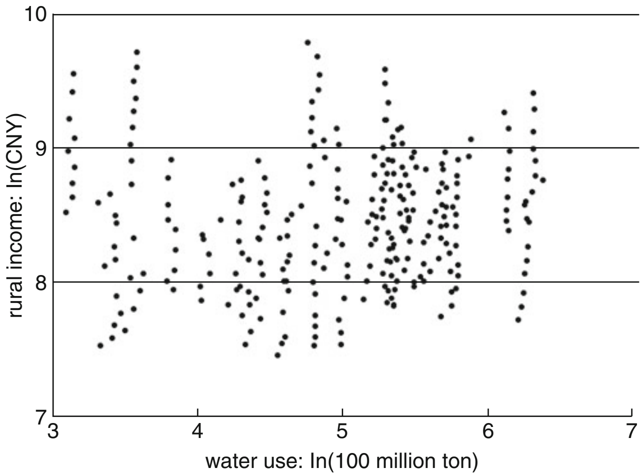

Fig. 2 Scatter plot of unobserved relationships between water use and farmer income in China in Napierian logarithmic numbers for the years 2004 through 2012 (Reprinted from Zhan Wang et al. (2015) with permission of Physics and Chemistry of the Earth)

market equilibrium points back to the optimum path. Under the assumption of unlimited natural resource with unlimited technology improvements, higher demand of resource consumption kicks the critical point at the higher price, driving the bigger gap between demand and supply that leads to market failures when faced with limited resource supply in reality. Water is a kind of special goods, which carries the capacity of both goods and bads. The more water intake, the more discharge with pollution are generated over spatiotemporal distribution. Kelman (1978) reinforced an ideology in Coase theorem by introducing a case study of externality of upstream water pollution in a maximum production process influencing to downstream residential water consumption and bringing about potential agricultural loss of environmental deterioration. These unpredictable losses are caused by overconsumption and disordered exploration of natural resource in the transaction process of economic development with consumption demand increases. Furthermore, it is quite difficult to evaluate social welfare benefited from industrial transformation but lose from environmental deterioration in the past two centuries, although residential quality of life in some regions has been improved. However, that overuse of water and exploration of other resources are still a hard-core strategy for world development. Indeed, China's water shortage has been harming farmer income and threatening worldwide agricultural production due to huge demand of food security. Therefore, the debates between theoretical detection and empirical study have arisen to discuss utilization of water resource in sustainability.

In this research, we aim to study farmer income (*lnfinc*) changes caused by water consumption and seek the impact of sparing water use (*lnwater*) on farmer income changes. We started from a Pool-OLS regression as the following Eq. 1 shows, which will give a brief picture of the relationships between dependent and independent variables:

$$\ln finc = \alpha + \beta_1 \ln pop + \beta_2 \ln water + \beta_3 \ln ele + e \quad (1)$$

where β_1 is the elasticity of how many percent changes in farmer income (*lnfinc*) in 1% changes in population (*lnpop*), β_2 presents how many percent changes in farmer income (*lnfinc*) in 1% changes in water use (*lnwater*) changes, and β_3 is the elasticity of how many percent changes in farmer income (*lnfinc*) in 1% changes in electric power (*lnele*). α is the unknown intercept, and e is the error term.

Viewed from the macroperspective on water allocation, electric power usually is used for representing the capability of water achievement in a region, which is assumed economic assessment of a level of regional development inclines to the level of electric power consumption, and presents the difference of regional characteristics of regional economies in China. For this reason, we set a fixed effect model to further look over both structural changes and variation changes at the provincial level from year 2004 to 2012 in the following constructed Eq. 2:

$$\ln finc_{it} = \alpha_{it} + \beta_1 \ln pop_{it} + \beta_2 \ln water_{it} + \beta_3 \ln ele_{it} + \mu_i + \sigma_{it} \quad (2)$$

where μ_i catches the individual-level effect in each region $i = 1,2,\ldots 31$ in China and captures the cross-sectional effect of panels over variant time t = year 2004, 2005,. . ., 2012.

To examine temporal impacts of regional characteristics of independent variables on farmer income, all variables in a panel dataset have to be tested in a stationary series. Intuitively, economic indices including farmer income, population, and electric power consumption would be in a stationary increasing trend. While water use depends on the fluctuated supply of natural resource over time, it may not be in stationary. If the unit root test for panel-data models proves the above assumptions by using Stata software, the results reported by fixed effect model may distort temporal impacts of water use on farmer income. In order to stick out those defects, a dynamic panel-data model would be considered to suit for this issue. In other words, the results of fixed effect model will prove that the impacts of water-use changes on farmer income cannot be ignored even if this model not suitable for this case study.

Data Description

Data are derived from the NBSC (year 2004–2012). Specified variables include dependent variable, farmer income (*lnfinc*), and independent variables, population (*lnpop*), water use (*lnwater*), and electric power (*lnele*) of 31 provinces of China. All variables are transformed into Napierian logarithmic format for estimating relationships in elasticity. The following Table 4 presents the summary statistics of all the variables of 31 provinces of China.

Empirical Analysis Results

The results from Pool-OLS report biased estimation of the increase of water use having negative impacts on farmer income in China. See Table 5. The arguments here are that coefficient of water use with a negative sign is not statistically

Table 4 Data description of specified variables of 31 provinces of China during years 2004–2012

Variable		Mean	Std. dev.	Min	Max	Observations
Farmer income	Overall	8.41	0.56	7.29	9.88	$N = 372$
[lnfinc]	Between	0.37		7.88	9.29	n = 31
	Within	0.42		7.68	9.19	T = 12
Population	Overall	8.06	0.87	5.55	9.27	$N = 434$
[lnpop]	Between	0.88		5.65	9.17	n = 31
	Within	0.05		7.84	8.31	T = 14
Water use	Overall	4.94	0.84	3.09	6.38	N = 279
[lnwater]	Between	0.85		3.13	6.30	n = 31
	Within	0.06		4.73	5.14	T = 9
Electric power	Overall	6.18	1.00	2.56	8.44	$N = 603$
[lnele]	Between	0.91		2.92	7.44	n = 31
	Within	0.63		4.63	7.66	T = 19

Note: N is the observations in n provinces in T time periods. Data within the missing years did not participate analysis (Reprinted from Zhan Wang et al. (2015) with permission of Physics and Chemistry of the Earth)

significant. Then, the fixed effect model is designed for specifying stability of the regression with regional characteristics of water use for farmer income in each province. Exactly as our assumptions, the estimation results show that water use is one of the key elements to farmer income. Comparing to individual effect, within-panel serial correlation in the idiosyncratic error term is much lower. It indicates that heterogeneity in fixed effect model inclines to regional identification with less heteroscedasticity, so that the regional characteristics are significantly distinguished (Table 5). However, the unit root test with Fisher option of either Dickey-Fuller test or Phillips-Parron test proves our previous assumptions that the fixed effect model may distort stochastic error term in temporal variation because all test results fail to reject the null hypothesis that unit root exits in the variables of farmer income, population, and electric power, but not in water use.

To study further variation of impacts over time and to identify the possibility of distortion due to autocorrelation, the dynamic panel-data model with systematic GMM (DPD-SYS) is introduced to specify time lags caused by autocorrelation in error term. Empirical results of DPD-SYS show statistical significance of population size in China to farmer income. Slightly negative impact of population size at 1% showed on farmer income which increased to 0.15%. However, exactly as our assumptions, the Sargan test for validation of overidentifying restrictions rejected the null hypothesis, and the intercept is statistical significant. Both of that represent some unknown time lags that are still needed to be identified.

After taken into consideration of time lags of farmer income and water use as instrumental variables within GMM estimators, the empirical results of the Blundell-Bond dynamic panel-data model prove that the level of contemporaneous farmer income has relationship with the previous farmer income and water use. Previous farmer income affects the variation of population, water use, and electricity at the different levels in each province of China. The robust empirical results show slightly

Table 5 Estimation results on the impact of water use on farmer income in provincial level of China during years 2004–2012

Variables	Pool-OLS	Fixed effect	DPD-SYS robust	Blundell-Bond robust DPD	BB robust DPD GMM of lag farmer income
Population	−0.356	0.776	−0.150	−0.355	−1.479
[lnpop]	(0.0587)***	(0.1578)***	(0.0237)***	(0.2688)	(0.5919)**
Water use	**−0.027**	**0.641**	**0.077**	**0.118**	**0.190**
[lnwater]	**(0.0436)**	**(0.1028)*****	**(0.0222)*****	**(0.0495)****	**(0.1108)****
Electric power	0.484	1.000	0.096	0.259	0.415
[lnele]	(0.0411)***	(0.0246)***	(0.0152)***	(0.0710)***	(0.1145)***
Intercept	8.234	−7.698	0.5819	0.280	4.703
[_cons]	(0.2373)***	(1.3483)***	(0.1341)***	(0.2363)	(1.841)**
L1.lnfinc	–	–	0.965	1.083	0.768
	–	–	(0.0125)***	(0.0678)***	(0.1035)***
L2.lnfinc	–	–	–	−0.077	0.028
	–	–	–	(0.0764)	(0.1085)
L1.lnpop	–	–	–	0.257	0.912
	–	–	–	(0.2537)	(0.4960)*
L1. lnwater	–	–	–	**−0.085**	**−0.351**
	–	–	–	**(0.0485)***	**(0.1398)*****
L1.lnele	–	–	–	−0.201	−0.041
	–	–	–	(0.0622)***	(0.1318)
sigma_u	–	1.968	–	–	–
sigma_e	–	0.089	–	–	–
rho	–	0.998	–	–	–
R-squared	0.348	0.934	–	–	–
Sample size[N]	277	277 ($n = 31$)	277 ($n = 31$)	246($n = 31$)	246($n = 31$)
Arellano-Bond DPD: GMM type for differenced equation, L(2/.).lnfinc L(1/.).lnwater; standard, LD.lnfinc D.lnpop D.lnwater D.lnele					
DPD-SYS and Blundell-Bond DPD: GMM type for level equation, LD.lnfinc D.lnwater; standard: _cons					
Arellano-Bond test for H0: no autocorrelation in first-differenced errors, Fail to reject, Fail to reject					

Note: N is the observations in n provinces in T time periods. Data within the missing years did not participate analysis

* stands for $0.05 \leq p \leq 0.1$, ** stands for $0.01 \leq p \leq 0.5$, and *** represents statistical significance in values of $p \leq 0.01$ (Reprinted from Zhan Wang et al. (2015) with permission of Physics and Chemistry of the Earth)

positive impact of water use and electric power consumption which are statistically significant to increase contemporaneous farmer income. It seems to match classical consumption theory in that the total consumption brings flourishing. However, it is statistically significant that 1% changes in the first difference time lag of water use has 0.085% of negative impacts on farmer income. It demonstrates that water-saving has positive 0.085% of impacts on an increase of farmer income in the following year. Moreover, the coefficient of first difference time lag of farmer income is over one. It further interprets that overconsuming water harms farmer income in the following year. Comparing the results of Pool-OLS, the causality of the negative sign of water use on farmer income can be explained by two parts in the results of the Blundell-Bond dynamic panel-data model with GMM estimators: water use has positive relationship with contemporaneous farmer income and has negative relationship with future farmer income.

To address robust results of this causality, we assume all future regional development depending on the technology improvement at the last level of farmer income. Then, the GMM estimator of just farmer income is set in the Blundell-Bond dynamic panel-data model. The analysis results indicate the causality is statistically significant in which water use has positive relationship with contemporaneous farmer income and has negative relationship with future farmer income. One percent changes in water use will cause 0.19% increases in contemporaneous farmer income but 0.35% decreases to farmer income in the following year.

Regional diversification can be presented in three sub-models for Eastern, Central, and Western China separately. Table 6 shows the first difference of farmer income which predetermine to the following year in all three parts of China. Especially, in Western China, the farmer income is highly dependent on the previous level of farmer income. Moreover, population has negative relationships with farmer income in China. In Central China, it is statistically significant that 1% increase in population will induce 0.276% decrease in farmer income. In Western China, 1% increase in population will induce 0.063% decrease in farmer income. Water use has positive relationship with contemporaneous farmer income in both Central and Western China. In Central China, the average per capita water use was 462 ton which was the highest in three large regions of China in year 2012. The coefficients of water use to farmer income are over 0.124, but it is not significant, although it is much higher than that in Western (0.03) and Eastern (−0.04) China. It indicates that increase in farmer income is much dependent on current water consumption because the quotient between water use and population (average water use) in Central China is much higher than that in Western and Eastern China.

Eastern China is more developed than the Central and Western China. The total population in three large regions of China was, respectively, 558.5 million in Eastern, 425.1 million in Central, and 364.3 million in Western. The average farmer income in Eastern China was 1870.6 in 2012 USD, which was higher than 1215.2 in 2012 USD in Central China, and 951.8 in 2012 USD in Western China, while per capita water use in Eastern was 390.53 ton in year 2012, which was lower than 462 ton in Central China. Urban expansion has forced land use changes in cultivated land in China; resulting water demand has been increasing

Table 6 Empirical analysis results of impact of sparing use of water on farmer income in three large regions of China during years 2004–2012

	Eastern	Central	Western	China in total
Variables	DPD-SYS			Blundell-Bond DPD
Population	−0.025	−0.276	−0.063	−0.355
[lnpop]	(0.0426)	(0.0906)***	(0.0333)*	(0.2688)
Water use	**−0.040**	**0.124**	**0.033**	**0.118**
[lnwater]	**(0.0199)****	**(0.0570)****	**(0.0256)**	**(0.0495)****
Electric power	0.085	0.222	0.029	0.259
[lnele]	(0.0320)***	(0.0275)***	(0.0230)	(0.0710)***
Intercept	−1.122	1.642	0.061	0.280
[_cons]	(0.5036)**	(0.6197)***	(0.2264)	(0.2363)
L1.lnfinc	0.973	0.840	1.027	1.083
	(0.0222)***	(0.0255)***	(0.0204)***	(0.0678)***
L2.lnfinc	–	–	–	−0.077
	–	–	–	(0.0764)
L1.lnpop	–	–	–	0.257
	–	–	–	(0.2537)
L1.lnwater	–	–	–	**−0.085**
	–	–	–	**(0.0485)***
L1.lnele	–	–	–	−0.201
	–	–	–	(0.0622)***
Sample size[N] Group number[n]	99 11	72 8	106 12	277 31
DPD-SYS and Blundell-Bond DPD				
Instruments for differenced equation: GMM type, L(2/.).lnfinc L(1/.).lnwater; standard, D.lnpop D.lnwater D.lnele				
Instruments for level equation: GMM type, LD.lnfinc D.lnwater; standard, _cons				
Arellano-Bond test for H0: Fail to reject, Fail to reject, Fail to reject, Fail to reject				

Note: N is the observations in n provinces in T time periods. Data within the missing years did not participate analysis

* stands for $0.05 \leq p \leq 0.1$, ** stands for $0.01 \leq p \leq 0.5$, and *** represents statistical significance in values of $p \leq 0.01$. Because the availability of sample size is limited, dynamic panel-data model with systematic GMM estimator is used for regional diversification (Reprinted from Zhan Wang et al. (2015) with permission of Physics and Chemistry of the Earth)

for residential living and eco-environmental protection (Zhao et al. 2010). In Eastern China, having a higher rate of urbanization than other regions in China, the empirical results of DPD-SYS model reported statistically significant negative impacts of overconsumption of water on farmer income. It demonstrates the potential trade-offs between rural water loss and urban water use. Numerically, with increase in 1% of total amount of water use, the contemporaneous farmer income will lose 0.04% in Eastern China.

The impact of electric power on farmer income has been attained statistically significant in Eastern and Central China. We discuss the autocorrelation in error term due to correlation of water use and electric power consumption. The Sargan test gives some hints to further identify autocorrelation between water use and electric power in error term. First-time lag differencing autoregression strokes systematic variance-covariance of autocorrelation. Although the chi-square results of the Sargan test are still not in well satisfaction because of its theoretically inefficient structure, the robust results of the Blundell-Bond dynamic panel-data model with GMM estimators of farmer income reported that electric power consumption has inconstant impacts on contemporaneous rural income in the following year. Therefore, water use as a kernel variable is statistically significant. It illustrates that 1% of water-saving will result positive impacts of 0.085~0.35% on farmer income in the following statistical year.

Heihe River Basin (HRB) Land Use Change and Agricultural Expansion

Heihe River Basin (HRB)

HRB is located in Northwest China (38°N–42°N, 98°E–101°E), covering an area over 143.29 thousand kilometers (Fig. 3). HRB is a typical arid region in China. The annual average precipitation is about 37 mm, 45 mm, and 55 mm according to the monitoring result of local meteorological stations of Ejin, Guaizihu, and Dingxin in HRB, while the annual average evaporation exceeded 3000 mm (Xiao et al. 2015).

The Heihe River is the second longest inland river in the arid region of Northwestern China. The total length of the Heihe River reaches 821 km (Huai et al. 2014). According to the location of hydrometric stations of Yingluoxia and Zhengyixia, the Heihe River is divided into upper, middle, and lower reaches. The upper reaches of HRB are runoff formation areas where cold desert accounted for 22% of the total area. The middle reaches of HRB are runoff-using areas where most of the agricultural oasis, population, and GDP (gross domestic product) are concentrated. The lower reaches of HRB are a runoff-fade area with a huge evaporation capacity. The oasis strip in HRB plays a vital ecological role in Northwest China. In past decades, with the continuous expansion of the agricultural oasis, the demand for irrigation water has significantly increased, which has triggered a great deal of ecological and environmental problems.

Land Use Patterns and Changes in HRB

Unused land comprised the largest proportion (67.99%) of HRB in 1986. The proportion of grassland was also high, reaching 23.08% (Fig. 3). However, the proportions of the agricultural oasis, forestry areas, water areas, and built-up areas are as low as 3.45%, 4.11%, 1.06%, and 0.31%, respectively. Gobi is the primary land use type within unused land, contributing to 50.32% of the total. The bare rock and sandy land also take up 23.77% and 13.76% of unused land.

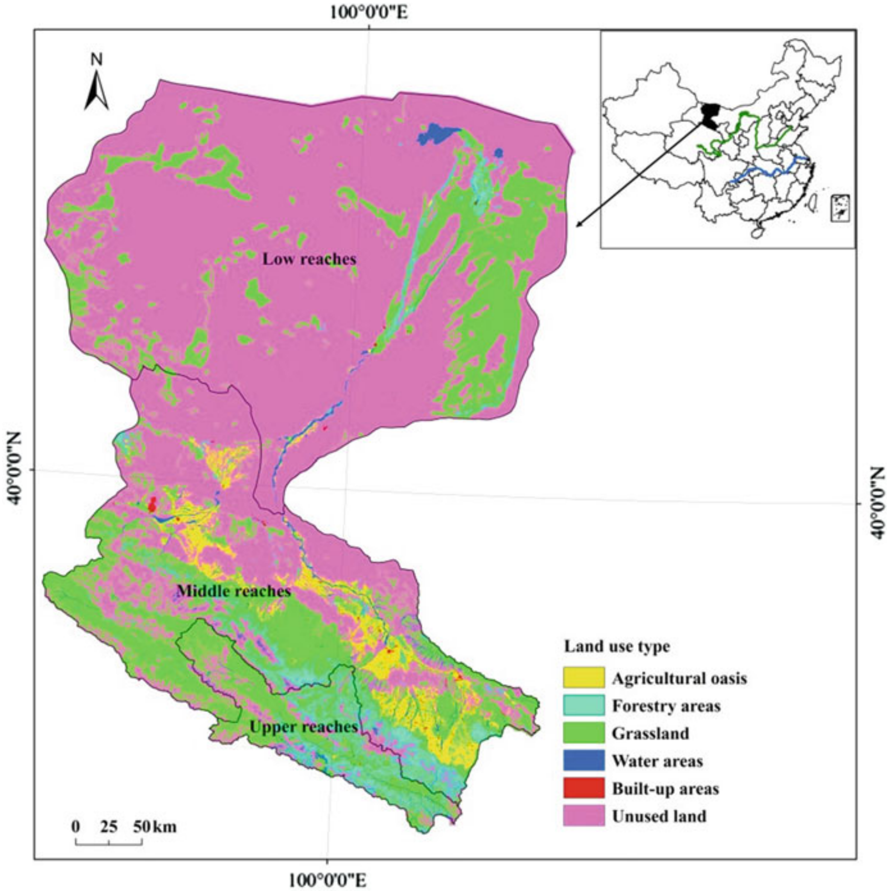

Fig. 3 The location and land use patterns of the Heihe River Basin in 1986 (Reprinted from Wei Song and Deng (2015) with permission of Physics and Chemistry of the Earth)

The distribution of the six land use types showed obvious reaches in variation. The area proportions of upper, middle, and lower reaches in HRB are 7.01%, 59.64%, and 33.35%, respectively. However, 96.58% of the agricultural oasis and 92.73% of built-up areas concentrated in middle reaches, while 72.44% of unused land distributed in the lower reaches. The proportions of forestry areas, grassland, and water areas in middle reaches are also as high as 48.25%, 44.36%, and 49.50%, respectively. Nevertheless, the proportions of the three land use types are all lower than the area proportions of middle reaches (59.64%).

The most significant land use changes from 1986 to 2000 in HRB were the expansion of agricultural oases (25.11%) and water areas (206.06%) and the shrinkage of forestry areas (78.00%) and grassland (27.30%) (Fig. 4). In addition, built-up areas in HRB significantly decreased by 19.02% from 1986 to 2000 in spite of the

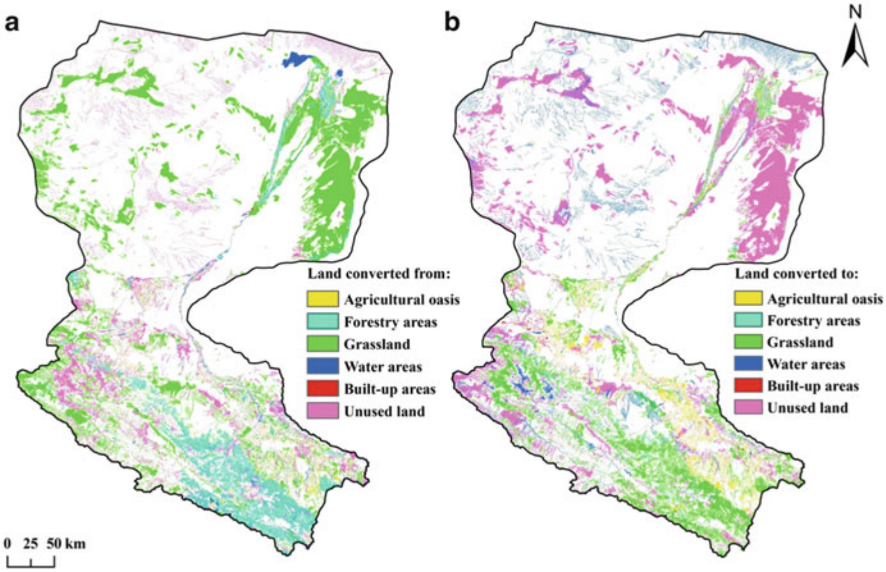

Fig. 4 Land use changes in the Heihe River Basin, 1986–2000 (Reprinted from Wei Song and Deng (2015) with permission of Physics and Chemistry of the Earth)

rapid growth of the population and economy. Unused land also rapidly expanded by 9.60% during this period. In the upper reaches of HRB, the most significant land use changes are the expansion of the agricultural oasis (98.73%) and the shrinkage of forestry areas (−87.17%). In the middle reaches of HRB, water areas significantly expanded by 162.02%, while forestry areas decreased by −78.80%. In the lower reaches of HRB, water areas and built-up areas expanded by 359.72% and 56.01%, respectively, while grassland decreased by 84.29%.

The agricultural oasis continued with positive changes in area, with an increase rate of 14.82% from 2000 to 2011, while the five other land use types all presented opposite trends (Fig. 5) compared to the previous period. Forestry area, grassland, and built-up areas changed from negative trends from 1986 to 2000 to positive trends from 2000 to 2011, with increase rates of 11.57%, 0.95%, and 47.54%, respectively. Water areas and unused land ceased the positive changes in the previous period and decreased by 0.86% and 1.99% from 2000 to 2011, respectively. Although the agricultural oasis increased at the whole HRB, it decreased by 17.37% in the upper reaches of HRB. In middle reaches of HRB, built-up areas significantly increased by 45.63%, while water areas and unused land decreased by 3.08% and 4.28%, respectively. In the low reaches of HRB, the agricultural oasis and built-up areas expanded by 14.83% and 47.69%, respectively, while unused land decreased by 1.49%. As a whole, the predominant land use changes during this period were the expansion of the agricultural oasis and built-up areas.

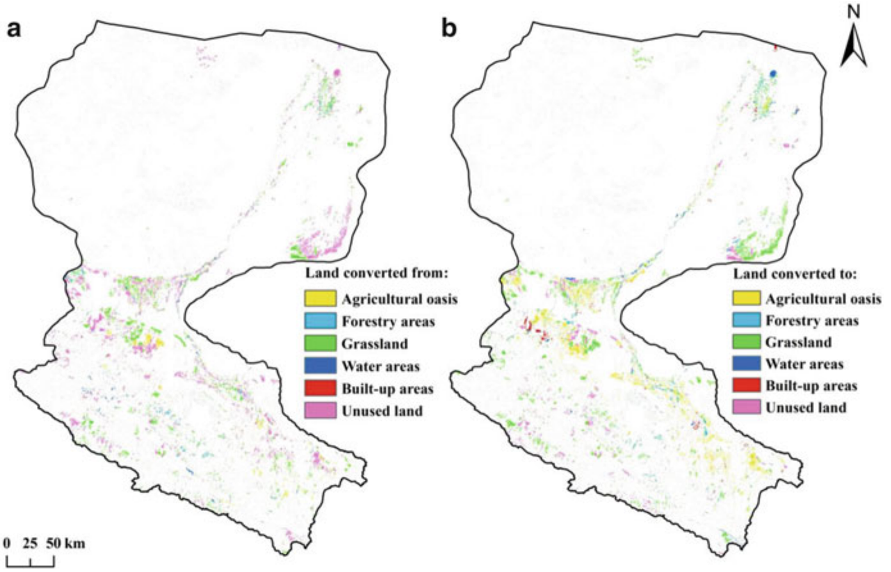

Fig. 5 Land use changes in the Heihe River Basin, 2000–2011 (Reprinted from Wei Song and Deng (2015) with permission of Physics and Chemistry of the Earth)

Expansion of Agricultural Oasis in HRB

The agricultural oasis in HRB changed from 4942.59 km^2 in 1986 to 6183.67 km^2 in 2000, with an expansion rate of 25.11% (annual rate of 1.79%). In the subsequent period (2000–2011), the agricultural oasis increased from 6183.67 km^2 in 2000 to 7100.14 km^2 in 2011, with an increase rate of 14.82% (annual rate of 1.35%). The agricultural oasis expanded continuously during the two periods, while the annual expansion speed decreased over time.

Drastic conversions existed in the agricultural oasis in HRB. A total of 1845.81 km^2 of other land use types was converted into an agricultural oasis from 1986 to 2000 (Table 4), among which grassland contributed to 45.93%, unused land 26.97%, built-up areas 11.57%, forestry areas 8.27%, and water areas 7.26%. The reclamation of grassland was the primary approach to generate new agricultural oases. The agricultural oasis loss was more moderate compared to the expansion of agricultural oases. A total of 604.75 km^2 of agricultural oases was converted into other land use types during the period 1986–2000 (Table 7). Most of the lost agricultural oases were converted into grassland (41.60%), followed by unused land (28.18%), built-up areas (17.42%), water areas (8.94%), and forestry areas (3.87%). The conversions from agricultural oasis to grassland were the leading conversions in agricultural oasis change.

Similar conversions occurred in the latter period (2000–2011). A total of 1283.57 km^2 of other land use types was converted into agricultural oases, while only 366.88 km^2 of agricultural oases was converted into other land use types (Table 4).

Table 7 Land use conversions in agricultural oasis, 1986–2000 and 2000–2011

	Gained agricultural oasis (km^2)		Lost agricultural oasis (km^2)	
	1986–2000	2000–2011	1986–2000	2000–2011
Forestry areas	152.73	34.55	23.38	32.1
Grassland	847.77	433.42	251.57	166.61
Water areas	134.01	37.15	54.05	13.28
Built-up areas	213.53	17.54	105.33	85.86
Unused land	497.78	760.91	170.42	69.02
Total	1845.81	1283.57	604.75	366.88

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Unused land became the main contributor (59.28%) of newly added agricultural oases. Grassland changed to the second contributor (33.77%), followed by forestry areas (2.69%), water areas (2.89%), and built-up areas (1.37%). However, grassland was still the primary destination (45.41%) of the lost agricultural oases, followed by built-up areas (23.40%), unused land (18.81%), forestry areas (8.75%), and water areas (3.62%).

The expansion and shrinkage of agricultural oases mainly occurred in the counties of the middle reaches (Fig. 6). The expansion of the agricultural oasis in the Zhangye municipal district, Minle county, Jiuquan county, and Shandan county accounted for 17.60%, 14.02%, 13.88%, and 12.05% of total expansion, respectively. The counties of Shandan, Minle, Jinta, and Jiuquan city experienced severe agricultural oasis loss, accounting for 26.99%, 15.93%, 11.95%, and 10.45% of total loss, respectively.

In the latter period, agricultural oasis expansion was still concentrated in the same four counties with the former period. However, the orders of the four counties in agricultural oasis expansion slightly changed. Jinta instead of Zhangye municipal district changed to be the first contributor of agricultural oasis expansion, accounting for 18.04% of total, followed by Jiuquan (15.74%), Shandan (11.75%), and Zhangye (9.79%). The agricultural oasis loss at the county level during the period 2000–2011 was a little different from that of 1986–2000. Sunan Yugu changed to the primary region of agricultural oasis loss, accounting for 29.21% of the total. The agricultural oasis losses were also severe in Jiuquan city (12.95%), Zhangye municipal district (11.08%), Minle county (10.08%), and Shandan county (10.10%).

Methods of Measuring Water-Use Efficiency

Measurement of the Water-Use Efficiency for Soil Conservation

In its broadest sense, the water-use efficiency is the net return for a unit of water used, and in previous research the crop water-use efficiency is the amount of grain yield (e.g., kilograms of grain) obtained per unit of water consumption (e.g., cubic meters of water). Besides, depending on the type of water sources considered, crop water-use efficiency is generally expressed as grain yield per unit water

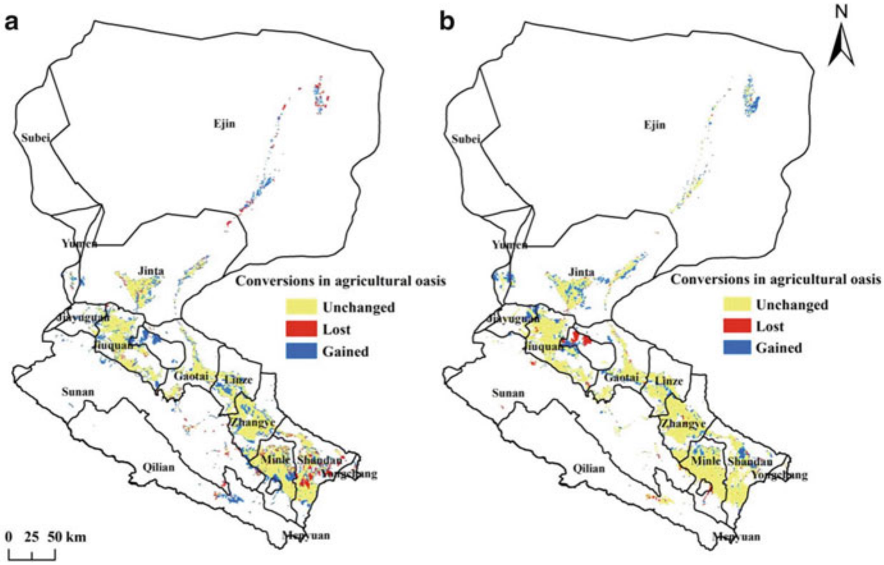

Fig. 6 Expansion and shrinkage of agricultural oasis in the Heihe River Basin, 1986–2000 (**a**) and 2000–2011 (**b**) (Reprinted from Wei Song and Deng (2015) with permission of Physics and Chemistry of the Earth)

evapotranspired or grain yield per unit total water input (irrigation plus rainfall). For example, there are three major definitions of water-use efficiency that are widely used, i.e., (1) gross primary production (GPP)-based water-use efficiency, GPP/ET; (2) net primary productivity (NPP)-based water-use efficiency, NPP/ET; and (3) net ecosystem carbon production (NEP)-based water-use efficiency, NEP/ET. All these definitions only reflect the water-use efficiency for primary production, but all involve ET, which the most active process in the hydrological cycle and is also a major component of energy and water balance in agriculture ecosystems, and therefore the water consumption is also represented with ET in this study. In addition, this study primarily focuses on the soil conservation service, which is the most important ecosystem services provided in the lower Heihe River Basin, and the water-use efficiency for the soil conservation is therefore calculated as the soil conservation amount divided by ET as follows:

$$WUE - SC = SC/ET \tag{3}$$

where WUE-SC is the water-use efficiency for soil conservation (unit: t•mm-1), SC is the soil conservation amount (unit: t), and ET is the evapotranspiration (unit: mm), which is assumed to be the consumptive water used by vegetation to provide the ecosystem services such as soil conservation. In this study, the average WUE-SC over a region was calculated as the area-weighted average value of all grid cells. It is noteworthy that the WUE-SC of water bodies was also calculated in the same way as other land cover types in this study.

Measurement of the Water-Use Efficiency for Agriculture

Agricultural water-use efficiency refers to the ratio of the minimum water consumption which can be realized theoretically to the actual water consumption with the predefined input and output level. There are a number of methods to analyze the agricultural water-use efficiency, and the most widely used ones were the parametric method, the stochastic frontier analysis (SFA), and the nonparametric method, DEA (Lin and Tseng, 2005). DEA analysis aims to establish a nonparametric frontier by using the data. The DEA was chosen to measure the agricultural water-use efficiency in this study. Aiming to analyze how to improve the water-use efficiency with the fixed water supply amount, we utilized input-oriented DEA. When the value of efficiency equals to 1, it means the decision unit is on the production frontier and the actual production value has no difference with the possible maximum value. When the efficiency is lower than 1, it implies that there is still improvement potential for the decision unit. In this research, when the value of the efficiency reaches 1, the water-use efficiency of this decision unit would be higher (Branda 2015). Suppose there are N(=1, 2, 3,. . ..0.8) decision units putting in I (=1, 2, 3. . .) factors at T (=1, 2, 3. . ..) time periods, then J (=1, 2, 3. . ....) kinds of outputs will be generated. When referring to the input-output index, we used X and Y to represent the input and output, and then the input-output index of N counties (which equal to the decision unit) during different periods can be marked as $x_{i,n}^{t}$ and $y_{i,n}^{t}$. If we set $x_i = (x_{1n}, x_{2n}, \ldots, x_{In})$ and $y_j = (y_{1n}, y_{2n}, \ldots, y_{Jn})$, the model is specified as follows:

$$\begin{cases} \min\theta = V_D \\ \sum_{n=1}^{8} \lambda_j X_i + S^- = \theta X_0 \\ \sum_{n=1}^{8} \lambda_j Y_j + S^+ = Y_0 \\ \lambda_j \geq 0, N = 1, \ldots, 8 \\ S^- \geq 0, S^+ \geq 0 \end{cases} \tag{4}$$

where $\theta(0 < \theta < 1)$ is the comprehensive technical scale efficiency. λ_j is the weighting variable, $S^-(S^- \geq 0)$ is the slack variable, $S^+(S^+ \geq 0)$ is the surplus variable, and ε is the Archimedes infinitesimal. The equation above is the DEA model based on constant scale returns; if $\theta = 1$, it means the county reaches the optimal situation of water use on the frontier.

The Malmquist total factor productivity index was utilized to compute the TFP growth rate and to analyze the improvement in technical efficiency and technical change (Afsharian and Ahn 2015). Supposing $D_c^t(x_t, y_t)$ are the distance functions, calculation of the Malmquist total factor productivity index based on the period t and $t + 1$ and calculation of comprehensive technical efficiency change are as follows:

$$M(x_t, y_t, x_{t+1}, y_{t+1}) = EC \times TC = \left[\frac{D_t^c(x_{t+1}, y_{t+1})}{D_t(x_t, y_t)} \times \frac{D_c^{t+1}(x_{t+1}, y_{t+1})}{D_c^{t+1}(x_t, y_t)} \right]^{\frac{1}{2}} \tag{5}$$

$$EC = M_t\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \frac{D_t^c\left(x_{t+1}, y_{t+1}\right)}{D_t(x_t, y_t)} \tag{6}$$

$$TC = M_{t+1}\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \frac{D_c^{t+1}\left(x_{t+1}, y_{t+1}\right)}{D_c^{t+1}(x_t, y_t)} \tag{7}$$

The Malmquist total factor productivity index is widely used to divide the rate of TFP change into technical efficiency change (EC) and technical change (TC). The technological development will bring about changes in the production frontier, and EC is the changes of TFP growth caused by the changes of production frontier within a certain time period. Technical efficiency refers to the changes in TFP caused by efficiency change of technology itself.

Driving Forces of Agricultural Water-Use Efficiency Using Tobit Model

The Tobit model shows superiority to the ordinary least squares regression when there are both continuous variables and discrete variables. In this study, the agricultural water-use efficiency ranges from 0 to 1; therefore the Tobit model is applied to analyze the effects of driving factors on agricultural water-use efficiency, which is as follows:

$$y_i^* = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \varepsilon_i \tag{8}$$

$$y_i = \begin{cases} 0\,, & if \quad y_i^* \in (-\infty, 0] \\ y_i^*\,, & if \quad y_i^* \in (0, 1] \\ 1\,, & if \quad y_i^* \in (1, +\infty] \end{cases} \tag{9}$$

where y_i represents the agricultural water-use efficiency in the i^{th} county and x_{ij} includes various factors influencing the agricultural water-use efficiency.

Results of Water-Use Efficiency

Spatiotemporal Variation of the Soil Conservation Amount

The results suggested that there was significant spatiotemporal variation of potential wind erosion amount, soil conservation amount, and soil conservation rate in the study area (Figs. 7 and 8). The annual soil conservation modulus in the study area ranged from 0 to 8822 $t{\cdot}km^{-2}{\cdot}a^{-1}$, with an average of 75.47, 71.38, and 137.18 $t{\cdot}km^{-2}{\cdot}a^{-1}$ in 2000, 2005, and 2008, respectively. Besides, the annual total soil conservation amount of the study area showed a first decreasing and then increasing trend during 2000–2008, reaching approximately 5.80 million ton, 5.48 million ton, and 10.55 million ton in 2000, 2005, and 2008, respectively. In addition to the spatiotemporal variation at the annual scale, the soil conservation amount also varied significantly at the monthly scale (Fig. 7). The climax of the soil conservation amount occurred during March and May in 2000 and 2008 and during April and June in 2005, while there is very limited soil conservation amount in other months, indicating the soil conservation mainly occurred in the spring during 2000–2008 (Fig. 7). There is frequently strong wind in the spring in the lower Heihe River Basin, which leads to the rapid increase of the potential wind erosion amount; what's worse, the vegetation coverage rate is still very low during the spring when most vegetation just begins to grow, making the study area extremely susceptible to the wind erosion.

Although the soil conservation amount in the study area varied substantially across the years, the overall spatial pattern of soil conservation kept consistent during 2000–2008, only with significant change in some part of the study area (Fig. 8). The soil conservation amount was generally very low in most part of the study area, and the high soil conservation amount only occurred in a few regions such as the northeast border region and the area near Gurinai Lake in the southeast border region. The soil conservation amount showed an obvious decreasing trend from the northeast to the southwest in the northeast border region during 2000–2008, and there was also an obvious decreasing trend of the soil conservation amount in the southeast border region in 2008. It is not surprising that the spatial pattern of the soil conservation amount is similar to that of the potential wind erosion amount, since the latter is the maximum of the former, but the soil conservation amount is also influenced by the vegetation coverage. What's more, the soil conservation amount

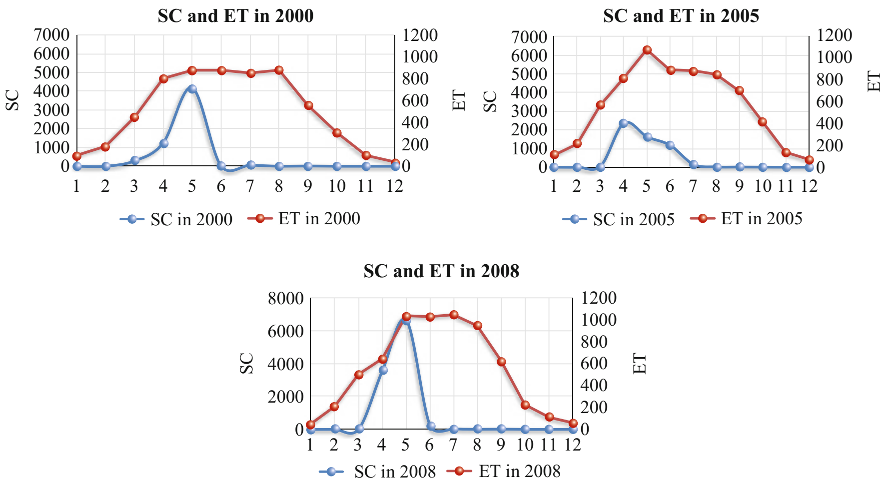

Fig. 7 The monthly soil conservation amount (SC) (unit: thousand ton) and ET (unit: thousand mm) in 2000, 2005, and 2008 (Reprinted from Haiming Yan (2015) with permission of Sustainability)

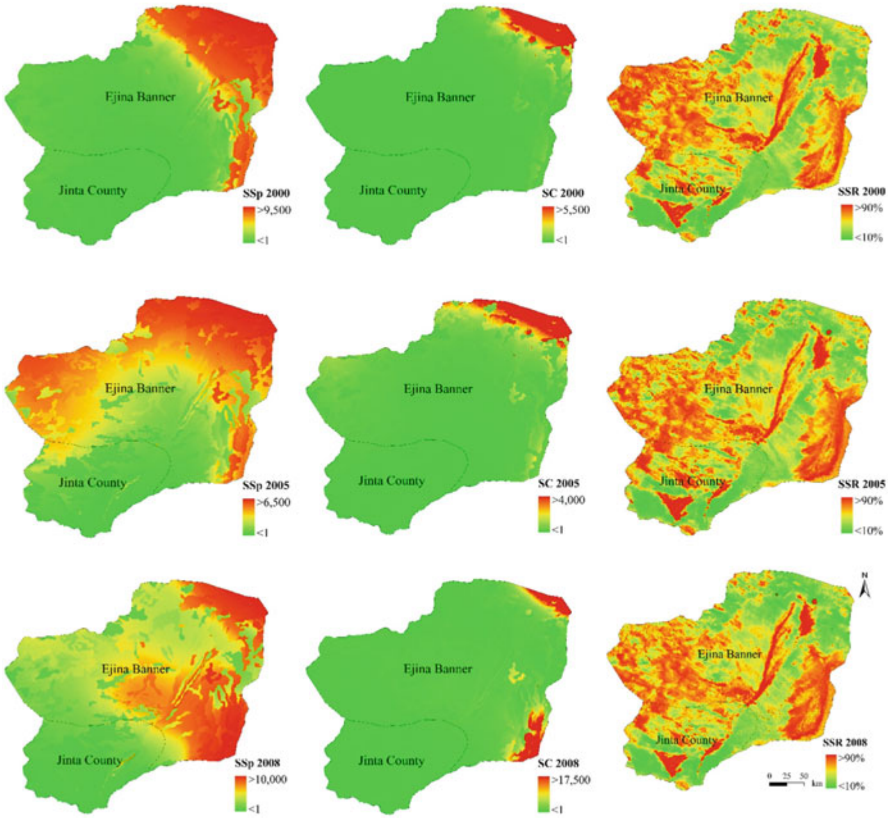

Fig. 8 The annual potential soil loss (SSp), annual soil conservation amount (SC) (unit: t), and soil conservation rate (SCR) in 2000, 2005, and 2008 (Reprinted from Haiming Yan (2015) with permission of Sustainability)

varied greatly among different land cover types. For example, the high soil conservation amount in 2008 occurred in the Gobi Desert in the northeast border region, the water body over East Juyanhai, the low-coverage grassland, shrub forest, and the sandy land in the southeast border region, where the vegetation coverage rate was generally low. The lowest soil conservation amount occurred in the Gobi Desert near the southwest border, where both the vegetation coverage rate and potential wind erosion amount were very low.

The soil conservation rate also showed obvious spatial heterogeneity (Fig. 8). The regions with the high soil conservation rate concentrated in the oases and irrigated area along the Heihe River, where the vegetation coverage was in good conditions and the major land cover types were cultivated land, shrub forests, closed forest land, and medium-coverage grassland or water bodies. Besides, the soil conservation rate ranged from 2.62% to 100% during 2000–2008, with the average of 55.32%, 57.36%, and 55.98% in 2000, 2005, and 2008, respectively, showing a first slight increasing and then slight decreasing trend, which is contrary to the changing trend of the soil conservation amount. Although the average soil conservation rate was the highest in 2005, the soil conservation amount in 2005 was the lowest, indicating there were still some other factors that influenced the soil conservation amount, e.g., spatial heterogeneity of the potential wind erosion amount. There was obvious spatial inconsistency between the potential wind erosion amount and the soil conservation rate, indicating that the correlation between them was not high. However, the spatial inconsistency between them has significant impacts on the soil conservation amount, especially in the southwest part of the study area, where there was a large area of high-coverage vegetation. There was a high vegetation coverage rate in oases in the southwest part of the study area, but the potential wind erosion amount is very low in this region, which leads to the extremely low soil conservation amount and fails to give full play to the potential of the high-coverage vegetation to reduce the soil erosion. The soil conservation amount is influenced by the potential wind erosion amount and the vegetation coverage rate; both of them generally show obvious spatial heterogeneity, leading to the high location dependence of the soil conservation amount, to which sufficient consideration should be given in the ecosystem management and land management.

Spatiotemporal Variation of Evapotranspiration

There was a significant spatial heterogeneity of ET, the spatial pattern of which showed no significant change during the entire period (Fig. 9). The annual ET ranged from 12.31 mm to 1344.07 mm during 2000–2008. It is very low in most part of the study area, where it generally ranged from 32 mm to over 100 mm, and it is high in only the oases, East Juyanhai, and the regions along the Heihe River. The highest ET was generally found in the forests, water body, as well as irrigated croplands, while the lowest ET was found in the desert area and Gobi area. In particular, the highest ET in 2005 and 2008 occurred in the water body of East Juyanhai Lake, which has reappeared since 2003. By comparison, ET was generally below 50 mm in the desert area, where the land surface is mainly covered by bare rock with sparse vegetation. There were widespread sandy land and Gobi Desert in most part of the study area, where the vegetation coverage rate was generally very low and the water availability is very low, while the high-coverage vegetation such as the cultivated land and forests was generally distributed in the oases and the regions along the main stream of the Heihe River, where there is high water availability for the vegetation growth and ET. Besides, the annual ET showed an increasing trend during the first half of the period (2000–2005), but a decreasing trend after that, with the average ET reaching 74.55 mm, 88.32 mm, and 84.88 mm in 2000, 2005, and 2008, respectively, and the overall increase was still significant in the entire study period. In addition, there was also obvious variation of the monthly ET, which is generally high during the growing season (from April to October) and low during the nongrowing season (Fig. 7). It is noticeable that there was obvious temporal inconsistency between the ET and the soil conservation amount. Most part of the ET occurred in the summer

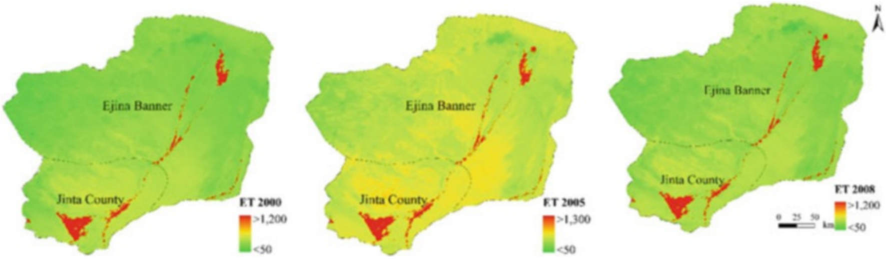

Fig. 9 Spatial pattern of the annual ET in 2000, 2005, and 2008 (Reprinted from Deng and Zhao (2015) with permission of Sustainability)

and autumn, while most part of the soil conservation amount concentrated in the spring, indicating only a part of the ET was used to provide the soil conservation service. What's more, since the precipitation of the study area is very limited (approximately 37 mm), it has very limited impacts on the change of ET; other factors such as the water diversion of the Heihe River and land use and land cover change may have played a key role in influencing the spatiotemporal variation of ET.

Spatiotemporal Variation of the Water-Use Efficiency for Soil Conservation

The WUE-SC in the study area showed significant spatial heterogeneity and ranged from 0 to 98.69 t·mm^{-1} during 2000–2008, indicating that approximately 98.69 t soil loss had been reduced by using 1 mm ET in a 1 km grid cell at most. The WUE-SC was generally below 1 t·mm^{-1} in most part of the study area, and the regions with high WUE-SC mainly concentrated in the northeast part and southeast part of the study area, showing a spatial pattern similar to that of the soil conservation amount during 2000–2008. For example, the highest WUE-SC occurred in the low-coverage grassland and Gobi Desert near the northeast broader region and low-coverage grassland, shrub forest, and sandy land near the northeast broader region, and the WUE-SC is also very high in the medium-coverage or low-coverage grassland in some part of the Ejina Oasis. Besides, the average WUE-SC reached 1.10, 0.89, and 1.68 t·mm^{-1} in 2000, 2005, and 2008, respectively, which was very low on the whole and showed a first slight decreasing and then rapidly increasing trend during 2000–2008 (Fig. 4). In addition, the spatial pattern of WUE-SC for soil conservation kept consistent in most part of the study area, only with some slight fluctuation, but it changed significantly in some regions in the southeast part and northeast part during 2005–2008. The WUE-SC decreased by 1–37 t·mm^{-1} in most regions in the northeast part of the study area, and it increased in only a few regions in the northeast part, with the increment showing a decreasing trend from the broader to the inner part. In particular, the WUE-SC has decreased very obviously in the water body of East Juyanhai, which has reappeared in 2003 due to the increased water diversion. By comparison, the WUE-SC increased significantly in the

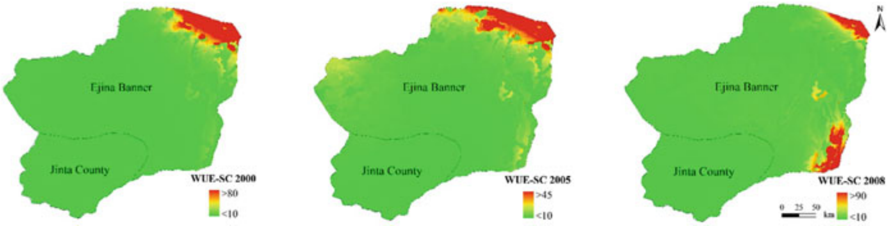

Fig. 10 The water-use efficiency for soil conservation (WUE-SC) in 2000, 2005, and 2008 (Reprinted from Deng and Zhao (2015) with permission of Sustainability)

southeast part of the study area during 2005–2008, with an increment of 1–10 t·mm^{-1} in the regions around Gurinai Lake and even 10–97 t·mm^{-1} in some part near the southeast broader (Fig. 10).

It has been reported that uneven changes in environmental factors can lead to the spatially heterogeneous responses of water-use efficiency to environmental change; the change in the WUE-SC is also due to the uneven changes in environmental factors. The average WUE-SC decreased by 19.09% during 2000–2005; the average ET increased by 18.47%, while there was no significant change in the soil conservation amount (decreasing by 5.42%), indicating that the change in the WUE-SC was mainly due to the change in the ET during 2000–2005. By comparison, the average WUE-SC increased by 88.76% during 2005–2008; the ET only decreased by 3.89%, while the soil conservation amount increased by 82.15%, suggesting the change in the soil conservation amount made great contribution to the increase of the average WUE-SC. Besides, there was no obvious change in the soil conservation rate during 2005–2008, reaching 57.36% and 55.98% in 2005 and 2008, indicating that the vegetation coverage change didn't lead to significant change in the soil conservation amount. However, during 2005–2008 the potential soil loss increased remarkably by 88.76%, which led to the significant increase of the soil conservation amount and consequently the improvement of the average WUE-SC. In particular, the potential soil loss increased most obviously in the southeast part of the study area, which is close to Badain Jaran Desert, with the increment of 1000–5000 t/km^2 and the increment rate of 20%–50% in most part of this region. Although there was no significant change in the soil conservation rate and the ET in this region, the remarkable increase in the potential soil loss made the ability of the vegetation to reduce the wind erosion fulfilled, leading to the significant increase of the regional soil conservation amount and improvement of the overall WUE-SC of the study area.

The overall low WUE-SC in the study area may be due to the spatiotemporal inconsistency between the potential soil loss and the vegetation coverage rate. For example, the potential soil loss is very low in most part of the study area, where the main land cover type is unused land and with low vegetation coverage, leading to the low soil conservation amount and consequently the low WUE-SC. Besides, the vegetation coverage rate is also very low in most part of the regions with the high potential soil loss; although ET is low in these regions and the soil conservation amount may be high, the soil conservation rate is generally very low, which indicates there is still some scope to increase the soil conservation amount and improve the WUE-SC. In addition, the potential soil loss is generally very low in the regions with a high vegetation coverage rate, especially in the western part of the study area, and the ability of the vegetation to reduce the wind erosion in these regions is not fulfilled, and the high ET due to high vegetation coverage rate leads to the even lower WUE-SC. What's more, the vegetation coverage is generally high in the summer and autumn; while the wind erosion which leads to the high potential soil loss mainly occurs in the spring, the temporal inconsistency between the vegetation coverage rate and the potential soil loss may also contribute to the low WUE-SC.

Changes of the Agricultural Water-Use Efficiency and TFP Rate

The results reveal that distinct disparities exist among different areas with regard to agricultural water-use efficiency. Figure 11 shows that the highest agricultural water-use efficiency appears in Ganzhou, with the value higher than 0.9 for most years, while the agricultural water-use efficiency in Jinta is comparatively low, with the values of many years lower than 0.5 during 2003–2012. In terms of the changes in agricultural water-use efficiency, disparities also still exist in different counties, with Ganzhou, Minle, and Linze showing slight changes while Jinta, Sunan, and Suzhou presenting relatively considerable fluctuations. Specifically, the agricultural water-use efficiency keeps high in Minle and Linze, whereas obvious declines occur since 2012, which is synchronous with the vegetable and livestock production development. In 2012, Minle and Linze produced a large variety of vegetables which may induce water loss. In Sunan, the agricultural water-use efficiency is lower than 0.5 before 2009; however, it improved markedly and approximated to the level of other counties during 2010–2012. Suzhou experienced the fluctuations with the rising at the beginning, declining in the middle, and increasing again. In general, the trajectory of the agricultural water-use efficiency change is consistent with the industrial adjustment, especially the development of cultural industries.

The results based on the Malmquist total factor productivity index showed a fluctuated variation pattern for TFP growth rate (Fig. 12), with its value more than 1 during 2003–2004, 2006–2007, 2009–2010, and 2011–2012 and less than 1 in 2004–2005, 2005–2006, 2008–2009, and 2010–2011 and no obvious change during 2007–2008.

Impacts of Driving Factors on the Agricultural Water-Use Efficiency

Undoubtedly, agricultural water-use efficiency changes are attributed to various physical and socioeconomic factors as well as their coupling effects. In this study, we focus on the influences of socioeconomic factors and choose a series of indicators, such as average net income of each rural resident representing the rural resident estates, change rate of investment in fixed assets, gross domestic product (GDP)

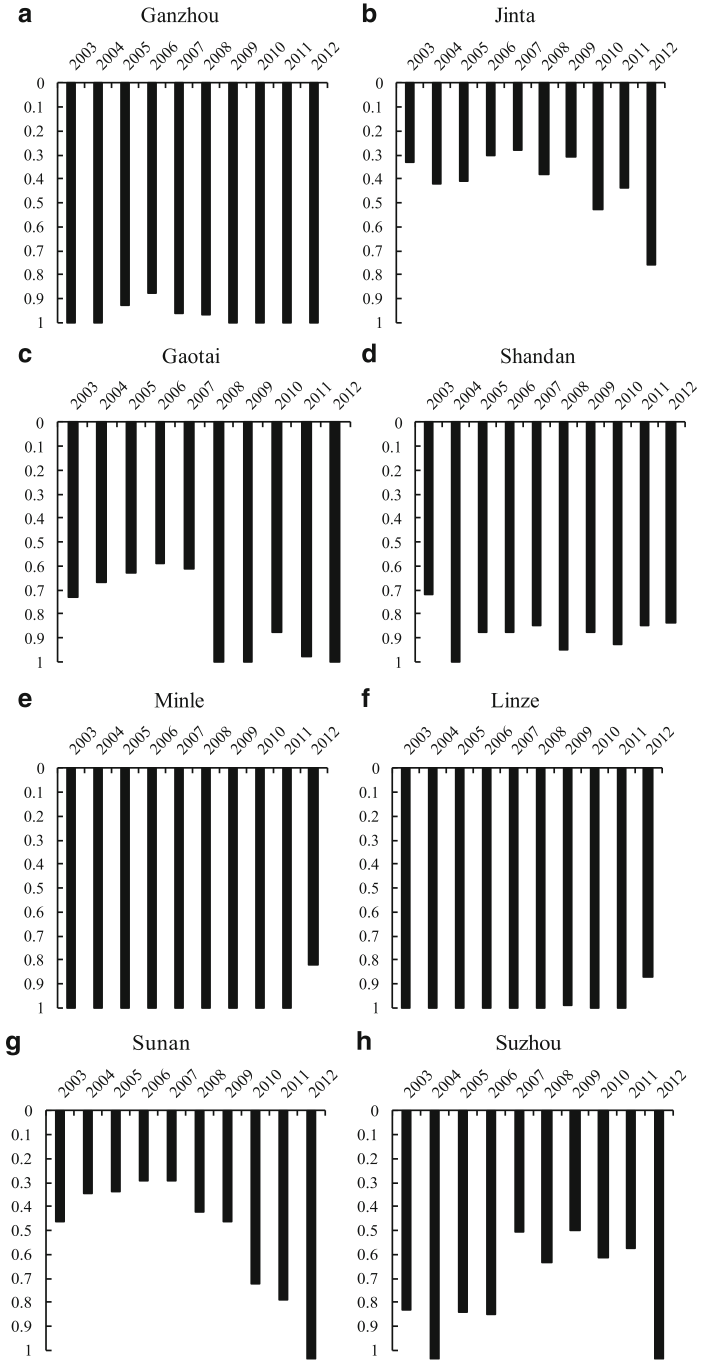

Fig. 11 County-level agricultural water-use efficiency in the Heihe River Basin during 2003–2012 (Reprinted from Guofeng Wang et al. (2015) with permission of Physics and Chemistry of the Earth)

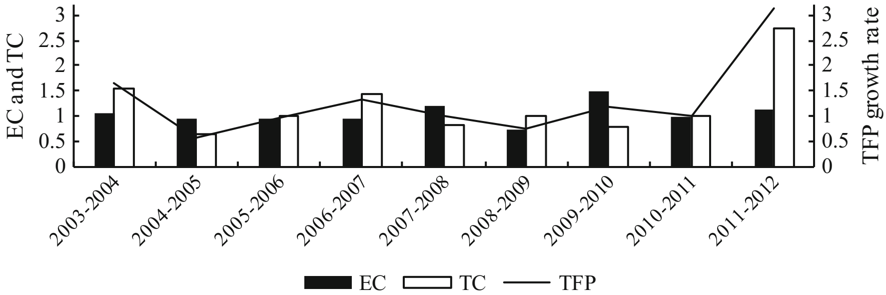

Fig. 12 TFP growth rates and Malmquist decomposition results in agricultural production areas in the Heihe River Basin (results for the whole study area where EC refers to technical efficiency change and TC refers to technical change) (Reprinted from Guofeng Wang et al. (2015) with permission of Physics and Chemistry of the Earth)

representing economic growth, the proportion of the agricultural industry value, the second industry value to GDP representing the industrial structure, the planting area of the corn and wheat, effective irrigation area, disaster area, and other crops representing the planting structure adjustment (Table 8).

There is a remarkable variation in the industrial structures in different counties, thus in the proportions of the output value of the three industries in GDP. In 2012, Suzhou had the lowest agricultural output value proportion, whereas Gaotai exhibited the highest agricultural output value proportion (Fig. 13).

The average net income of each rural resident (+0.08%) has positive impacts on the agricultural water-use efficiency. This is because higher net income enables farmers to use better agricultural facilities, e.g., irrigation machines and equipment, which can consequently improve the agricultural water-use efficiency.

Economic growth identified by the GDP at the local extent (−0.07%) will have negative effects on the agricultural water-use efficiency. It is justified that the growth of GDP is largely attributed to the development of industrial and service sectors, whereas agricultural sectors contributed a confined proportion, indicating the possibility that increasing the water consumption lowers the agricultural water-use efficiency.

The proportion of primary industry (+0.03%) has positive effects. Coupled with the economic development, the role of agriculture among the three industries will be gradually undermined, and it is the same case for the role of agriculture in improving the water-use efficiency. In order to promote the development of agriculture, the local people will make more investment in the agricultural irrigation infrastructure, which can consequently improve the agricultural water-use efficiency.

The wheat planting area (+0.22%) and other crop planting area (+0.16%) had significant positive effects on the agricultural water-use efficiency. Besides, the coefficient of the wheat planting area is larger than that of other crops, indicating that the changes of wheat planting area will have more powerful influence on agricultural water-use efficiency. It is feasible to improve the agricultural water-use efficiency by enlarging the planting area of wheat.

Table 8 Tobit regression results on the impacts of driving factors on agricultural water-use efficiency

Variables	Coefficient	Standard deviation	95% confidence interval
Corn planting area	0.003 (−0.06)	0.05	(−0.11, 0.10)
Wheat planting area	0.22*** (8.33)	0.03	(0.17, 0.27)
Other crop planting area	0.16*** (3.23)	0.05	(0.06, 0.26)
Average net income of each rural resident	0.08*** (3.57)	0.02	(0.03, 0.12)
Effective irrigation area	−0.07*** (2.90)	0.02	(−0.12, −0.02)
Disaster area	0.06*** (2.35)	0.03	(0.009, 0.11)
GDP	−0.04** (−1.61)	0.02	(−0.09, 0.02)
Proportion of primary industry	0.03 (1.23)	0.02	(0.06, 0.01)
Proportion of secondary industry	−0.06 (−2.58)	0.02	(−0.11, 0.01)
Change rate of investment in fixed assets	0.01** (0.80)	0.02	(−0.02, 0.05)
Constant	0.78 (45.77)	0.02	(0.74, 0.81)

Note: t statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1% (Reprinted from Guofeng Wang et al. (2015) with permission of Physics and Chemistry of the Earth)

The results of the Tobit model showed that increasing the investment, modification on plantation structure, and adjustment on industrial structure contributed to improving the agricultural water-use efficiency. Increasing 10% fixed assessment investment is capable of improving agricultural water-use efficiency by 0.1%; expanding 1% of the wheat area can improve agricultural water-use efficiency by 0.22%. As a result, during upgrading the industrial structure, it guarantees the agricultural water consumption and avoids low efficiency and waste.

Summary

Irrigational expansion of the agricultural oasis will inevitably enlarge the water demand and limit the ecological sustainability in HRB. Therefore, effective measures should be adopted to control the overexpansion. Rural labor forces should be gradually guided to transfer from the planting industry to non-planting industry and then to a nonagricultural industry. The policies of grain-for-green and grain subsidies should be appropriately adjusted. The grain subsidy in HRB should be canceled or

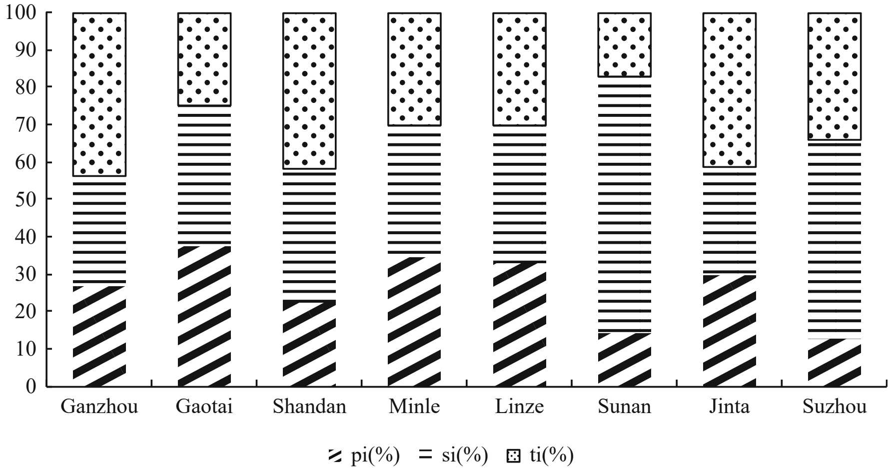

Fig. 13 Proportions of three industries in 2012 (*pi*, *si*, and *ti* refer to the proportion of the output value of the primary industry, second industry, and tertiary industry in local GDP, respectively) (Reprinted from Guofeng Wang et al. (2015) with permission of Physics and Chemistry of the Earth)

gradually reduced. However, the compensation of grain-for-green subsidies should be increased.

In this study, taking the Heihe River Basin in the Northwest China as a case study area, we have applied an integrated model to analyze the agricultural water-use efficiency. The importance of improving the agricultural water-use efficiency has been justified; the results revealed that the strengthening of agricultural infrastructure and increasing the percentage of agriculture and the planning structure both have positive effect on the improvement of agricultural water-use efficiency. But the influence from technological advancement is more powerful. In China, there are more than 459 irrigated areas with different irrigation technique levels, with a considerable number having the problem of high crop water-use efficiency but low agricultural water-use efficiency. In this sense, the accurate measurement on the agricultural water-use efficiency and its driving factors is conductive to the efficient water resource utilization.

Improving water-use efficiency is a complex process, in which the systematic and regional perspectives are in an anticipation to be integrated to seek the water-saving scheme in arid areas. Water conservation in crop and industry is suggested to be combined to improve the regional agricultural water-use efficiency. At regional level, regulations on improving agricultural water-use security by improving agricultural water-use efficiency are expected, and the zoning and categorization approaches are also advised to be implemented in precision management on agricultural water consumption in arid areas.

Impacts of water allocation on farmer income distribution need to be further investigated for regional policy implication of water resource management in different regions of China. Studying regional diversification of water use will contribute to understanding the knowledge of a comprehensive system of watershed management and reinforce the relationships between water allocation and farmer income distribution changes and trade-offs between rural and urban areas. For instance, water-saving for yield increase in northeastern China, water-saving for economic efficiency in Northwest China, water-saving for urban expansion in the middle of northern China, water-saving for pollution mitigation in southern China, and water-saving under regional climatic characteristics in the mountain area may further contribute to this issue. Furthermore, policies, reviews, and studies of water-saving are further needed to fulfill the strategic plan of "water-saving society" in China, for instance, the cost-benefit analysis dealing with relationships between water quota management and irrigation efficiency, the relevant subsidy of irrigation and monitoring system assessment, market-oriented water allocation and smooth transmission mechanism of water management, and so forth.

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